

Hohenheimer
Volkswirtschaftliche Schriften

67

Julian P. Christ

**Innovative Places
in Europe**

Research Clustering,
Co-Patenting Networks
and the Growth of Regions

PETER LANG

Frankfurt am Main · Berlin · Bern · Bruxelles · New York · Oxford · Wien
via free access

Julian P. Christ - 978-3-653-01778-6

Downloaded from <https://www.peterlang.com> at 11/16/2024 11:45:28 AM

Innovative Places in Europe

Hohenheimer Volkswirtschaftliche Schriften

Herausgegeben von

Prof. Dr. Michael Ahlheim, Prof. Dr. Thomas Beißinger, Prof. Dr. Ansgar Belke,
Prof. Dr. Rolf Caesar, Prof. Dr. Gabriel Felbermayr, Prof. Dr. Harald Hagemann,
Prof. Dr. Klaus Herdzina, Prof. Dr. Walter Piesch, Prof. Dr. Andreas Pyka,
Prof. Dr. Nadine Riedel, Prof. Dr. Ingo Schmidt, Prof. Dr. Ulrich Schwalbe,
Prof. Dr. Peter Spahn, Prof. Dr. Jochen Streb, Prof. Dr. Gerhard Wagenhals

Band 67



PETER LANG

Frankfurt am Main · Berlin · Bern · Bruxelles · New York · Oxford · Wien

Julian Phillip Christ

**Innovative Places
in Europe**

Research Clustering,
Co-Patenting Networks
and the Growth of Regions



PETER LANG

Frankfurt am Main · Berlin · Bern · Bruxelles · New York · Oxford · Wien

Bibliographic Information published by the Deutsche Nationalbibliothek

The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data is available in the internet at <http://dnb.d-nb.de>.

Open Access: The online version of this publication is published on www.peterlang.com and www.econstor.eu under the international Creative Commons License CC-BY 4.0. Learn more on how you can use and share this work: <http://creativecommons.org/licenses/by/4.0>.



All versions of this work may contain content reproduced under license from third parties.

Permission to reproduce this third-party content must be obtained from these third-parties directly.

This book is available Open Access thanks to the kind support of ZBW – Leibniz-Informationszentrum Wirtschaft.

D 100

ISSN 0721-3085

ISBN 978-3-653-01778-6 (E-Book)

DOI 10.3726/978-3-653-01778-6

ISBN 978-3-631-63303-8 (Print)

© Peter Lang GmbH

Internationaler Verlag der Wissenschaften

Frankfurt am Main 2012

www.peterlang.de

Julian Phillip Christ - 978-3-653-01778-6

Downloaded from PubFactory at 01/11/2019 11:19:23AM

via free access

Acknowledgements

I want to express my deep gratitude to my first supervisor, Prof. Dr. Harald Hagemann (University of Hohenheim), and my second supervisor, Prof. Dr. Jochen Streb (University of Mannheim), whose critical comments, encouragement and guidance were of significant importance to me throughout my doctoral studies. I am also grateful to Prof. Dr. Andreas Pyka (University of Hohenheim) for his fruitful comments and advice and for chairing my thesis committee.

During my doctoral studies, I benefited from several PhD courses, conferences and research seminars which significantly supported and influenced my research ambitions. I thank the participants of the First Graz Schumpeter Summer School 2007 (University of Graz), the participants of the Max Planck evolutionary economics PhD workshop 2008 (Jena), the participants of the ESSID 2008 PhD course (Monte St. Angelo, Italy), the participants of the International PhD course on economic geography 2010 (University of Utrecht), the participants of the Zvi Griliches research conference 2010 (Barcelona Graduate School of Economics), to name but a few. Moreover, the participants of the FZID PhD workshops and the PhD seminars of the economics department at the University of Hohenheim are gratefully acknowledged for valuable comments and critical discussions. Furthermore, I owe many thanks to my colleagues at the economics department for their encouragement and for giving me their friendship: Dr. Constanze Dobler, Patricia Hofmann, Ralf Rukwid, Arash Molavi Vasséi, Niels Geiger, Johannes Schwarzer, Larissa Talmon-Gros, Dr. Felix Geiger, Oliver Sauter, Lukas Scheffknecht, Dr. Tobias Börger, Martin Lempe. I enjoyed a very good research atmosphere and many lively discussions, economic and otherwise. Special thanks go to Ralf Rukwid for profound discussions, valuable comments and the very good cooperation on other research projects and to Christine Eisenbraun for her continuous support. I also want to thank Anika Weckemann for enriching discussions and her support regarding database technology. Furthermore, I sincerely thank Patricia Hofmann, Ralf Rukwid and André P. Slowak for their cooperation on different papers.

My heartfelt thanks go to my family. I thank my parents Wolfgang and Ulrike, whose trust, continuous encouragement and support have carried me through this part of my life, and my grandfather, Prof. Dr. Walter Christ, whose academic career was a great inspiration to me. Finally, I want to express my deepest gratitude to my wife Liane, who suffered long hours of neglect during the preparation of the thesis. I thank her for her love, support and patience.

Julian P. Christ
Stuttgart-Hohenheim, November 2011

Table of Contents

List of Figures	xi
List of Tables	xv
List of Boxes	xvii
List of Abbreviations	xix
1. Innovative Places in Europe	1
1.1. Introduction and Motivation	1
1.2. Outline of the Thesis and Research Questions	15
2. Research Clustering, Co-Inventor Networks and Innovative Places: A Literature Survey	21
2.1. A Survey of the Theoretical Literature	21
2.1.1. The Co-Evolution of Research Strands in the Cluster Literature	21
2.1.2. From First-Nature Agglomerations to Knowledge-Intensive Industries	25
2.1.3. Agglomeration, Indivisibilities and Fragmentation	28
2.1.4. Agglomeration, Clustering and External Economies	31
2.1.4.1. Industrial Districts and External Economies	31
2.1.4.2. Interpretations of Marshall's Agglomeration Economies	34
2.1.4.3. Agglomeration Economies, Spillovers and Networks: A Taxonomy	36
2.1.5. Agglomeration, Research Clustering and Pecuniary Externalities	37
2.1.5.1. Pecuniary Externalities, Local Scale and Efficiency	37
2.1.5.2. Localization Economies	39
2.1.5.3. Urbanization Economies	41
2.1.5.4. A Taxonomy of Urbanization and Localization Economies	42
2.1.5.5. Core-Periphery Structures and Endogenous Location	43
2.1.5.5.1. The Origins of the New Economic Geography	43
2.1.5.5.2. Industry Agglomeration, Core-Periphery and Footloose Labor	46
2.1.5.5.3. Alternative Core-Periphery Models	48
2.1.5.5.4. Critical Remarks and Discussion	49
2.1.6. Industry and Research Clustering and Innovation Externalities	51
2.1.6.1. Non-Pecuniary Externalities	51
2.1.6.2. Marshall-Arrow-Romer Externalities and Specialized Clusters	53
2.1.6.3. Jacobs Externalities and Diversity in Cities	55
2.1.6.4. Porter Externalities and the Competitive Advantage of Regions	57
2.1.6.5. A Taxonomy of Innovation Externalities	58
2.1.6.6. Endogenous Growth Theory and Research Clustering	59
2.1.6.6.1. Knowledge Stocks and Knowledge Spillovers	59

2.1.6.6.2.	Technological Externalities and Specialization	61
2.1.6.6.3.	Conclusions and Critical Remarks	62
2.1.6.7.	Research Clustering and Knowledge Flows in Core-Periphery Models . .	64
2.1.6.7.1.	Agglomerations, Blueprints and Technological Externalities	64
2.1.6.7.2.	Growth-Cum-Geography Models and R&D	66
2.1.6.7.3.	Critical Remarks and Discussion	70
2.1.7.	Agglomerations, Networks and Knowledge Transmission	71
2.1.7.1.	Knowledge Flows, Network Linkages and Spillovers	71
2.1.7.2.	Tacit versus Codified Knowledge and the Embodiment Concept	72
2.1.7.3.	Agglomerations, Innovative Milieus and the Proximity Hypothesis . . .	75
2.1.7.4.	Long-Distance Linkages and R&D Collaboration Networks	78
2.1.7.5.	Localized Networks versus Inter-Regional Network Linkages	80
2.1.7.6.	City Networks and Inter-Regional Research Collaborations	81
2.1.7.7.	Agglomeration vs. Networks: Critical Remarks	84
2.2.	A Survey of the Empirical Literature	86
2.2.1.	The Co-Evolution of Different Strands of Empirical Research	86
2.2.2.	Regional Disparities, Urbanization and Research Clustering	87
2.2.3.	The Regional Knowledge Production Function	91
2.2.3.1.	The Origins of the Knowledge Production Function	91
2.2.3.2.	The Regional Knowledge Production Function	93
2.2.3.3.	Knowledge Flows and R&D Spillovers in Europe and the US	94
2.2.4.	Localization, Urbanization and Regional Development	100
2.2.5.	Patent Citations, Paper Trails and Real Spillovers	102
2.2.6.	Researcher Mobility, Social Networks and Diaspora	106
2.2.7.	Research Collaborations and Co-Patenting Networks	110
3.	Innovative Places, Research Clustering and Co-Agglomeration	117
	in Europe	
3.1.	Analyzing Research Clustering in Europe	117
3.2.	Patent Data as Indicators in Empirical Analysis	122
3.2.1.	Advantages of Patent Data as Indicators	122
3.2.2.	Drawbacks and Technical Issues of Patent Data	125
3.3.	The Database: Patent Data, Regions and Research Activity	126
3.3.1.	Overview and General Information	126
3.3.2.	The Spatial Classification System	128
3.3.3.	The IPC-Technology Field Concordance	129
3.4.	Geographic Concentration and Regional Disparities of Research Activities	130
3.4.1.	Measuring Geographic Concentration and Regional Disparities	130
3.4.1.1.	Aggregate Distribution, Specialization and Disparity	130
3.4.1.2.	Skewness and Kurtosis	132
3.4.1.3.	The Herfindahl-Hirschman Index	133
3.4.1.4.	The Location Quotient and Relative Technological Advantage	134
3.4.1.5.	The Relative Technology Density	135
3.4.1.6.	The Locational Gini Coefficient	135
3.4.1.7.	The Spatial Gini Coefficient	140
3.4.2.	Three Decades of EPO Patenting in Europe	141

3.4.2.1.	Skewed Distributions and Core-Periphery Structures	141
3.4.2.1.1.	Whisker Box-Plot	141
3.4.2.1.2.	Core-Periphery Structures and Patent Densities	144
3.4.2.1.3.	Kurtosis, Skewness and Herfindahl-Hirschman Index	145
3.4.2.2.	Regional Patenting Activity and EPO Inventors in Europe	153
3.4.2.2.1.	Patent Applications by Technology Field	153
3.4.2.2.2.	EPO Inventors by Technology Field	156
3.4.2.2.3.	Revealed Technological Advantage	156
3.4.2.3.	Regional Disparities of EPO Patenting Activity	158
3.4.2.3.1.	Locational and Spatial Gini Coefficients by Technology Field	158
3.4.2.3.2.	Dynamics of Gini Coefficients by Technology Field	176
3.5.	Identifying Research Clusters and Co-Agglomeration in Europe	180
3.5.1.	Research Clusters, Cities and Inventorship	180
3.5.2.	The Research Cluster Index	181
3.5.2.1.	Constructing a Research Cluster Index	181
3.5.2.2.	Interpretation of the Research Cluster Index	183
3.5.3.	Patent Data, Regional Typology and Technology Fields	184
3.5.4.	Research Clusters in Europe by Technology Field	185
3.5.4.1.	Global Statistics: Research Clusters by Technology Field and Country	185
3.5.4.2.	Local Statistics: Innovative Places and Leading Regions	200
3.5.5.	Co-Agglomeration of Research Clusters in Europe	210
3.5.6.	Research Clustering in Urban Areas and Capital Regions	213
4.	European Co-Patenting Networks and Inter-Regional Linkages	219
4.1.	Analyzing European Research Collaborations	219
4.2.	Spatial Interdependence of European Patenting Activity	224
4.2.1.	Measuring Spatial Interdependence	224
4.2.1.1.	Explanatory Spatial Data Analysis	224
4.2.1.2.	Spatial Analysis and the Modifiable Areal Unit Problem	226
4.2.1.3.	Neighborhood Effects, Distances and Weight Matrices	227
4.2.1.4.	Spatial Dependence and Regional Spillovers	229
4.2.2.	Spatial Interdependence of Patenting Activity in Europe	232
4.3.	European Co-Patenting Networks and Foreign Co-Inventors	235
4.3.1.	International versus Inter-Regional Co-Patenting Linkages	235
4.3.2.	The Relational Database	236
4.3.2.1.	Regional Classification and Raw Data	236
4.3.2.2.	From IPC to Technology Field Aggregates	237
4.3.3.	The Research Methodology	238
4.3.3.1.	Calculating Co-Patenting Network Linkages	238
4.3.3.2.	Measuring Network Centralities of Regions	241
4.3.4.	Foreign Co-Inventors and Research Collaborations in Europe	243
4.3.5.	European Regional Co-Patenting Networks: Global Network Statistics	246
4.3.5.1.	Network Size and Structure by Technology Field	246
4.3.5.2.	Spatial Proximity versus Inter-Regional Linkages	249
4.3.5.3.	Core-Periphery Structures and the East-West Gradient	260
4.3.6.	European Regional Co-Patenting Networks: Local Network Statistics	276

4.3.6.1.	Co-Patenting Networks and the Centrality of Regions	276
4.3.6.2.	Co-Agglomeration of Co-Patenting Networks	280
5.	Research Clustering, Income Disparities and the Growth of Regions in Europe	283
5.1.	Analyzing Regional Disparities and Growth	283
5.2.	The Database: Regions, Patents and the Settlement Structure	291
5.3.	The Development of Income Disparities in Europe	292
5.3.1.	A Descriptive Overview	292
5.3.2.	Measures of Concentration, Disparity and Inequality	298
5.3.2.1.	Regional Disparities and the Gini Coefficient	298
5.3.2.2.	Measures of Regional Disparity and Inequality Decomposition	301
5.3.3.	The Development of European Income Disparities	304
5.3.3.1.	Global Income Disparities in Europe	304
5.3.3.2.	Regional Disparities within and between European Countries	308
5.4.	Research Activity, Settlement Structure and Regional Growth	309
5.4.1.	Income Levels and Regional Growth: A Descriptive Overview	309
5.4.2.	Unconditional Convergence and European Regional Growth	313
5.4.3.	Conditional Convergence and Regional Growth in Europe	316
5.4.3.1.	Conditional Convergence and Regional Growth	316
5.4.3.2.	Regional Growth in the EU-15	321
5.4.3.3.	Regional Growth in the New Member States	323
5.4.4.	European Regional Growth and Spatial Spillovers	325
5.4.4.1.	A General Spatial Model	325
5.4.4.2.	Regional Growth Models and Spatial Interdependence	327
5.4.4.3.	Estimation Results	330
6.	Summary, Conclusions and Future Research	337
6.1.	The Literature Review	337
6.2.	Research Clustering in Europe	342
6.3.	Inter-Regional Co-Patenting Linkages in Europe	345
6.4.	Regional Growth and Income Disparities in Europe	349
A.	Appendix: Figures	xxiii
B.	Appendix: Tables	lxxiii
	Bibliography	lxxxvii

List of Figures

1.1.	Patent applications at the EPO 1977-2005	6
1.2.	Patent applications at the EPO 1977-2005 by country	7
1.3.	EPO patent application density 2003-2004	9
1.4.	Number of EPO patent applications with foreign co-inventors	11
3.1.	Lorenz curve of an unweighted Gini coefficient	137
3.2.	Lorenz curve of a weighted Gini coefficient	138
3.3.	The Lorenz curve of a locational (and spatial) Gini coefficient	139
3.4.	Spatial distribution: patent application density of European regions by country	142
3.5.	Spatial distribution: patent application density of European regions by country	143
3.6.	Spatial distribution: patent application density of European regions by country	144
3.7.	Patent density (per million inhabitants) by region 1985-1986	146
3.8.	Patent density (per million inhabitants) by region 2003-2004	147
3.9.	High-tech EPO patent density (per million inhabitants) by region 1985-1986	148
3.10.	High-tech EPO patent density (per million inhabitants) by region 2003-2004	149
3.11.	Share of European regions with $n > 0$ patent applications by TF	155
3.12.	Share of European regions with $n > 1$ inventor IDs by TF	157
3.13.	Share of European regions with $RTA > 1$ by TF	159
3.14.	Change of regions w/ $RTA > 1$ by TF: 1988-1990 vs. 2002-2004	160
3.15.	European regions w/ $RTA > 1$ of regions w/ $n > 0$ patent applications	161
3.16.	Locational Gini: regional disparity of EPO patenting by TF (1)	162
3.17.	Locational Gini: regional disparity of EPO patenting by TF (1)	163
3.18.	Locational Gini: regional disparity of EPO patenting by TF (2)	166
3.19.	Locational Gini: regional disparity of EPO patenting by TF (2)	167
3.20.	Locational Gini: regional disparity of EPO patenting by TF (3)	168
3.21.	Locational Gini: regional disparity of EPO patenting by TF (3)	169
3.22.	Spatial Gini: regional disparity of EPO patent applications by TF	171
3.23.	Spatial Gini: regional disparity of EPO patent applications by TF	172
3.24.	Locational Gini: regional disparity of EPO patent applications (all IPC) (a)	174
3.25.	Locational Gini: regional disparity of EPO patent applications (all IPC) (b)	175
3.26.	Change (%) of locational Gini: regional disparities by TF (819 TL3)	177
3.27.	Change (%) of locational Gini: regional disparities by TF in EU-15 and NMS	178
3.28.	Change (%) of spatial Gini: development of regional disparities by TF	179
3.29.	Structure of research clusters by TF and RCI class, 1990-1994	186
3.30.	Structure of research clusters by TF and RCI class, 2000-2004	187
3.31.	Change of research clusters by TF and RCI class, 2000-2004 vs. 1990-1994	189

3.32.	Change of research clusters by TF with $RCI > 16$	191
3.33.	Change number and structure of research clusters by TF	196
3.34.	Change of research clusters (RCI) in ERA by TF	201
3.35.	Co-agglomeration of TF cluster (RCI), 2000-2004	212
3.36.	Density function of clusters with $RCI > 81$, 1990-1994 and 2000-2004 . . .	217
3.37.	Density function of clusters with $RCI > 81$, 1990-1994 and 2000-2004 . . .	218
4.1.	Inter-regional knowledge pipelines and co-patenting network linkages	223
4.2.	Aggregation, zones and concentration measures	227
4.3.	Inter-regional co-patenting network linkages	240
4.4.	Number of EPO patents with foreign co-inventors by country (1)	244
4.5.	Number of EPO patents with foreign co-inventors by country (2)	245
4.6.	Structure of European co-patenting networks, 1990-1994	253
4.7.	Structure of European co-patenting networks, 2000-2004	254
4.8.	Changing structure of inter-regional network linkages	259
4.9.	Change (number) of co-patenting linkages between NMS and EU-15	264
4.10.	Change (%) of co-patenting linkages between NMS and EU-15	265
4.11.	European co-inventor network: TF10 Basic chemicals, 1990-1994	266
4.12.	European co-inventor network: TF10 Basic chemicals, 2000-2004	267
4.13.	European co-inventor network: TF13 Pharmaceuticals, 1990-1994	268
4.14.	European co-inventor network: TF13 Pharmaceuticals, 2000-2004	269
4.15.	European co-inventor network: TF38 Measuring instruments, 1990-1994 . .	270
4.16.	European co-inventor network: TF38 Measuring instruments, 2000-2004 . .	271
4.17.	European co-inventor network: TF41 Watches & clocks, 1990-1994	272
4.18.	European co-inventor network: TF41 Watches & clocks, 2000-2004	273
4.19.	European co-inventor network: TF42 Motor vehicles, 1990-1994	274
4.20.	European co-inventor network: TF42 Motor vehicles, 2000-2004	275
4.21.	Geographical coincidence of TF: degree centrality	281
5.1.	GDP per capita (PPP) year 1995	294
5.2.	GDP per capita (PPP) year 2006	295
5.3.	Growth Rates of GDP per capita (PPP) 1995-2006	297
5.4.	Boxplot: GDP per capita (PPP) level vs. growth rate	299
5.5.	Kernel density: density function of income distribution TL3 regions by group	300
5.6.	Development of regional disparities in GDP/capita (PPP) by group	305
5.7.	Locational Gini coefficients of GDP per capita (PPP) (a)	306
5.8.	Locational Gini coefficients of GDP per capita (PPP) (b)	307
5.9.	Income inequality decomposition: EU-23, CH, NO	310
5.10.	Income inequality decomposition: EU-14 group	311
5.11.	Income inequality decomposition: NMS group	312
5.12.	Scatterplot GDP/capita level (1995) vs. growth rate (1995-2006), EU-15 . .	313
5.13.	Scatterplot GDP/capita level (1995) vs. growth rate (1995-2006), NMS . .	314
5.14.	Scatterplot GDP/capita level (1995) vs. growth rate (1995-2006), EU-25 . .	314
A.1.	EPO Patent Applications: Share by Region and Quantile	xxiv
A.2.	High-tech EPO Patent Applications: Share by Region and Quantile	xxv
A.3.	Aviation Technology: EPO Patent Application Density by Region	xxvi

A.4. Computer & Office Machines: EPO Patent Application Density by Region	xxvii
A.5. Communication Technology: EPO Patent Application Density by Region	xxviii
A.6. Microorgan. & Genetics: EPO Patent Application Density by Region	xxix
A.7. Laser Technology: EPO Patent Application Density by Region	xxx
A.8. Semiconductors: EPO Patent Application Density by Region	xxxix
A.9. Share of European regions with $n > 9$ patent applications by TF	xxxii
A.10. Share of European regions with $n > 9$ inventor IDs by TF	xxxiii
A.11. Share of European regions w/ $RTA > 1$ of regions w/ $n > 0$ patent applications	xxxiv
A.12. Austria: Locational Gini of EPO Patent Applications by TF (a)	xxxv
A.13. Austria: Locational Gini of EPO Patent Applications by TF (b)	xxxvi
A.14. Belgium: Locational Gini of EPO Patent Applications by TF (a)	xxxvii
A.15. Belgium: Locational Gini of EPO Patent Applications by TF (b)	xxxviii
A.16. Switzerland: Locational Gini of EPO Patent Applications by TF (a)	xxxix
A.17. Switzerland: Locational Gini of EPO Patent Applications by TF (b)	xl
A.18. Germany: Locational Gini of EPO Patent Applications by TF (a)	xli
A.19. Germany: Locational Gini of EPO Patent Applications by TF (b)	xlii
A.20. France: Locational Gini of EPO Patent Applications by TF (a)	xliii
A.21. France: Locational Gini of EPO Patent Applications by TF (b)	xliv
A.22. Italy: Locational Gini of EPO Patent Applications by TF (a)	xlv
A.23. Italy: Locational Gini of EPO Patent Applications by TF (b)	xlvi
A.24. Netherlands: Locational Gini of EPO Patent Applications by TF (a)	xlvii
A.25. Netherlands: Locational Gini of EPO Patent Applications by TF (b)	xlviii
A.26. Sweden: Locational Gini of EPO Patent Applications by TF (a)	xlix
A.27. Sweden: Locational Gini of EPO Patent Applications by TF (b)	l
A.28. United Kingdom: Locational Gini of EPO Patent Applications by TF (a)	li
A.29. United Kingdom: Locational Gini of EPO Patent Applications by TF (b)	lii
A.30. Change of research clusters (RCI) in ERA by TF (2)	liii
A.31. Co-agglomeration of TF cluster (RCI), 1990-1994	liv
A.32. Technological diversity, co-agglomeration and clustering in capital regions	lv
A.33. Technological diversity, co-agglomeration and clustering in metro regions	lvi
A.34. Technological diversity, co-agglomeration and clustering in urban regions	lvii
A.35. Technological diversity, co-agglomeration and clustering in intermediate regions	lviii
A.36. Technological diversity, co-agglomeration and clustering in rural regions	lix
A.37. Data selection method for inter-regional co-inventorship network analysis	lx
A.38. Share of EPO patents with foreign co-inventors by country (1)	lxi
A.39. Share of EPO patents with foreign co-inventors by country (2)	lxii
A.40. Foreign co-inventorship structure by country	lxiii
A.41. Foreign co-inventorship structure by country (cont'd)	lxiv
A.42. Number of European co-patenting network linkages, 1990-1994	lxv
A.43. Number of European co-patenting network linkages, 2000-2004	lxvi
A.44. Geographical coincidence of TF: betweenness centrality	lxvii
A.45. Geographical coincidence of TF: eigenvector centrality	lxviii
A.46. Income inequality decomposition: EU-15 vs. NMS	lxix
A.47. GDP per capita (2000) and Regional Typology	lxx
A.48. Patenting Activity in Europe 1995	lxxi

List of Tables

2.1.	Innovation vs. efficiency externalities	38
2.2.	Taxonomy of agglomeration economies	40
2.3.	Pecuniary externalities	43
2.4.	Innovation externalities	60
2.5.	Cumulative causation and forces of agglomeration	67
2.6.	Mechanisms of knowledge acquisition	71
2.7.	Modes of transfer of tacit and codified knowledge	74
2.8.	Transfer channels of knowledge via agents, goods and documents	75
2.9.	Network linkages and externalities	79
3.1.	Descriptives: EPO patent applications by technology field	151
3.2.	Descriptives: EPO inventors by technology field	152
3.3.	Descriptives: Change of EPO inventors and patent applications by TF	154
3.4.	Research clusters by TF and country with $RCI > 1$, 2000-2004	193
3.5.	Research clusters by TF and country with $RCI > 16$, 2000-2004	194
3.6.	Change (percentage) of research clusters (RCI) in ERA by TF	197
3.7.	Change (percentage) of research clusters (RCI) in ERA by TF	198
3.8.	Change (percentage) of research clusters (RCI) in ERA by TF	199
3.9.	Ranking of RCI: TOP20 cluster regions by technology field	205
3.10.	Ranking of RCI: TOP20 cluster regions by technology field (cont'd)	206
3.11.	Ranking of RCI: TOP20 cluster regions by technology field (cont'd)	207
3.12.	Ranking of RCI: TOP20 cluster regions by technology field (cont'd)	208
3.13.	Ranking of RCI: TOP20 cluster regions by technology field (cont'd)	209
3.14.	Co-agglomeration of research clusters and regional typology	214
4.1.	Moran's I z-scores by technology field and threshold ϑ	234
4.2.	Number of connected regions in co-patenting networks	248
4.3.	Number of inter-regional co-patenting network linkages	251
4.4.	Inter-regional linkages by technology field: structural change (1)	255
4.5.	Inter-regional linkages by technology field: structural change (2)	256
4.6.	Structure of European co-patenting networks: unique linkages	257
4.7.	Structure of network linkages between the NMS and EU-15	261
4.8.	Degree centrality ranking of TOP10 regions (1-5)	278
4.9.	Degree centrality ranking of TOP10 regions (6-10)	279
5.1.	Unconditional and conditional convergence for EU-25, EU-15 and NMS	316
5.2.	Robust OLS estimation results: national growth regressions (1)	316
5.3.	Robust OLS estimation results: national growth regressions (2)	317
5.4.	Dependent variable, covariates and controls	320
5.5.	Expected signs of explanatory variables	320

5.6.	Robust regression for EU-15 regions	324
5.7.	Robust regression for NMS	326
5.8.	Spatial regression (ML-SAR) for EU-15 regions	333
5.9.	Spatial regression (ML-SAR) for EU-15 regions (cont'd)	334
5.10.	Spatial regression (ML-SAR) for NMS regions	335
B.1.	Overview of selected empirical studies	lxxiv
B.2.	SQL database structure	lxxv
B.3.	RegPAT and the NUTS3/TL3 classification	lxxvi
B.4.	IPC - technology field concordance	lxxvii
B.5.	Distance weights and spatial lags	lxxviii
B.6.	Research clusters by TF and country with $RCI > 1$, 1990-1994	lxxix
B.7.	Research clusters by TF and country with $RCI > 16$, 1990-1994	lxxx
B.8.	Change (numbers) of research clusters (RCI) in ERA by TF	lxxxii
B.9.	Betweenness centrality ranking of TOP10 regions (1-5)	lxxxii
B.10.	Betweenness centrality ranking of TOP10 regions (6-10)	lxxxiii
B.11.	Spatial maximum likelihood regression (ML-SAR) for EU-15	lxxxiv
B.12.	Spatial maximum likelihood regression (ML-SAR) for NMS	lxxxv

List of Boxes

Box 1.1	The European Research Area	14
Box 3.1	Patent Applications	121
Box 3.2	The European Patent Convention and the EPO	124
Box 3.3	The International Patent Classification - IPC	130
Box 3.4	Preferable Axioms of Inequality Measures	132
Box 4.1	Spatial Interdependence and Autocorrelation	226
Box 4.2	Interpreting Moran's <i>I</i>	232
Box 5.1	European Regional Policy	286
Box 5.2	Regional Growth Studies - A Short Overview	289

List of Abbreviations

2SLS	Two-stage least squares
A	Atkinson index
a.k.a.	also known as
AT	Austria
AIC	Akaike information criterion
BBR	Bundesamt für Bauwesen und Raumordnung
BE	Belgium
CEEC/CEE-10	Central and Eastern European Countries
CES	Constant elasticity of substitution
CH	Switzerland
CMSA	Consolidated metropolitan statistical area
CP	Core-periphery
CRS	Constant returns to scale
CY	Cyprus
CZ	Czech Republic
DE	Germany
DK	Denmark
DPMA	Deutsches Patent- und Markenamt
e.g.	exempli gratia
EC	European Community
EE	Estonia
EEG	Evolutionary economic geography
emp.	employment
EPC	European Patent Convention
EPO	European patent Office
ERA	European Research Area
ERDF	European Regional Development Fund
ES	Spain
ESDA	Exploratory spatial data analysis
ESF	European Social Fund
ESPON	European Spatial Planning Observation Network
EU	European Union
EU-15	European Union of 15 member states
EU-25	Enlarged European Union of 25 member states
EU-27	Enlarged European Union of 27 member states
FC	Footloose capital
FE	Footloose entrepreneur

FI	Finland
FR	France
GDP	Gross domestic product
GE	Generalized entropy index
GINI	Gini Index
GIS	Geographical information system
GLOC	Locational Gini
GMM	Generalized method of moments
GR	Greece
GSPACE	Spatial Gini
GVA	Gross value added
HHI	Herfindahl-Hirschman index
HME	Home market effect
HRST	Human resources in science and technology
HT	High-technology
HU	Hungary
i.a.	inter alia
ICT	Information and communications technology
ID	Identifier
IE	Ireland
i.e.	id est
innov.	innovation
IPC	International Patent Classification
IPR	Intellectual property rights
ISI	Fraunhofer-Institut für System- und Innovationsforschung
IT	Italy
IV	Instrumental variable
JPO	Japan Patent Office
KPF	knowledge production function
kurt.	kurtosis
LKS	Localized knowledge spillover
LM-ERR	Lagrange multiplier error
LM-LAG	Lagrange multiplier lag
log (ln)	Logarithm (natural)
LQ	Location quotient
LT	Lithuania
LU	Luxembourg
LV	Latvia
M&A	Mergers and acquisition
MAR	Marshall-Arrow-Romer
MAUP	Modifiable area unit problem
max.	maximum
min.	minimum
mio.	million
ML	Maximum likelihood

MSA	Metropolitan statistical area
MT	Malta
NACE	Statistical Classification of Economic Activities in the European Community
nb.	number
NEG	New economic geography
NEGG	New economic geography growth
NFS	Non-full specialization
NGT	New (endogenous) growth theory
NIC	Newly industrialized country
NL	Netherlands
NMS	New member states
NO	Norway
NUTS	Nomenclature of Territorial Units for Statistics
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
P30	30th percentile
P50	50th percentile
P70	70th percentile
PCT	Patent Cooperation Treaty
pop.	population
PPP	Purchasing power parity
prod.	productivity
PT	Portugal
RCI	Research cluster index
R&D	Research and development
reg.	regional
RegPAT	OECD RegPAT database
RID	Relative inventor density
RIS	Regional systems of innovation
RPPD	Relative population patent density
RSPD	Relative spatial patent density
RTA	Revealed technological advantage
RTD	Relative technology density
SAR	Spatial autoregressive regression
SER	Spatial error regression
SER	Spatial error regression
SD	Standard deviation
SE	Sweden
SER	Spatial error
SI	Systems of Innovation
SI	Slovenia
SIC	Standard Industrial Classification
SK	Slovakia
skew	skewness

SNA	Social network analysis
STI	Science technology innovation
TCA	Transaction cost approach
TF	Technology field
TL	Territorial level (OECD)
TL1	Territorial level 1: country-level (OECD)
TL2	Territorial level 2: regional-level 1 (OECD)
TL3	Territorial level 3: regional-level 2 (OECD)
tot. nb.	Total (absolute) number
UK	United Kingdom
USA	United States
USPTO	United States Patent and Trademark Office
VL	Vertical linkage
w/	with
w/o	without
WIPO	World Intellectual Property Office
z-score	Standard score

1. Innovative Places in Europe

1.1. Introduction and Motivation

Regional disparities and the processes of regional divergence and spatial clustering are ubiquitous in today's world. Researchers frequently point to the emergence and existence of dense urban areas and systems of cities around the globe (Krugman, 2009; Desmet and Rossi-Hansberg, 2010; Henderson, 2010).¹ They discuss the nature of the emergence and growth of metropolises, megalopolises and large core cities along seaboard and rivers, which are connected to large industrial belts (Acs, 2002; Fujita and Krugman, 2003; Combes and Overman, 2004).² Accordingly, the spatial clustering of production and employment is ubiquitous in regions across the world and is considered to be only partially dependent on physical geography.

Hinloopen and van Marrewijk (2004) reported an uneven distribution, irrespective of the kind of activity or level of economic and regional aggregation.³ In the same vein, Krugman (1992, 5) has argued:

“Step back and ask, what is the most striking feature of the geography of economic activity? The short answer is surely concentration [...] production is remarkably concentrated in space.”

Once a core of economic activity has been established, be it a large city or an agglomerated region, it increases in overall size and processes of self-reinforcement increase its importance due to centripetal (agglomerative) forces and cumulative circular causation (Duranton and Puga, 2004; Combes *et al.*, 2008). Accordingly, the propensity of economic clustering can be observed on many spatial levels: the spread of blocks and downtown areas of metropolises; the formation of megalopolises; core-periphery structures at the regional level; the emergence of industry agglomerations within countries; and the spatial concentration of economic activity in a few countries within federal unions, e.g., the European Union (EU) and the United States (Combes and Overman, 2004; Fujita and Mori, 2005). Today, clustering is a phenomenon that determines the structure of both wealthy, industrialized regions and countries and also regions and countries which are in a period of transition (Duranton and Puga, 2004; Desmet and Rossi-Hansberg, 2010; Henderson, 2010).

Furthermore, Hinloopen and van Marrewijk (2004) mentioned several stylized facts which are related to the geography of economic activity. They argued that there exists a series of possible combinations of types of economic activity, its distribution, its economic and geographic aggregation, and the interaction between locations. The authors condensed the

¹ See also Duranton and Puga (2004).

² Refer also to Fujita and Mori (2005) and Florida *et al.* (2008).

³ Similar results have been reported by Brakman *et al.* (2005). See Audretsch and Feldman (1999) and Audretsch and Thurik (2001) for similar arguments.

real-world complexity of the distribution of economic activity to a few stylized facts and argued that: (i) the distribution is generally uneven, regardless of the type of economic activity; (ii) the distribution is generally uneven, regardless of the geographic aggregation level; (iii) the distribution is generally uneven, regardless of the level of economic aggregation; (iv) there is a remarkable regularity in the spatial distribution of economic activity; and (v) there exists a remarkable regularity in the interaction between regions and centers of economic activity.⁴ This study aims to approach some of these stylized facts with special focus on research activity, i.e., patenting activity, research clustering and inter-regional co-patenting networks at the level of European regions.⁵

According to recent findings which have been recorded in the economic geography literature (Krugman, 2009; Fujita and Thisse, 2009), in the urban economics literature (Duranton and Puga, 2001; Henderson, 2010) and in the economics and geography of innovation literature (Feldman, 2000; Feldman and Kogler, 2010; Malecki, 2010), spatial structure should nowadays be challenged as a central determinant of distributional dynamics and regional development, particularly in the context of knowledge-intensive industries (Tichy, 1998; Capello, 2009; Feldman and Kogler, 2010). Geographic proximity is considered to be a crucial factor with regard to innovative activity and research clustering (Camagni, 1991b; Capello, 2009; Malecki, 2010). This argument is based upon the observed “tacitness” of knowledge, which is considered to enforce the spatial concentration of research activity and thus to increase regional disparities (Lissoni, 2001; Breschi and Lissoni, 2001a; Gertler, 2003). Countries are believed to progressively shift towards knowledge-based economies and thus to generate an increasing demand for basic knowledge and highly-skilled people (Feldman, 1999; Florida, 2002b; Foray and Lissoni, 2010).

A key argument which is discussed in the literature on inventorship location and co-location is that it is not only pecuniary transactions and formal collaborations in dense, anonymous markets that matter. Research collaborations in persistent R&D networks and informal social networks between researchers are considered to be of pivotal importance for research clusters and regional development.

From a theoretical point of view, geographical economics, economic geography proper and innovation system adherents have developed an established tradition of studying spatial clustering and agglomeration phenomena in respect to the benefits of geographical proximity for innovative activity, which is often labeled as “Marshallian externalities of the third kind” (Breschi and Lissoni, 2001a; Lissoni, 2001; Henderson, 2003a).⁶ In addition to knowledge transmission via formal linkages, such as research collaborations, there is a wide consensus that knowledge spillovers constitute an important working channel for knowledge transfer at the individual and regional levels, and that these externalities have a positive

⁴ See also Duranton and Puga (2001), Combes and Overman (2004) and Hinloopen and van Marrewijk (2006).

⁵ Co-patenting or co-authorship refers to a situation in which a patent document/application either lists more than one individual as a designated inventor (co-inventor or co-assignee) or a patent is applied for by more than one individual. Within this study, the terms co-inventorship, co-authorship, co-inventing and co-patenting are used interchangeably, although the inventor address is applied in all analyses. Furthermore, the terms “research activity,” “patenting activity” and “inventorship activity” are used interchangeably, although they are indeed not perfectly overlapping (see chapter 3, section 3.2).

⁶ See also Duranton and Puga (2004).

effect on regional innovative capacity, inventive activity, per capita income, productivity and employment growth (Bottazzi and Peri, 2003; Moreno *et al.*, 2005a; Usai, 2008).⁷ The main argument is that agents (researchers, entrepreneurs), located close by and especially in cities (and clusters), should be able to innovate faster than agents located in the periphery, as spatial proximity induces spatially bounded externalities and eases the transmission of distance-sensitive tacit and codified knowledge (Florida, 1995; Fujita and Thisse, 1996; Audretsch and Feldman, 2004).⁸ It is generally argued that research collaborations and knowledge spillovers predominantly take place between neighboring regions over a short distance (Feldman, 1999; Lissoni, 2001; de Groot *et al.*, 2009).⁹ High-technology industries in particular are believed to exhibit strong tendencies to cluster in space and to co-agglomerate across a small number of regions because of their strong dependence on specific labor and capital inputs, on the transfer of tacit knowledge within formal and informal networks, and on distance-sensitive down- and upstream interactions with suppliers and customers (Feldman, 1994b; Audretsch and Feldman, 1996, 1999; Scherngell, 2007).

However, it has also been argued that essential factors for production, e.g., technology-specific R&D tasks, are increasingly external to the region (Bathelt *et al.*, 2004; Powell and Giannella, 2010; Hoekman *et al.*, 2010). According to this argument, regions are becoming increasingly dependent on the inter-regional transmission of pieces of valuable information and knowledge. In this respect, several studies have mentioned that research activities show ongoing dispersion tendencies and that research collaboration increasingly takes place via long-distance linkages within inter-regional co-inventor networks between centers of research excellence. In this regard, research collaborations that shape inter-regional networks are assumed to represent pivotal carriers of tacit and codified knowledge (Johansson, 2005; Ejermo and Karlsson, 2006; Maggioni and Uberti, 2009).¹⁰ For this reason, regions (and clusters) are considered to be positively affected by knowledge inflows, by their position in inter-regional research networks and by their international connectedness to knowledge hot spots and centers of excellence (Bathelt *et al.*, 2004; Saxenian, 2006, 2007).

Social and private marginal returns do not generally coincide in agglomerations and clusters, which is said to justify policy intervention (Duranton, 2008a). Regarding this issue, policy programs at the regional level, with the explicit aim to strengthen local and regional innovation potentialities, have become very popular within the last decade, especially at the European level but also across the OECD member states (OECD, 1999, 2007c,a, 2009a). European policymakers have shown, and are still showing, an increasing interest in regional policy programs, especially with regard to cluster creation and cluster promotion (Werker, 2006; PRO INNO Europe, 2010; Europe INNOVA, 2011).¹¹ Regional, national and European authorities are increasingly applying Science-Technology-Innovation (STI) policy programs in order to have an impact on the intra- and inter-regional growth potentialities, regional knowledge bases and regional absorptive capacities with regard to new knowledge and new technologies (Rodríguez-Pose, 2001; Vieregge and Dammer, 2007). In

⁷ See also Greunz (2003a), Greunz (2004), Greunz (2005) and Crescenzi *et al.* (2007b).

⁸ For an overview refer to Feldman (2000).

⁹ See also Camagni (1991b) and Capello and Faggian (2005).

¹⁰ See also Johnson *et al.* (2006).

¹¹ See, e.g., PRO INNO Europe (2010); Cluster Excellence (2011); Europe INNOVA (2011). Nevertheless, quantitative studies on the distribution are still missing.

this respect, regional programs on spatial clustering and inter-regional research networks are considered to intensify inter-regional knowledge flows and knowledge externalities, and to improve the attractiveness of high-technology (knowledge-intensive) locations for firms (Rodríguez-Pose and Fratesi, 2007; Hoekman *et al.*, 2010).

With regard to the European research landscape and the European cohesion and technology policy (i.e., the Europe 2020 program), three priorities can be identified (European Commission, 2011a,j): (i) smart growth and the development of a knowledge- and innovation-based economy; (ii) sustainable growth and the promotion of resource-efficient competitive industries and economies; (iii) inclusive growth, which enforces a high-employment economy with social, economic and territorial cohesion. According to the green paper of the European Commission, the intended “European Research Area” (ERA), as presented in Box 1.1, which is a policy tool but also an explicit policy target, is considered to serve several aims: (i) a significant interdisciplinary flow and exchange of researchers with high levels of mobility between institutions, regions, sectors and member states; (ii) excellent, interdependent infrastructures for research, accessible to research teams across the European regions; (iii) research organizations, which are engaged in public-private partnerships and co-operations, that are forming the core of European research clusters; (iv) clusters specialized in interdisciplinary areas and technologies and a critical mass of resources (see also Cluster Excellence, 2011); (v) an effective diffusion of knowledge between public and private research; (vi) European research programs, public research investment with common priorities, coordinated implementation and joint evaluation; (vii) increased openness of the ERA with an emphasis on neighboring regions and countries; and (viii) a clear vision and strong commitment among Europe’s partners to addressing European and global challenges (European Commission, 2011a,j). With regard to the aforementioned features, the analysis of regional disparities and the clustering of European research activities and the identification and analysis of inter-regional research collaborations is considered to be of vital importance for a detailed understanding, conclusions and normative reflections.¹²

However, research agendas have mainly emphasized the structures and dynamics of European income distribution, the development of blue- and white-collar work, the effects of trade specialization and diversification on national growth, the effects of economic integration via freeness of trade and labor mobility, and changing national growth performances from a convergence-divergence perspective (Combes and Overman, 2004; Abreu *et al.*, 2005). Spatial disaggregation and the need for an explicit recognition of geographic characteristics and regional interdependence did not become a central issue until the late 1990s. As a consequence, the analysis of the distributional dynamics of knowledge-intensive tasks and processes, i.e., regional research and patenting activity, has only ever occupied an inferior position on research agendas and in regional studies (Combes and Overman, 2004; Harris, 2008). In contrast to the well-developed theoretical and empirical literature on the structures and dynamics of production and employment at the national level, the literature on research clustering, i.e., regional patenting activity, still offers unexplored fields and unanswered research questions. In the European context, it is argued that empirical studies on the distribution and clustering of research and patenting activity have, unfortu-

¹² For a comprehensive overview refer to European Commission (2011a,j). See also Werker (2006) for an overview of the European regional policy and Hagemann and Geiger (2009) for productivity developments in Europe, the New Economy and the Lisbon agenda.

nately, occupied a rather minor position on research agendas. Furthermore, the majority of studies focused directly on spillovers, growth effects or the micro-foundations of knowledge transmission (de Groot *et al.*, 2009; Beaudry and Schiffauerova, 2009). Fortunately, the empirical literature has grown considerably, and today contains a large number and variety of seminal qualitative case studies (Saxenian, 1990; Kenney and von Burg, 1999; Glaeser, 2005b) and quantitative studies of selected countries and predefined groups of regions (Archibugi and Pianta, 1992; Amiti, 1999; Midelfart-Knarvik *et al.*, 2004). Nevertheless, a comprehensive, harmonized and quantitative pan-European study at the regional level, which challenges the aforementioned issues for a meaningful number of technology fields, and which covers the 1980s, 1990s and 2000s, is still missing. Moreover, the empirical literature is still lacking a harmonized, technology field-specific quantitative research cluster study, which applies a balanced regional classification, and which identifies research clustering through the application of a harmonized, multidimensional measure for the entire population of the 819 European TL3 regions (Martin and Sunley, 2003). Regarding the last three decades, it is still unclear whether the entire population of European regions is characterized by a decrease, increase or a lack of change in regional disparities in technology field-specific research and patenting activity.

A glance at European patent statistics demonstrates that patenting activity has increased since the 1980s (van Zeebroeck *et al.*, 2008, 2009).¹³ Figure 1.1 illustrates that the number of patent applications at the European Patent Office (EPO) has increased since the 1980s.¹⁴ The largest fraction of EPO patent applications within the EU-27 group originates from the EU-15 countries. The New Member States (NMS, also CEEC) account for a small but increasing share of EPO patent applications.¹⁵

From a national perspective, figure 1.2 highlights the number of EPO patent applications by country since 1977.¹⁶ This more disaggregated view demonstrates that patenting activity in Europe is highly skewed. Leading positions in patenting activity are occupied by, among others, Germany, France, Denmark, Italy, the United Kingdom, the Netherlands, Belgium, Sweden and Switzerland, and are today recognized as a stylized fact.¹⁷ In comparison, the less prolific countries with regard to patenting activity include Estonia, Latvia, Bulgaria, Cyprus and Malta. However, even within the EU-15 group, Greece, Portugal and large parts of Italy and Spain show rather modest levels of patenting activity and represent, together with the NMS, the lower end of the distribution. Furthermore, it is obvious from these statistics that the NMS mainly started to file patent applications at the EPO in the second half of the 1990s.

The skewness of the distribution of EPO patent applications at the national level provides unambiguous evidence that research activity is generally unevenly distributed across coun-

¹³ A similar trend is visible for patent applications at the USPTO by American inventors since 1985 (Kortum and Lerner, 1997; Hall and Ziedonis, 2001; Hall, 2005). Similarly, EPO President Benoît Battistelli has argued in January 2011 that “[t]hese figures clearly indicate that demand for patent protection is on the rise again, after the economic downturn of the previous two years.” (European Patent Office, 2011c).

¹⁴ For an overview of the structure and mission of the EPO refer to European Patent Office (2011b).

¹⁵ The CEE-10 are also labeled New Member States (NMS). In the following, the terms CEEC, CEE-10 and NMS are used interchangeably.

¹⁶ A complete list of the EU-27 countries and abbreviations is presented in table B.3 in the appendix.

¹⁷ For a comprehensive overview, refer to Combes and Overman (2004) and Frietsch and Schmoch (2006).

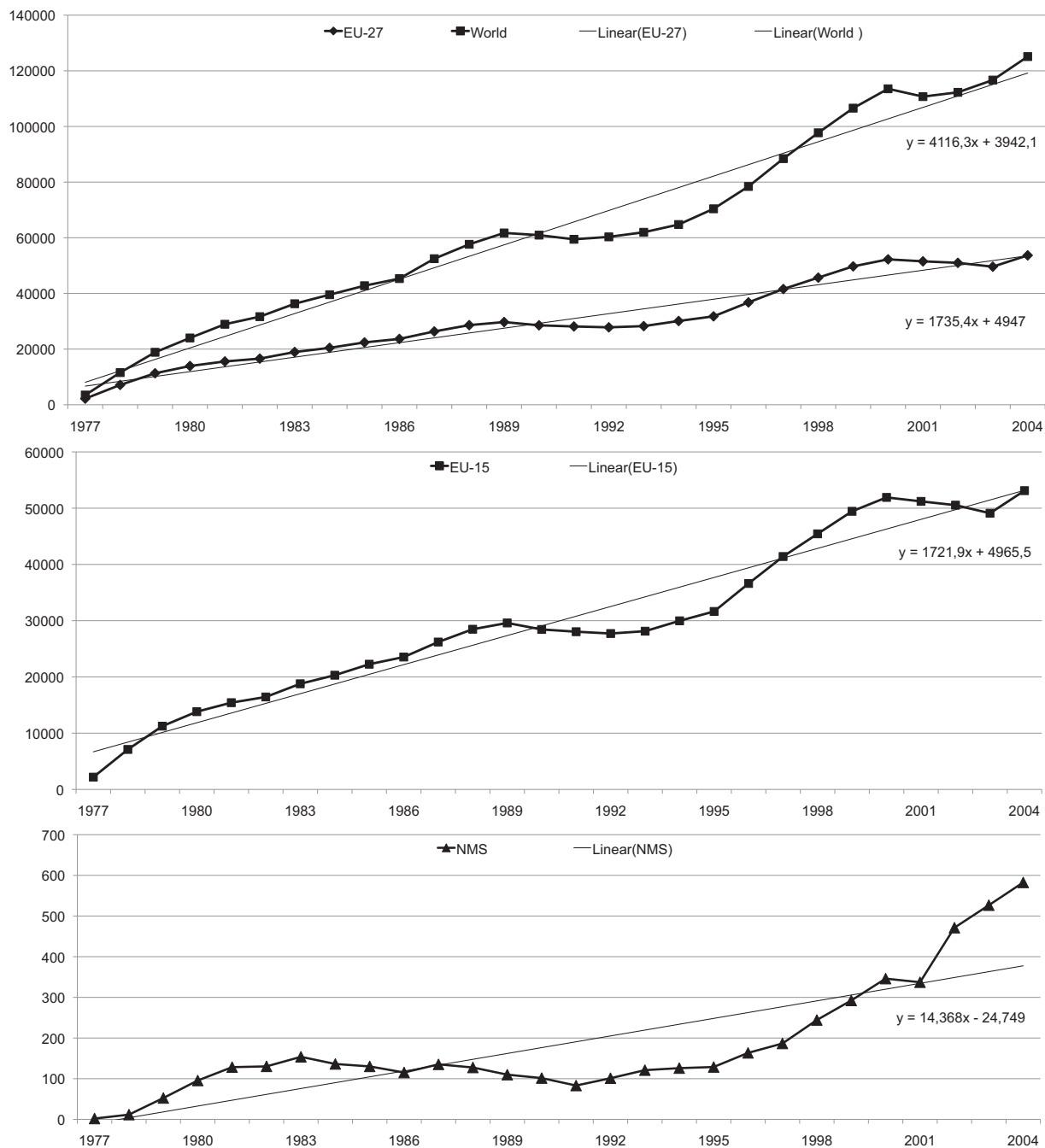


Fig. 1.1. Patent applications at the EPO 1977-2005
 Source: own illustration. Notes: Number of EPO patent applications; data extracted from OECD RegPAT (January 2009) and OECD (2009d); fractional counts.

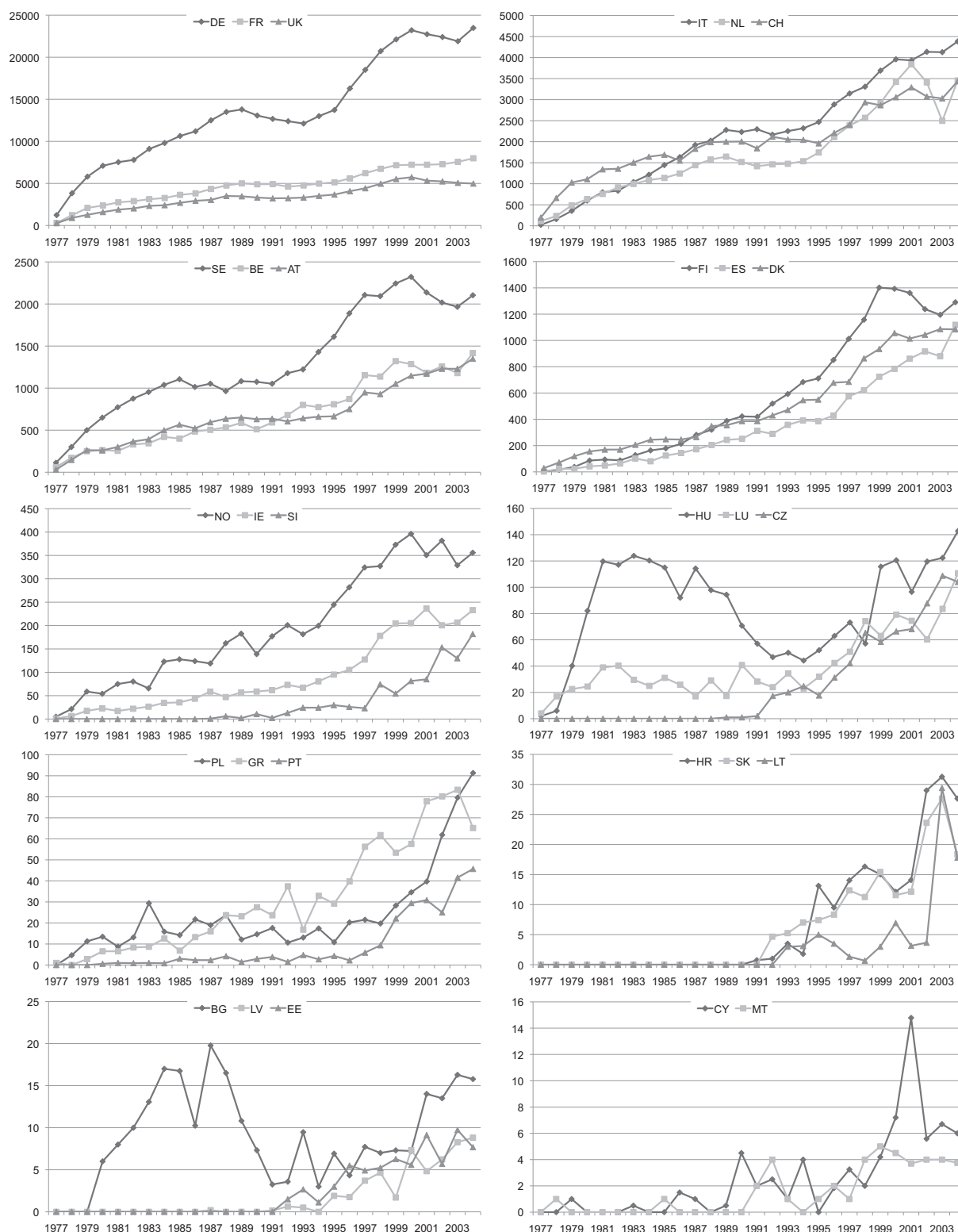


Fig. 1.2. Patent applications at the EPO 1977-2005 by country
 Source: own illustration. Notes: Number of EPO patent applications; data extracted from OECD RegPAT (January 2009) and OECD (2009d); fractional counts.

tries. However, the observed national values and obvious national disparities are solely reflections of distributions at a more disaggregated level, i.e., at the regional level. According to Combes and Overman (2004), country-level studies and cross-country comparisons have hit fairly rapidly decreasing returns. In opposition, statements about economic activity at the regional level are much more difficult to make and, up to today, only a few trans-regional studies exist. There is a meaningful lack of comprehensive pan-European studies on inventorship distribution at the regional level. Unfortunately, regional R&D data for a comprehensive number of countries and regions at the TL3 level do not exist. In this respect, the analysis of patent statistics at the regional level is considered to be a key approach to unfolding and understanding the geographic nature and regional disparities in research (patenting) activity. Moreover, it is assumed that regional studies generally overcome the significant conceptual issues which are inherent in studies that are conducted at the national level, as meaningful processes and factors are only observable at lower levels of spatial aggregation, i.e., research clustering, the inter- and intra-regional migration of researchers and localized co-patenting networks within countries (Combes and Overman, 2004; Dewhurst and McCann, 2007). This is particularly a severe issue when normative conclusions and reflections have to be developed in a political economy context.

Taking into account the criticisms presented above, the following map (figure 1.3) highlights the regional densities of EPO patent applications (2003-2004) for the 819 European TL3 regions that represent the EU-25, Switzerland and Norway (OECD, 2003, 2006).¹⁸ It is obvious that the distribution is highly skewed and that the European landscape of regions is determined by noticeable core-periphery structures.

It can be concluded that the aforementioned values of EPO patenting activity at the country level mainly result from a highly skewed distribution at the regional level. Accordingly, it seems that only a small fraction of European regions account for the majority of European research and patenting activities. Although the manifold economic factors and incentives that lead to agglomeration and clustering cannot be depicted in this study, it is nevertheless desirable for the empirical analyses to make an empirical contribution to the regional disparities illustrated above. This is one of the main objectives of this study. Hitherto, no pan-European studies exist that cover a comprehensive number of technology field aggregates and the entire population of European regions at the TL3 level. Therefore, this study presents and discusses methodologies and empirical results which are related to the structure and dynamics of research clustering and regional disparities in patenting activity in a comprehensive range of technology field aggregates in the 1980s, 1990s and 2000s, and covers the entire population of 819 European regions (EU-25, Switzerland and Norway). In addition, this study introduces a multidimensional research clustering index for harmonized global statistics and the identification of research/ innovation clusters in Europe.

Nevertheless, clustering of research and patenting activity represents only one structural aspect of the European research landscape. With regard to the previous waves of globalization, and in particular to the meaningful technological progress which has been made in the field of ICT, researchers frequently discuss the “death of distance” and “weightless

¹⁸ Regarding data generation and methodological issues refer to chapter 3, section 3.3.

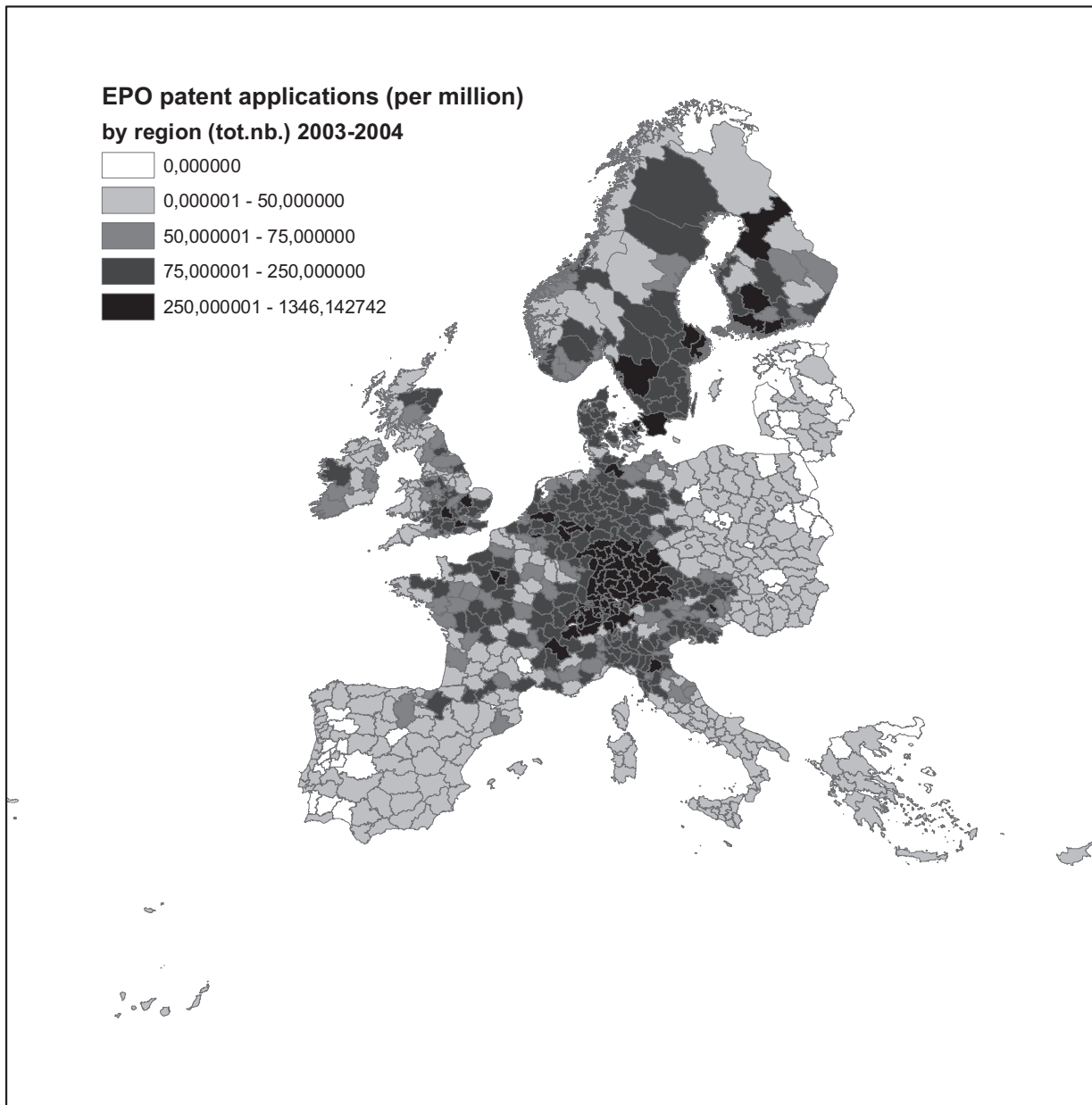


Fig. 1.3. EPO patent application density 2003-2004

Source: own calculations and illustration. *Notes:* EPO patent application density by region (per million population); data extracted from RegPAT (January 2009); fractional counts. Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.

economy” (Audretsch, 1998; Giddens, 2000; Crafts and Venables, 2003).¹⁹ Inter-regional research collaborations, such as border-crossing co-inventor activities in research networks, are considered to represent pivotal factors for regional development (Rodríguez-Pose and Crescenzi, 2008; Maggioni and Uberti, 2009; Capello, 2009). The internationalization of technology and R&D shows large cross-country differences (Guellec and van Pottelsberghe de la Potterie, 2001; Belitz *et al.*, 2006). However, the regional level has been the subject of only preliminary research. Furthermore, the analysis of patent data as relational data in this study is additionally motivated by the fact that European member states show an increasing number (and share) of EPO patent applications that originate from research activities and collaborations with foreign co-inventors and researchers located in other regions (Frietsch and Schmoch, 2006; Blind *et al.*, 2006).²⁰ Figure 1.4 illustrates this general trend at the country level for the European member states. However, it has to be argued that the observed co-patenting tendencies at the level of European member states are, once again, merely reflections of possible variations in developments at the regional level (Maggioni and Uberti, 2009; Hoekman *et al.*, 2010). Another crucial aspect is that different technology fields have different patenting propensities, which has to be taken into account in co-patenting studies (Frietsch and Schmoch, 2006). Therefore, co-inventorship activity and co-patenting networks have to be examined at both the regional and technological levels. In this respect, a pivotal part of the empirical analysis in this study is dedicated to inter-regional co-patenting network structures and their dynamics since the 1990s according to the different technology fields.

It has been argued in a few studies that European research networks are characterized by a significant dispersion and expansion (Hagedoorn, 2003; Paci and Usai, 2009; Hoekman *et al.*, 2010). Unfortunately, the empirical literature only shows a small amount of progress regarding the structure and dynamics of inter-regional co-patenting activity and technology field-specific co-inventor networks within and between European regions, as most studies have focused on single countries (Ejermo and Karlsson, 2004; Ponds *et al.*, 2010). A pan-European analysis of joint patenting for a comprehensive number of technology fields at the regional level does not exist. Hence, the structural characteristics and dynamics of inter-regional research networks at the level of smaller European regions, i.e., at the level of the 819 European TL3 regions of the enlarged EU, including Switzerland and Norway, are still unexplored. Regarding the geographic and technological dimension of European network structures, there is still a significant lack of knowledge and a continuing lack of research, which leads to a symptomatic deficit in positive results and normative reflections.²¹ Accordingly, it is unclear whether the last two decades have brought about a stronger spatial dispersion or concentration of technology field-specific co-inventor networks. This research gap is best described by TerWal and Boschma (2009) and Malecki (2010), among others. TerWal and Boschma (2009, 742), albeit rather too pessimistically, argued that

¹⁹ Refer also to Cairncross (2001).

²⁰ A co-inventor is an inventor whose name appears alongside the name of at least one other inventor in a patent application/patent document and who has contributed to the patented invention. Such a person is also called a “joint inventor” or “co-assignee.” The terms “co-inventor,” “co-patentee” and “co-assignee” will be used interchangeably in this study, as well as “co-inventor network,” “co-patenting network” and “co-inventorship network.”

²¹ Malecki (2010, 505) has recently argued, “[h]owever, we still know far too little about when - and whom and where - knowledge flows.”

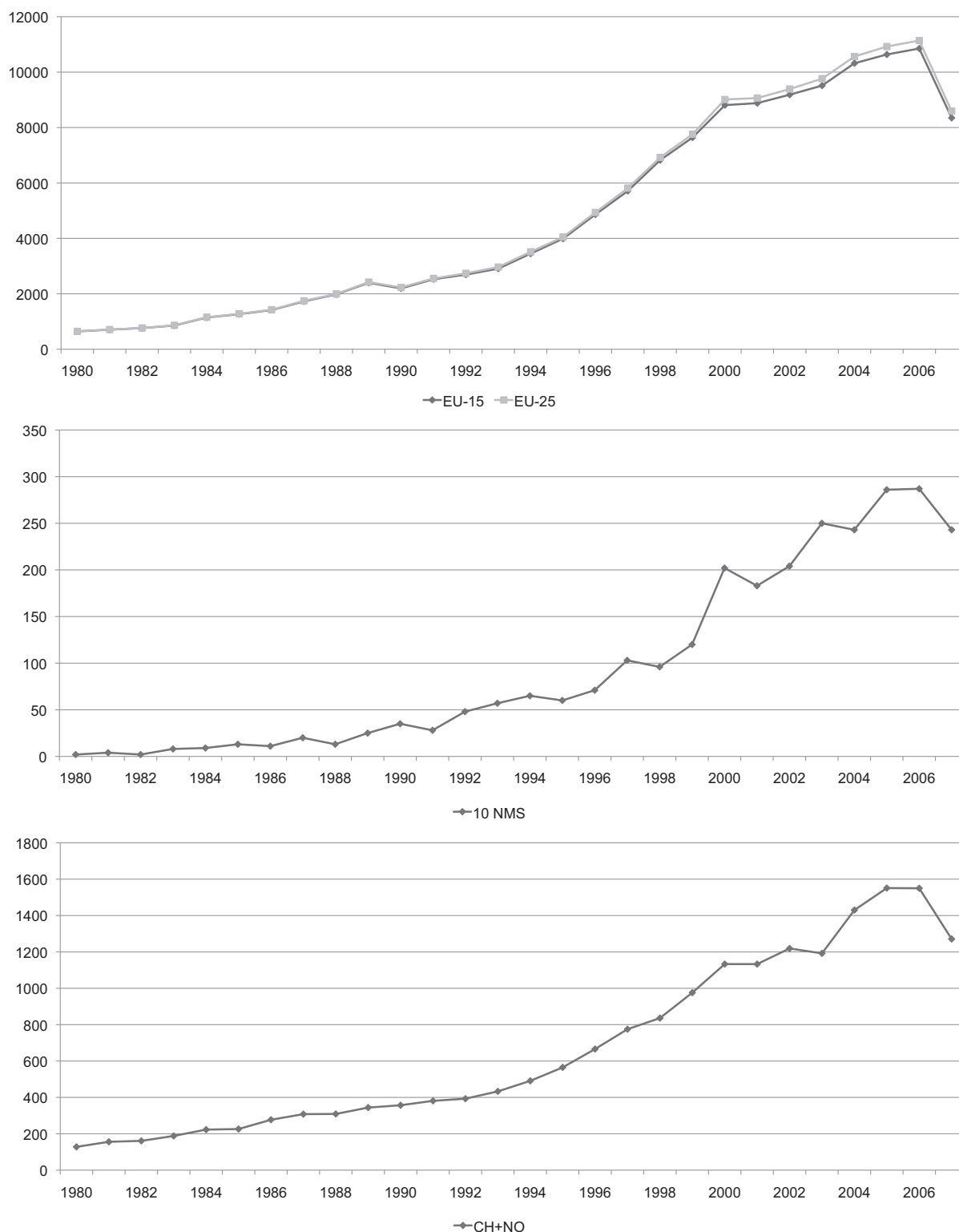


Fig. 1.4. Number of EPO patent applications with foreign co-inventors
Source: own calculations and illustration. *Notes:* Number of patents with foreign co-inventors since 1980 for selected country groups; total co-operations (EPO co-patents) with abroad; EU-15, EU-25, NMS and CH and NO; data extracted from RegPAT (January 2009) and OECD (2009d); fractional counts.

“[v]irtually no studies on the dynamics of the structure of networks in space exist [...]. [F]urther research is needed on how the structure of networks evolves over time and space and, particularly, how the evolution of networks is related to the evolution of clusters. [...] treating patent data as relational data provides us with considerable opportunities to study the dynamics of regional innovation networks, which is, till today, a rather unexplored though promising field of study.”

These impressions can be considered to be a starting point for the organization of a theoretical review and particularly for the development of the empirical research methodology applied in this study. A significant expansion of technology field-specific, inter-regional, border-crossing co-inventor networks, measured according to their inter-regional co-patenting linkages, can be interpreted as evidence for an increase in the number of inter-regional research collaborations and an ongoing integration of European regions into complex inter-regional European research networks. Such a development would correspond with the European Community’s explicit target to create an integrated and dynamic research area (i.e., the ERA).²²

To the best of the author’s knowledge, this study is the first to analyze the structure and dynamics of inter-regional co-patenting networks between more than 800 European TL3 regions and a comprehensive number of technology fields. The main objective of this co-patenting analysis is to explore the development of inter-regional co-inventor networks since the 1990s and to identify key regions in these networks. Furthermore, the current position of the NMS regions in these networks is ambiguous. Similarly, evidence regarding the network position of the regions of the cohesion countries, i.e., Greece, Spain and Portugal, and the NMS is rather weak.²³

Regarding income disparities and regional growth in Europe, the distribution of patenting activity may also be related to regional convergence of per capita income and the issues associated with technological congruence (Quah, 1996; Abreu *et al.*, 2005; Henderson, 2010). In a global context, income disparities are generally assumed to vanish as national per capita incomes show meaningful convergence in a cross-country perspective (Sala-i-Martin, 2006; Brakman and van Marrewijk, 2008). At the regional level, urbanization and development are considered to go hand-in-hand (Williamson, 1965; Henderson, 2010).²⁴ A natural starting point is the work of Kuznets (1955) and Williamson (1965) on income inequality and regional disparities. According to the Kuznets curve, developing countries suffer from a meaningful increase in income disparities in the earlier stages of development, followed by a decline in income disparities in later stages. The result is the popular inverted U-shaped relationship between per capita income and inequality. Williamson (1965) claimed that national development creates increasing regional disparities in the early stages of development, while later stages of regional development are characterized by regional convergence (Martin *et al.*, 2008; de Dominicis *et al.*, 2008; Henderson, 2010). Following Williamson (1965), regional disparities are said to increase at the beginning, because growth is mostly local and hence increases inequalities. It is argued that catching-up countries are mainly driven by a small number of regional “growth poles” in the early stages of development, in which physical capital, skilled workers and research activity are concentrated. Productivity,

²² For further details on ERA, refer to European Commission (2011i).

²³ See also European Commission (2011g).

²⁴ For an overview refer to Capello (2007).

gross value added (GVA) and GDP per capita accelerate only in these core regions, which leads to significant increases in regional disparities and core-periphery structures (Szörfi, 2007). At later stages of economic development, these core regions exhibit higher factor costs (labor, capital, land) and meaningful diseconomies of agglomeration, i.e., centrifugal forces, which emerge in the growth pole regions and work against the centripetal forces. Then, capital accumulation and human capital are assumed to relocate to the periphery, where factor costs are lower, which finally leads to dispersion and some kind of convergence. Accordingly, it is argued that spatial concentration and inequality are part of the development process (World Bank, 2009; Henderson, 2010). Therefore, the study addresses whether or not capital regions and urban and metropolitan regions exhibit higher growth rates of GDP per capita between 1995 and 2006 and compares the NMS and the EU-15.

Regarding European enlargement, accession and cohesion countries generally undergo severe structural adjustments (Hagemann, 2004). With regard to regional development, economic and technological convergence represent essential targets of the European Community's policy (see Box 1.1).²⁵ It is therefore particularly important to analyze the development of regional disparities in per capita income in a pan-European context. Although European member states seem in general to converge at the national level with regard to economic activity, i.e., the legendary 2% rate of convergence (Sala-i-Martin, 1996; Hagemann, 2004; Abreu *et al.*, 2005), several studies point to persistent regional disparities or even divergence (Duro, 2004; Rodríguez-Pose and Fratesi, 2007).²⁶ Moreover, a few empirical studies reported preliminary evidence that regions within the 10 NMS are diverging, compared to the EU-15 group of regions (Rodríguez-Pose and Fratesi, 2007; Paas and Schlitte, 2008). At the same time, as a consequence of the European enlargement process, the core of European growth and the center of gravity for future regional European cohesion policy has expanded and shifted to the eastern and southern parts of Europe. Eastern European enlargement has induced an increase of more than 30% of the European areal surface and an increase in the European population of more than 25%, but neither a relevant increase in the average per capita GDP nor a meaningful increase in average research activity (Szörfi, 2007; Paas and Schlitte, 2008; European Commission, 2011b).²⁷

However, one of the central European Community's objectives is to enhance economic and social cohesion within Europe. As a consequence, European enlargement activities and regional policy have to deal with the issue of considerable regional disparities within and between the European member states (Arbia *et al.*, 2005; European Commission, 2011h). The question arises of whether the initial income levels of poorer and technologically and economically backward regions (and countries) will converge to the level of the leading industrialized European core regions (and countries), which has essential implications for future regional growth paths, integration policy, structural funding and STI policy targeted at the regional level (Rodríguez-Pose and Fratesi, 2007). Regarding innovative capacities (i.e., research and patenting activities), it is still an open question as to whether or not patenting activity (i.e., high-technology and non high-technology patenting activity) is positively related to regional growth. Furthermore, to the author's knowledge, growth

²⁵ See also European Commission (2011i).

²⁶ For further details refer to Abreu *et al.* (2005), Brühlhart and Traeger (2005), Szörfi (2007), Paas and Schlitte (2008) and Crespo Cuaresma *et al.* (2010).

²⁷ For more details refer to European Commission (2011e).

regressions at the TL3 level which control for regional typologies are still missing in a European context.

Box 1.1: The European Research Area

The creation of the so-called European Research Area (ERA) was suggested by the European Commission (EC) in its official communication “Towards a European Research Area” (European Commission, 2000, 2007b; European Council, 2010; European Commission, 2011b,j). The objective of creating the ERA was affirmed by the European Union at the Lisbon European Council (in March 2000). The construction of the ERA is considered to work against the past fragmentation of the European research landscape and knowledge economy. Accordingly, the ERA represents the general idea of implementing and supporting a coherent policy framework, which is considered to be conducive to European research activities. The ERA programs aim to mobilize a critical mass of research(ers), to reduce costly overlaps in knowledge-intensive tasks and to improve research efficiency. Another aspect of the ERA is the coordination and integration of mechanisms involving all levels of policy intervention in Europe (European Commission, 2011b). The ERA also aims to achieve an increase in coherence at the level of European regions. Convergence (i.e., dispersion of R&D, GDP, GVA) is one of the key policy foci (see also chapter 5, Box 5.1). Several programs and actions have been started in order to enforce the establishment of the ERA (e.g., a threshold target for the European R&D investment intensity at 3% of countries’ GDP) (European Commission, 2011a). Research, education and innovation are particularly considered to represent the key drivers within the knowledge-based society and future industries. In order to establish the ERA, research is regarded as to develop strong(er) linkages to education and innovation (European Commission, 2007a, 2011b,j).

The ERA includes several key programs and general frameworks. These European initiatives are considered to represent valuable steps for further progress (European Commission, 2011b,j).

After a first stage of development (2000-2006), the ERA experienced a renewal and strategic advancement in 2007 with the publication of the green paper on its future development (European Commission, 2007a, 2011b). In 2008, the member states and the EC defined the so-called “2020 Vision” for the ERA, i.e., the “Ljubljana Process” (European Commission, 2011j). The member states launched several partnership initiatives to affect several areas: the co-operation and mobility of researchers; the personal careers and working conditions; joint research programs; the support and creation of modern research infrastructures; increasing knowledge transfer and co-operation between industry and public research organizations; international co-operation in science and technology (European Commission, 2011b,j).

To conclude, the thesis aims to contribute with global findings on the distribution of European inventorship/ research activity, with an alternative “top-down” cluster analysis and a very general identification and structural analysis of inter-regional co-patenting linkages (and networks) in a pan-European context. In addition, the study offers an analysis of European regional income disparities and regional growth. Special emphasis is placed on the significance of the regional settlement structure; it is tested whether or not capital regions and urban and metropolitan regions exhibit higher growth rates of GDP per capita. As the spatial distribution of knowledge stocks and researchers is considered a crucial factor for regional development, persistent core-periphery structures in patenting activities should then be reflected in significant differences regarding regional growth rates. This hypothesis is empirically addressed in chapter 5.

1.2. Outline of the Thesis and Research Questions

With regard to the aforementioned research gaps and issues, the main objective of this study is to elaborate on the development of the regional disparities and territorial dynamics of patenting activity in Europe and to analyze the development of European inter-regional co-patenting linkages and network structures. Moreover, pan-European growth regressions at the regional level complement this study. The study is organized in six chapters.

The literature survey in the second chapter offers the theoretical and empirical foundation for the subsequent empirical analyses. It reviews major mechanisms, causes and effects that determine the spatial distribution of knowledge-intensive activities and the emergence, stability and growth of clusters and core-periphery structures.

The first part of the literature survey offers a review of different schools of thought that challenge agglomeration economies, clustering, spatial concentration, co-agglomeration and networks, and outlines the relevant theoretical debates (section 2.1.1). The main objective is to elaborate on the different mechanisms which lead to a skewed geographic distribution and clustering of research and patenting activity, i.e. core-periphery structures.²⁸ The theoretical review addresses core-periphery structures relating to first- and second-nature causes and effects of co-location, agglomeration and co-agglomeration, paying special attention to the distribution of research and patenting activity. In opposition to first-nature causes of agglomeration and clustering, second-nature agglomerative forces are independent from physical geography. In this context, the concepts of the division of labor and indivisibilities (section 2.1.3) and the well-known concept of external economies (section 2.1.4) are presented, as they bring together the different epistemic communities. With regard to external economies, the theoretical review discusses the concept of pecuniary and non-pecuniary externalities and the concept of urbanization and localization economies and offers a detailed taxonomy (sections 2.1.4.3, 2.1.5 and 2.1.6). Regarding pecuniary externalities, section 2.1.5.5 briefly reviews the central conclusions of pivotal new economic geography models, which offer some theoretical working channels of clustering and the relocation of economic activity. In this respect, the crucial drawbacks of early new economic geography models will be discussed, especially those relating to the missing channels of knowledge diffusion and their inability to explain research clustering and the (re-)location of knowledge intensive tasks. Regarding technological externalities, an emphasis will be placed upon the missing circular causalities and cumulative causations in endogenous growth models in section 2.1.6.6. It is argued that, although these models address knowledge externalities as the pivotal reason for persistent regional disparities, they are generally unsuited to explaining the process of industry agglomeration via relocation and research clustering dynamics. The subsequent section 2.1.6.7 then briefly reviews new economic geography growth models (growth-cum-geography models) and offers conclusions with respect to research clustering and the development of regional disparities. Finally, the theoretical review in section 2.1.7 is extended to issues relating to knowledge spillovers, knowledge flows, linkages and the effects of knowledge attributes on research clustering, with a special focus on knowledge-intensive industries, research clustering and inter-regional co-patenting networks. Essential

²⁸ Co-agglomeration is defined as agglomeration of two or more technology fields/industries in the same location; co-location, in comparison, is defined as the siting of two or more firms in the same location that form an agglomeration (Roos, 2002, 168; Gallagher, 2008).

elements in this context are distance decay effects and the possible spatial overlaps of agglomerations and networks. Knowledge transmission is considered to be dependent on the different attributes of knowledge, i.e., tacitness, codification, excludability and rivalry. Regarding the nature of inventive collaboration, the review differentiates between research collaborations and knowledge flows within long-distance networks on the one hand and spillovers at a proximate distance on the other. Section 2.1.7.5 discusses the tension between region-specific agglomeration economies at a proximate distance and the benefits of external knowledge that enters the region via inter-regional research linkages.

The second part of the chapter (section 2.2) represents the empirical literature survey. It offers a review of the current state of research and the different strands of empirical analysis (section 2.2.1), which are related to the distribution of research activities in Europe, the distribution of research networks and the analysis of knowledge flows and spillovers. In addition to discussing methodological issues and the empirical results of studies on the concentration and regional disparities of patenting activities in Europe (section 2.2.2), the review also addresses the regional knowledge production function approach (section 2.2.3), the localization-urbanization approach (section 2.2.4), the patent citation approach (section 2.2.5), the social network and inventor mobility approach (section 2.2.6), and the co-patenting/co-inventor network approach (section 2.2.7). The empirical review is essential to work out the advantages, drawbacks and shortcomings of central research approaches, to develop a comprehensive database and to define the research methodology for own empirical analyses. The review will demonstrate a meaningful need for additional empirical research on regional disparities in patenting activity and on the structures and development of European inter-regional co-patenting network linkages.

The third chapter represents the first empirical part of the study and offers a detailed descriptive analysis of the regional disparities of European research activities, i.e. EPO patenting activities. This analysis provides insights into the structure and distribution of patenting activity across European regions. Moreover, the analysis incorporates a multidimensional quantitative approach for the identification of research clusters at the regional level.

In the first part of the chapter, section 3.1 introduces the research topic. The subsequent section 3.2 presents the central issues relating to the application of patent data and section 3.3 introduces the regional database and applied spatial classification system. The analysis uses extractions of EPO patent applications (fractional counting) and EPO inventor IDs (full counting) based on OECD RegPAT data (January 2009) and links them to 819 European TL3 regions (EU-25, Switzerland and Norway). All EPO patent applications between 1977 and 2007 are regionalized and linked to 43 technology fields (ISI-SPRU-OST concordance) and 6 high-technology fields EUROSTAT (2009). In section 3.4, the analysis focuses on regional disparities and spatial concentration of research activities in Europe, i.e., patent applications at the EPO. The analysis contributes empirical findings on the distribution and geographic concentration of European patenting activity at the level of European TL3 regions according to technology field and country. Global descriptive distributional measures are applied in order to answer the question of whether or not overall EPO patenting activity according to technology field is highly concentrated and therefore unevenly distributed across European countries and regions. In addition, the

empirical analysis answers the question of whether or not Europe is determined by an increasing share of specialized regions, and whether technology fields in general have shown tendencies of spatial dispersion within the last two decades. Besides reporting the standard descriptives, the empirical analysis also covers Herfindahl-Hirschman indices, location quotients, relative patent densities, revealed technological advantage indices and Gini coefficients. The Gini calculations explicitly take into account the heterogeneity of regions in terms of regional population and area size.

In the second part, section 3.5 offers a descriptive framework for identifying research clustering in the European research landscape, i.e., the ERA. A harmonized, multidimensional descriptive measure of research clustering at the regional level is introduced. The proposed research cluster index (RCI) uses information on regional EPO patenting activities and EPO inventors according to technology field and region, as well as information on regional population, the size of the area and relative regional specialization. Based upon the computed RCI, the empirical analysis emphasizes global statistics on European research clustering by technology field and country and the identification of leading research clusters according to technology field and country (number, share, strength of clusters). The computation of the RCI for two periods, 1990-1994 and 2000-2004, offers the opportunity for a dynamic analysis. The empirical analysis additionally links the computed technology-specific RCI to the regional settlement structure in order to examine whether or not urban and metropolitan European regions host a remarkably larger number of technology-specific research clusters compared to intermediate and rural regions. Moreover, the computed RCI is used to examine core-periphery structures in Europe, i.e., north-south and/or east-west gradients, with a particular focus on the emergence and development of research clusters in leading EU-15 countries and the NMS. This chapter also offers empirical results regarding the geographic coincidence/ co-agglomeration of research clusters at the regional level relating to the regional typology (i.e., capital regions, metro regions, urban and rural regions).

In the fourth chapter of this study, the empirical analysis places the emphasis on the identification and exploration of European inter-regional co-patenting networks and the analysis of spatial interdependence of EPO patenting activities at the regional level.

Section 4.1 represents the introductory part of the chapter. In the first empirical part of the chapter (section 4.2), issues of spatial interdependence and regional spillovers from patenting activity are discussed. Strong regional disparities in patenting activity may be accompanied by spatial autocorrelation of regional EPO patenting activity. An explanatory spatial data analysis (ESDA) is used to test for the presence of spatial dependence of EPO patenting activity in 51 technology field aggregates. The analysis of different spatial distance bands addresses distance decay effects and functional boundaries. In the second part, the chapter addresses innovative collaboration, i.e., co-patenting activity (section 4.3). The methodology and relational database are presented and discussed in sections 4.3.1, 4.3.2 and 4.3.3. In a first step (section 4.3.4), the empirical analysis emphasizes co-patenting activity at the national level. Therefore, the analysis explores foreign co-patenting activities of the European member states since the 1980s. Border-crossing collaborations between European researchers and fractional counting of patent applications may represent possible origins of significant and positive spatial dependence. The empirical analysis of international co-inventor activity focuses on the absolute numbers and shares of EPO patent

applications with foreign co-inventors since the early 1980s. The study presents results for the EU-15 and NMS group and for selected extra-European countries (e.g., Switzerland and Norway) and examines whether or not co-patenting activity with foreign co-inventors from other countries has increased since the 1980s. The analysis of co-patenting activity at the country level represents a necessary pre-analysis for the subsequent co-patenting study at the regional level. In a second step, the study presents empirical results relating to co-patenting linkages (and networks) between European regions (section 4.3.5). Based on EPO co-patenting information for the reference periods 1990-1994 and 2000-2004, the empirical analysis places the emphasis on the spatial configuration of 43 technology field-specific co-patenting networks between European regions at different spatial levels (TL3 regions, TL2 regions and TL1 countries). The study analyzes whether or not these 43 technology field-specific co-patenting networks differ in terms of their overall size (nodes, linkages) and whether or not the networks are dominated by similar groupings of regions. The comparison of the networks at different spatial levels aims to distinguish between inter- and intra-regional co-patenting linkages, as spatial aggregation to larger regions transforms inter-regional linkages into intra-regional ones. The empirical analysis of the overall and unique network linkages contributes to a detailed picture and understanding of European research network structures. In addition to global network statistics (network size, nodes, unique and overall linkages), the empirical analysis also contributes local network statistics, i.e., the network centrality of regions (degree, betweenness). The analysis identifies the core-units of European technology field-specific co-patenting networks, but also the most peripheral regions. From a core-periphery perspective, the empirical analysis depicts possible “hub-and-spoke” structures of technology fields, as not all European regions exhibit a central position in co-patenting networks. In addition, the study analyzes whether or not some regions represent “multi-technology hubs” due to their diversified co-patenting activity and research strength in several technology fields.

The fifth chapter represents the third empirical part of the study and focuses on the European growth process and income disparities at the regional level between 1995 and 2006. Section 5.1 introduces the chapter and focuses on research gaps and the central issues with regard to regional inequality, convergence and growth studies. The subsequent section 5.2 then offers an overview of the database which was employed, containing regional data and the spatial classification systems. The first step involves an empirical analysis of European regional income disparities at the regional level (section 5.3). The analysis centers on the distributional dynamics of GDP per capita (PPP) across European regions and asks whether or not European regional disparities in GDP per capita are generally decreasing since the 1990s. Moreover, the analysis decomposes overall regional income disparity into within-subgroup and between-subgroup disparity, indicating that income inequality originates from income disparity across regions within countries and income disparity between countries. Accordingly, the empirical analysis examines whether or not convergence of per capita income levels is mainly a national phenomenon. Moreover, Gini indices and generalized entropy measures at the regional level are applied. Furthermore, the analysis examines whether or not the EU-15 countries exhibit similar trends in income disparities when compared to the NMS. In a second step, the analysis emphasizes cross-sectional unconditional and conditional pan-European growth regressions for EU-15 and NMS regions (section 5.4). The empirical analysis examines whether or not regional growth is differing with regard to the level of regional technological knowledge and research activity (mea-

sured by EPO patenting activity), and the regional settlement structure (capital regions, metropolitan, urban, intermediate and rural areas). This analysis addresses whether or not capital regions and urban and metropolitan regions exhibit higher growth rates of GDP per capita between 1995 and 2006. As spatial dependence could potentially be an issue, meaning that regional growth could be affected by neighboring regions' growth processes, tools of spatial econometrics, e.g., spatial maximum likelihood estimations, are additionally applied.

The sixth chapter comprises a summary of the empirical results of the previous chapters. It offers concluding remarks, a discussion of technical issues, drawbacks and shortcomings and some normative aspects with regard to the geographic distribution of European research activity, research clustering, inter-regional co-patenting networks and growth differences relating to the regional settlement structure and regional patenting activity. Some policy-related conclusions are elaborated on with regard to the observed regional patterns and structural dynamics of research clustering and inter-regional co-patenting networks in the ERA. Finally, the chapter offers a discussion of methodological and data related shortcomings of the presented empirical analyses and elaborates on issues of data availability and the direction of future research in a pan-European context.

2. Research Clustering, Co-Inventor Networks and Innovative Places: A Literature Survey

2.1. A Survey of the Theoretical Literature

2.1.1. The Co-Evolution of Research Strands in the Cluster Literature

As centuries of research have been dedicated to land-use, core-periphery structures and industry location, the research of economists and geographers has led to a broad and complex body of literature (Feldman, 1999; Harris, 2008; Thisse, 2011).²⁹ Therefore, these theoretical contributions need to be classified into several research lines, which will subsequently be presented and discussed in the following sections, even though the main focus of this study is on research clustering and the distribution of inventorship activity.

One suggestion regarding the origin of regional disparities and the causes and effects of clustering can be found in the work of Ottaviano and Thisse (2001, 159), who argued that

“[i]f we want to understand something about the spatial distribution of economic activities and, in particular, the formation of major economic agglomerations [...] we must assume either (i) that *space is heterogeneous* (as in the neoclassical theory of international trade or in land-use models à la von Thünen), or (ii) that *production and consumption externalities exist* and are many (as in modern urban economics) or (iii) that *markets are imperfect* (as in spatial competition theory or in economic geography).”³⁰

Today, it is quite common in the literature to separate the aforementioned elements into the following groups of the causes and effects that determine the (re-)location, co-location and co-agglomeration of research and production activities: (i) comparative advantage; (ii) externalities; and (iii) imperfect competition (i.e., monopolistic and oligopolistic competition) (Combes *et al.*, 2008, 42). However, the history of the literature on clustering, agglomeration economies and regional disparities can be traced back to the beginning of the 19th century. Nevertheless, for a long time, the processes of agglomeration and concentration occupied an inferior position on research agendas in the field of economics, and especially the role of spatial proximity and concentration with regard to innovative capacity, inventorship activity and innovation. Researchers have recently focused their attention on the conceptual relationship between agglomeration and concentration tendencies and the established spatial convergence studies that can be regarded as their empirical counterpart

²⁹ See also Scott (2000), Clark *et al.* (2000) and Sheppard (2000).

³⁰ The main advantage of the second source, namely technological externalities, is that this concept is compatible with perfect competition.

(Martin and Ottaviano, 2001; Brakman and van Marrewijk, 2008; Thisse, 2011).³¹ Agglomeration and spatial concentration is nowadays increasingly challenged in economic theories (Rosenthal and Strange, 2001, 2003; Henderson, 2003a) and empirical analysis (Brühlhart and Traeger, 2005; Geppert *et al.*, 2006; Fornahl and Brenner, 2009). Furthermore, the issues associated with divergence and spatial clustering have become highly visible with the emergence of metropolises, industrial belts and urban areas all around the globe, meaning that the world is considered to have become more “spiky” (Fujita and Krugman, 2003; Crescenzi and Rodríguez-Pose, 2008; Brakman and van Marrewijk, 2008).³² As has been argued by many researchers, the earliest approaches and concepts date back to the seminal contributions made by Ricardo (1821), Launhardt (1882), Marshall (1920b), among others, and back to German location theory in particular (Thünen, 1966; Weber, 1929; Christaller, 1933; Lösch, 1954).³³ Regarding the different sources of agglomeration economies and factors that influence industry concentration and clustering of knowledge-intensive tasks, the work of Alfred Marshall (1890) is considered to be of central importance for both geographers and economists; especially the so-called “Marshallian externalities of the third kind” (Breschi and Lissoni, 2003; Press, 2006a; Capello, 2007).³⁴ A few decades after these externalities were proposed, in the 1950s and 1960s, the neoclassical literature on location was classified as the successor of the aforementioned classical contributions (Roos, 2002b; Press, 2006a).³⁵ The neoclassical approaches (a.k.a. regional science) improved the classical concepts of location, co-location and land-use; however, most contributions were unable to explain the processes of co-location, agglomeration and dispersion by means of different centripetal and centrifugal forces (Cruz and Teixeira, 2007; Blum, 2008). Moreover, heterogeneous space and region-specific set-ups were not considered to be central elements. An exception to this rule are “comparative advantage models,” which are based upon physical geography and heterogeneous spatial structures (i.e., natural endowments) and are well-known in trade theory and cross-country trade studies (Combes *et al.*, 2008; Krugman, 2009; Thisse, 2011).³⁶

The second half of the 20th century was determined by a meaningful expansion of the literature on clusters and by “new regionalism” (Storper, 1997, 2000; Scott and Storper, 2003), even though the contributions placed emphasis on different factors and relationships and originated from different schools of thought (Maggioni, 2002; Press, 2006a; Capello, 2007).³⁷ In light of these different theoretical advancements, which resulted in what Scott (2000) called “the great half-century” in economic geography, a broad range of concepts can be observed in retrospect.³⁸ Many of the concepts which were proposed could be classified

³¹ For an overview refer to Krugman (1992), Ellison and Glaeser (1997), Arbia (2001) and Baldwin and Martin (2004).

³² Refer also to Fujita and Mori (2005).

³³ For a detailed literature survey, refer to Scott (2000), Keilbach (2000), Marques (2001), Martin and Sunley (2003), Jonas (2005), Press (2006a), Cruz and Teixeira (2007), Capello (2007), Eckey (2008), Freund (2008), Blum (2008) and Thisse (2011). For a comprehensive review and discussion of the growth and development theories between the 1950s and 1980s refer to Hagemann (2006) and Capello (2007).

³⁴ For an overview refer to Keilbach (2000) and Cruz and Teixeira (2007).

³⁵ See Isard (1956), Myrdal (1957), Alonso (1964) and Perroux (1970). For an overview refer to Keilbach (2000), Roos (2002b) and Press (2006a).

³⁶ For an overview refer to Roos (2002b) and Capello (2007).

³⁷ See also Scott (2000), Roos (2002b) and Martin and Sunley (2003).

³⁸ Refer also to Scott (2000) for a detailed survey of the intellectual history of economic geography.

as knowledge-based cluster approaches, including the following: the well-known “Italian industrial districts” or “neo-Marshallian industrial districts” which consist of small Italian manufacturing firms with a region-specific tradition (Brusco, 1982; Becattini, 2002); the Californian School of geographers and their concept of “new industrial spaces” which focuses on the division of labor, vertical disintegration, transaction costs and path dependencies (Scott, 1988; Storper, 1997; Scott, 2000); the French approach of the “innovative milieus,” developed by the GREMI group, which focuses on territorial specificities, networks and untraded interdependencies with respect to the innovation process (Aydalot, 1986; Camagni, 1991b, 1995; Capello and Faggian, 2005); the “neo-Marshallian nodes” (i.e., clusters) that are integrated into a global production network (Amin and Thrift, 1992); the “Porterian industrial cluster” approach, which is well-known from STI policy (Porter, 1998a; Delgado *et al.*, 2010); the “learning regions” approach that revolves around learning processes, networks and region-specific factors (Florida, 1995; Asheim and Isaksson, 2002; Asheim and Gertler, 2005); and finally the “systems of innovation literature,” i.e., regional innovation systems, which center around learning processes, region-specific aspects and the institutional characteristics that influence the innovation process (Cooke, 2001; Doloreux and Parto, 2005; Cooke, 2008).³⁹

The concepts and approaches listed above have contributed to our understanding of clustering, co-location, agglomeration and co-agglomeration in a meaningful way. Although inter-regional linkages are considered in these conceptions in some way, spatial proximity has remained the primal source of cluster dynamics, as it facilitates face-to-face interaction, networking and the exchange of tacit and codified knowledge between agents in knowledge-intensive industries. Furthermore, geographers and economists have found their own specific research agendas, although there is a considerable overlap in several fields with regard to theorizing and empirical analysis (Rodríguez-Pose, 2010).

In economics, the growing interest of researchers (and politicians) in a neoclassical tradition has led to the emergence of the so-called “new economic geography” (Krugman, 1991; Krugman and Venables, 1995a) (i.e., “geographical economics”), “urban economics” (Fujita and Thisse, 1996; Combes *et al.*, 2008) and the “endogenous growth theory” (Romer, 1986, 1990b). The community of researchers on geographical economics has contributed with new generations of models of co-location and agglomeration, which are mainly built upon pecuniary externalities that lead to an ever-contracting space (Krugman, 1991, 2009).⁴⁰ As a consequence, location, co-location and relocation are modeled as the outcome of an optimization process. The distribution of economic activity, i.e., industry location, and the emergence of regional disparities are solely dependent on centripetal and centrifugal forces that lead to either a symmetric distribution or a core-periphery structure. Consequently, the salient feature of the new economic geography is the formalization of cumulative circular causality, based upon factor mobility, vertical linkages or the accumulation of capital. In comparison to the “geography of innovation” literature (Feldman, 1999), urban economics similarly challenges knowledge diffusion and technological externalities with special focus

³⁹ The emergence of national, sectoral, technological and regional conceptualizations of the innovation system approach is the outcome of an intellectual debate on spatial heterogeneity, system boundaries and perspective/dimension of analysis (Cooke *et al.*, 1997; Fischer, 2001; Edquist, 2005; Doloreux and Parto, 2005; Cooke, 2007, 2008). See also Christ (2007) for an overview.

⁴⁰ For a comprehensive review see Martin (1999), Krugman (2000), Fujita and Krugman (2003), Fujita and Mori (2005), Combes *et al.* (2008), OECD (2009a), Rodríguez-Pose (2010), Thisse (2011).

on city structures and regional spillovers (Duranton and Puga, 2001; Storper and Venables, 2003; Henderson, 2010).⁴¹ Thisse (2011, 7) noted that

“urban economics now has strong links to theories of social networks and other forms of local interactions, the urban neighborhood being the place where many non-market relationships are developed.”

The contributions to the endogenous growth theory are heavily built upon the ideas of Arrow (1962a,b) and the seminal work of Romer (1986) and Lucas (1988).⁴²

In opposition to the optimization approach in geographical economics, researchers from the “evolutionary economics” and “economic geography proper” traditions have challenged the existence of clusters, agglomerations and varying economic development paths of regions differently (Martin, 1999; Garretsen and Martin, 2011).⁴³ They point to varying technological regimes, path dependencies, populations of heterogenous agents (e.g., entrepreneurs and researchers), institutional differences at the regional, sectoral and national levels, cultural differences and the informal institutions and networks that shape the regional landscape (Sheppard, 2000; Scott, 2000; Press, 2006a).

In an R&D clustering context, the knowledge-, learning- and innovation-based approaches to clustering, agglomeration and growth (a.k.a. “geography of innovation” literature) place the emphasis exclusively on the transmission and diffusion of channels of knowledge, interpersonal relationships in networks, interactive learning processes, cultural and institutional factors, and also on the sociological and behavioral aspects of the innovation process (Feldman, 2000; Bathelt *et al.*, 2004; Lundvall, 2007).⁴⁴ Moreover, one line of research focuses in particular on the distribution of creativity, i.e., researchers and entrepreneurs (Fujita and Thisse, 1996; Andersson *et al.*, 2005; Fingleton *et al.*, 2007). In addition, empirical studies nowadays focus on the mobility (and migration history) of researchers (Almeida and Kogut, 1999; Saxenian, 2006; Breschi and Lissoni, 2009), on co-patenting activities between individuals, firms and regions (Maggioni *et al.*, 2007; Maggioni and Uberti, 2009; Kroll, 2009), and on “paper trails” of knowledge diffusion that are measured by using patent citations (Jaffe *et al.*, 1993; Maurseth and Verspagen, 2002; Paci and Usai, 2009).

Recent analyses have placed a special emphasis on the formal and informal linkages between agents and different forms of proximity (spatial, technological, cultural). Consequently, the exploration of intra- and inter-regional networks lies at the heart of recent studies (Bergman, 2009; Burger *et al.*, 2009; Wilhelmsson, 2009).⁴⁵ As it is argued, the economic geography of innovation is increasingly combined with the concept of “open innovation,” which encompasses the analysis of spatial knowledge domains, the outsourcing and fragmentation of R&D, and the transfer of different forms of knowledge across sectors and space (Cooke, 2007; Powell and Giannella, 2010).⁴⁶

⁴¹ See also Glaeser (2000), Puga and Duranton (2000) and Combes *et al.* (2008).

⁴² For an overview refer to Grossman and Helpman (1991a), Grossman and Helpman (1994), Rima (2004), Jones (2004), Chandra and Sandilands (2005), Solow (2007), Harris (2008) and OECD (2009a).

⁴³ See also Boschma and Frenken (2006) and Boschma and Frenken (2009a).

⁴⁴ For further discussion and reviews refer to Feldman (1999), Asheim (2000), Audretsch and Feldman (2004), Jonas (2005), Press (2006a), Cruz and Teixeira (2007) and Blum (2008).

⁴⁵ See also Porter *et al.* (2005), Capello (2007) and Bergman and Maier (2009).

⁴⁶ Capello (2009) offered a comprehensive review of the conceptual approaches to agglomeration economies and develops a diachronic perspective; she argues that the 1970s were dominated by the

A complementary view that links several of the aforementioned approaches and epistemic communities is the “agglomerations and networks” line of research (Powell and Grodal, 2005; Johansson, 2005; Breschi *et al.*, 2005).⁴⁷ Today, geographers and economists are both increasingly emphasizing the idea that spatial interaction, networks and places are the key factors of regional development and key units of empirical analysis (Overman, 2003; Rodríguez-Pose, 2010; Garretsen and Martin, 2011). The central merit of these approaches is their specific emphasis on the identification and explanation of different effects and working channels of knowledge transmission, unintentional knowledge spillovers and network linkages in a spatial context.

In summary, for both economists and geographers alike, the world is considered to have become more “convex” and “spiky,” and to be dominated by large and increasingly interconnected agglomerations separated by growing economic “deserts” (Florida, 2005; Duranton and Rodríguez-Pose, 2005; Rodríguez-Pose, 2010).

Unfortunately, a comprehensive review and discussion of all of the aforementioned theoretical concepts, approaches and research streams in the context of (research) clustering is clearly beyond the scope of this thesis.⁴⁸ Despite their general methodological and conceptual differences, meaningful overlaps and conceptual similarities between the aforementioned concepts and approaches can be observed, which will be illustrated in the subsequent theoretical review.⁴⁹

In the following, the literature review summarizes major working channels and forces that determine clustering and agglomerative tendencies. A special emphasis is placed on research clustering and regional disparities of research and patenting activity. The empirical review in section 2.2 builds upon the theoretical survey and represents the starting point of the empirical analyses in this study.

2.1.2. From First-Nature Agglomerations to Knowledge-Intensive Industries

First-nature causes of co-location and agglomeration emerge from physical geography and are thus related to land use, climate, navigable waterways, immobile production factors

“industry” dimension, the mid-1970s by the “socio-cultural” dimension; the 1980s by the “cognitive” dimension, the 1990s solely by the “spatial” dimension, the late 1990s by the “geographic/industry” dimension and finally the 2000s onward by an “integrated approach” (Capello, 2009, 148).

⁴⁷ See also Breschi and Lissoni (2009) and Bergman (2009).

⁴⁸ The interested reader will find detailed reviews and surveys of the entire body of literature on clusters in, e.g., Feldman (1999), Roos (2002b), Maggioni (2002), Bathelt and Glückler (2003), Press (2006b) and Capello (2009), Rodríguez-Pose (2010), Garretsen and Martin (2011), Thisse (2011), among others.

⁴⁹ For discussion and reviews refer to Overman (2003), Duranton and Puga (2004), Duranton and Rodríguez-Pose (2005), Polenske (2007), Capello (2007) and Harris (2008). Duranton (2008b, 10) has argued that “[t]he relationship between [economic geographers and economists] has been fraught with difficulties. On the one hand, many geographers react very negatively to the renewed interest by economists in spatial issues. On the other hand, economists tend to ignore the work done by economic geographers. Despite these difficulties, geographers may learn something from the economists’ more rigorous approach while the greater breadth of geographers may offer a great source of inspiration for economists.” For further comparisons of the different research communities see Castellacci (2007), Castellacci (2008), Rodríguez-Pose (2010).

such as labor and natural resources, among others. The spatial typology and regional (natural) endowments cannot be transformed or substituted (Mellinger *et al.*, 2000; Venables, 2006; Sachs and McCord, 2008).⁵⁰ Therefore, a region's natural endowments can be considered to significantly influence agglomeration and co-agglomeration of industries but also the spatial structure of innovative activity.⁵¹ Accordingly, comparative advantage emerges from the heterogeneity of space and thus presupposes an uneven distribution of technologies, natural endowments, assets, or agents (Acs, 2002; Roos, 2002a; Combes *et al.*, 2008). Regarding physical geography, unfavorable characteristics of a location might be a mountainous surface and geographic remoteness, which provide inferior infrastructure potentialities, suboptimal climate conditions; favorable ones are, e.g., the availability of mineral resources, fertile soil, navigable seaways (rivers and harbors) (Eaton and Kortum, 2002; Roos, 2002b,a; Puga, 2010).⁵² Trade structures are seen as the outcome of physical geography as has been reviewed by, e.g., Crafts and Venables (2003). As Hinloopen and van Marrewijk (2004, 3) stated,

“the wood industry is usually located in areas with lots of trees; big harbors are usually at the mouth of a navigable river.”⁵³

In a US context, Ellison and Glaeser (1999) discussed the natural advantage (abundance) of the Washington state area in low-cost hydroelectric power, which has led to a significant co-agglomeration of energy intensive industries (see also Acs, 2002, 3). Accordingly, exogenous location determinants, which are not influenced endogenously by locations and their agent structure, represent a first group of exogenous agglomeration and location factors that can lead to core-periphery structures. The economic literature defines such factors (and effects) as “first-nature” agglomeration effects (or causes) as has already been stated by Marshall in his *Principles of Economics* ([1890] 1920). Marshall himself regarded such first-nature advantages as an important attribute for location in a historical context (see also Roos, 2002b, 66). In this respect, first-nature causes represent an origin of spatial heterogeneity.⁵⁴ Researchers have tried to measure the distribution of industries but also to quantify the importance of such exogenous location factors, especially related to issues of industrial production and the specialization of industries. Head *et al.* (1995) related the location decision of agents to spatial factor endowments, which represents the classical

⁵⁰ Gallagher (2008), among others, differentiated between first-degree linkages (transaction costs) and second-degree linkages (knowledge spillovers, labor pooling, input/market sharing, and natural advantage), which differs slightly from the applied classification in this study. For further ideas refer to Rosenthal and Strange (2004).

⁵¹ The Heckscher-Ohlin framework and modeling alternatives of international trade are about first-nature causes of specialization in production (but not about agglomeration per se). On the basis of input endowments, these models are able to demonstrate why firms in one region tend to produce labor intensive, and in another region capital intensive goods. For a comprehensive review of the trade theory in economics see, e.g., Harris (2008) and Hofmann (2009).

⁵² A comprehensive review of the relationship between geography and development and the importance of physical geography and continental patterns for location and co-location can be found in Mellinger *et al.* (2000).

⁵³ To give an additional examples: Napa Valley (California) has a specific climate, which is conducive to the harvesting of grapes and other fruits. Thus, the location is today a central node for the US wine and fruit industry, which co-agglomerate in the same location (Acs, 2002; Gallagher, 2008).

⁵⁴ As Marshall has emphasized “[t]he chief causes [of industry localization] have been physical conditions; such as the character of the climate and the soil, the existence of mines and quarries in the neighborhood, or within easy access by land or water” (Marshall, [1890] 1920, 269).

idea of endowment-driven industry location (see also Feldman, 2000). In the same line, Ellison and Glaeser (1999) showed that about one-fifth of spatial clustering of US-industrial production can be explained by an (even incomplete) set of natural advantage. Audretsch and Feldman (1996, 268) similarly reported evidence for centripetal forces originating from natural endowments that are independent from the industry life-cycle. They argued that

“[t]he positive and statistically significant coefficients of natural resources suggest that a high dependence on natural resources tends to result in a greater geographic concentration of production in all four of the [industry] life cycle phases.”

According to Acs (2002, 3), the former strength of the legendary US manufacturing belt in the northeastern and eastern part of Americas midwest (Wisconsin, St. Louis, Baltimore, Maine) was primarily based on physical geography, such as iron intermediates from Minnesota, coal inputs from mountains and water inputs from places nearby. Besides Ellison and Glaeser (1999), also Rosenthal and Strange (2001), Audretsch and Feldman (1996), and Kim (1995), among others, discussed natural endowment abundance as a significant driver of agglomeration and co-agglomeration. However, according to Ellison and Glaeser (1999), these factors can only explain 20-50% of industrial concentration. As a consequence, it can be argued that the concentration of industries is not solely determined by physical geography, i.e., first nature (Ottaviano and Thisse, 2004; Head and Mayer, 2004; Holmes and Stevens, 2004).⁵⁵ According to the issues raised by Acs (2002, 2), it is therefore essential to analyze in a European context (i) if industries and knowledge-intensive tasks are still highly localized in a few locations, (ii) if they relocate, to explain why they move to other locations or why activity shows dispersion, (iii) how firms and entire industries can (frequently) relocate with parts of their knowledge base. Obviously, additional drivers of agglomeration and dispersion seem to exist. Similar to Acs (2002), Krugman (1992, 5) was asking why the spatially concentrated US manufacturing belt could persist for such a long time, although the gravity centers of mineral products and other inputs have relocated.⁵⁶ The main objective of this thesis is to analyze the distribution of patenting activity in Europe and to explore the spatial structure of co-patenting activity.⁵⁷

With regard to technological progress, Sachs and McCord (2008) argued that advancements in telecommunication technology are significantly affecting the global division of labor and the nature of agglomeration economies, which should give rise to “secondary growth poles.” Regarding patenting and research activity, such developments might also exist in a European context, which will be addressed in chapters 3 and 4. Nevertheless, location still seems to matter a lot. In the US context, it has been argued by Acs (2002), among others, that many processes within the manufacturing value chain can still exist in the neighborhood because of an established regional knowledge base that has induced agglomerative forces by itself (see also Krugman, 1995; Audretsch, 1998; Klein and Crafts,

⁵⁵ See also Combes and Overman (2004).

⁵⁶ Krugman (1992, 5) argued: “*Think of the United States: most of the population of huge, fertile country lives along parts of two coasts and the great lakes [...]. [T]hese urban areas in turn are highly specialized, so that production in many industries is remarkably concentrated in space. This geographic concentration of production is clear evidence of the pervasive influence of some kind of increasing returns.*”

⁵⁷ For a detailed discussion refer to Glaeser *et al.* (1992), Jaffe *et al.* (1993), Rosenthal and Strange (2001), Cappellin (2001), Roos (2002b), Johansson and Quigley (2003), Abreu *et al.* (2004), Henderson and Thisse (2004), Ottaviano and Thisse (2004) and Klein and Crafts (2010).

2010). However, the relocation of some gravity centers has also initiated the creation of new high-technology industries and modern knowledge bases in other areas. One of these high-technology locations became known as the popular Silicon Valley in California. According to Acs (2002), most registered US inventors (and applicants of patent applications) in high-technology are today located in a few famous high-technology agglomerations and centers of research excellence, such as Cambridge, Massachusetts and Silicon Valley, but not in the former industrial centers, e.g., Detroit, Cleveland, Dayton (see also Audretsch and Feldman, 1996).⁵⁸ With regard to the aforementioned aspects, Florida (2002b, xi) noted that

“[t]he new geography [...] is not the result of natural endowments of land, labor and capital [...]. Rather, [...] it is powered by innovation and entrepreneurship; and this in turn is the product of real people acting in real places. In other words, the factors that really matter are the ones we create for ourselves. That is because they are able to attract, mobilize and connect the factors that really matter - innovative people and creative entrepreneurs. [...] It was clear to me and to others that innovation is a geographically concentrated process; and there were certainly studies of this. But no one had really nailed it down. A big piece of the problem was that the field lacked the kind of measures required to probe this issue.”

In the context of knowledge-intensive industries, one promising line of reasoning and currently popular line of research grounds on the assumption that knowledge bases are becoming increasingly global and mobile, which implies that research activities and co-inventor network linkages take place at a distance and that inventor networks frequently relocate in space (Breschi and Lissoni, 2009).⁵⁹ Therefore, this development is regarded as a fundamental change in the geography of innovation because research collaboration linkages between agents and firms are becoming increasingly border-crossing and international (Maggioni and Uberti, 2009; Hoekman *et al.*, 2010; Powell and Giannella, 2010).⁶⁰ Such developments should change the distribution of patenting activity and the spatial structure of co-patenting linkages. The thesis challenges this idea empirically in a pan-European context.

2.1.3. Agglomeration, Indivisibilities and Fragmentation

Modern literature on agglomeration economies is considered to represent a collection of reinterpretations and formalizations of different dimensions on the micro foundations of

⁵⁸ Acs (2002, 4), among others, reported empirical evidence for this hypothesis by contrasting inventorship activity of the American sunbelt states and the former industrial heartland. Today, the leading innovative US regions are Santa Clara (CA), Los Angeles (CA), Cook (IL), Middlesex (MA), Norfolk (MA), Orange (CA), Bergen (NJ), New York (NY), Fairfield (CN), Nassau (NY), Dallas (TX), San Diego (CA). It is clearly visible that not only most innovations come from states such as California, Massachusetts, New York and New Jersey, but also that these US states provide the majority of population employed in high-tech manufacturing and knowledge intensive services (see also Audretsch and Feldman, 1996, 2004).

⁵⁹ For an overview refer to Almeida and Kogut (1999), Agrawal *et al.* (2006) and Oettl and Agrawal (2008).

⁶⁰ It should be possible to recognize the spatial shift of inventorship activity in patent documents, i.e., the relocation of innovative activity in terms of inventorship relocation.

increasing returns and agglomeration economies from the last century (Duranton and Puga, 2004; Combes and Overman, 2004; Capello, 2009).⁶¹

According to Starrett's "spatial impossibility theorem," any competitive equilibrium will feature autarchic locations under the assumption of homogeneity of space, without increasing returns or indivisibilities, and the presence of transportation costs (Starrett, 1978).⁶² Starrett (1978, 27) argued that,

"[a]s long as there are some indivisibilities in the system (so that individual operations must take up space) then a sufficiently complicated set of interrelated activities will generate transport costs."

Fujita and Krugman (2003), among others, pointed out that the competitive framework can, however, not explain the occurrence of agglomerations in a closed, homogeneous space under constant returns to scale (CRS) production technologies without first-nature heterogeneity, as described in the last section, and/or indivisibilities.⁶³ Otherwise, increasing land rents would lead to a dispersion of production activity. However, as soon as economic activities are not perfectly divisible, they have a certain (sustainable) location (Fujita and Krugman, 2003; Duranton and Puga, 2004; Behrens and Thisse, 2006).

Capello (2009) argued that the concept of agglomeration economies can generally be classified into three micro-foundations: (i) indivisibilities, (ii) synergies and (iii) spatial proximity (see also Capello, 2007). The concept of indivisibilities is generally built upon an industrial (only implicitly geographic) dimension and places emphasis on productivity effects that originate from large-scale production and shift a firm's production or cost curve (Edwards and Starr, 1987; Rosenthal and Strange, 2001; Roos, 2002b).⁶⁴

In an urban economics context, an evident cause of concentration of production and co-location of different firms is based on the advantages associated with the division of labor, which allows specialization and large-scale production yielding lower costs per unit of output (Duranton and Puga, 2004; Combes *et al.*, 2008; Capello, 2009). Duranton and Jayet (2005) differentiated between two strands of the literature on the division of labor. In a continuous framework, labor specialization can become ever narrower as the market size increases and the fragmentation of tasks increases with the market size. If, however, the

⁶¹ See also Rima (2004), Chandra and Sandilands (2005) and Combes *et al.* (2008).

⁶² For an overview see Ottaviano and Thisse (2001), Duranton and Puga (2004), Combes *et al.* (2008), Baumol (2008) and Puga (2010). Refer also to Ottaviano and Thisse (2000), Fujita and Krugman (2003) and Duranton (2008b).

⁶³ It is generally assumed that goods are consumable in infinitely divisible quantities. On the production side of the market, indivisible equipment is identical to "fixed costs" and inputs only exist in minimum quantities. Thus, indivisible inputs are associated with scale economies on the production side. Moreover, if the indivisible inputs are not overly specialized, they can be implemented in diversified processes at a lower cost compared to separately specialized plants, i.e., economies of scope (Edwards and Starr, 1987; Duranton and Puga, 2004; Combes *et al.*, 2008; Duranton, 2008b).

⁶⁴ Similarly, Kaldor (1966) has addressed this idea by distinguishing between increasing returns in the manufacturing industry and decreasing returns in the primary sector what became known under the label Verdoorn's law or Kaldor's second growth law (see also Seiter, 1997; Rima, 2004; Seiter, 2005; Capello, 2007; Combes *et al.*, 2008; Capello, 2009). Kaldor (1972, 1243) mentioned the importance of Allyn Young's contribution to the debate: "[Young's article] was so many years ahead of its time that the progress of economic thought has passed it by [...] partly because its criticism of general equilibrium theory could not be appreciated at the time when that theory itself was not properly understood."

benefits from the division of labor originate from small indivisibilities at the worker level, then the fragmentation of tasks proceeds discontinuously as the market size increases. Employing a worker in different tasks would cause set-up costs as it prevents specialization. Given a sufficient scale, it is preferable to allow the fragmentation of tasks and thus labor specialization, which avoids switching costs. In a spatial context, the presence of more workers in a given activity within a location may increase the output more than proportionately as it allows them to specialize in a narrower set of tasks (Duranton and Puga, 2004; Kim, 2006; Puga, 2010).⁶⁵ Consequently, if the division of labor (i.e., vertical disintegration and fragmentation of tasks) is significantly distance-sensitive and/or shows other forms of indivisibilities, then it becomes clear why co-location and co-agglomeration are beneficial for agents.⁶⁶

In a similar way, Combes *et al.* (2008, 39) argued that the existence of non-ubiquitous agents (i.e., human capital) and scale economies can be interpreted as specific forms of indivisibilities. However, an increasing sub-division/fragmentation of tasks (i.e., division of labor) raises scale economies and the heterogeneity of skilled labor, which may also increase labor-matching costs.

Duranton and Puga (2004, 2065) brought forward the critique that it is hard to think of any single activity or facility subject to meaningful indivisibilities to justify the emergence or existence of cities and metropolises. Accordingly, they present three mechanisms in the context of agglomeration economies. Spatial proximity helps in (i) sharing, (ii) matching and (iii) learning.⁶⁷ A larger market allows sharing mechanisms that cover the sharing of indivisible facilities, the sharing of gains from a wider variety of input suppliers in a location, sustained by a larger final good industry, the sharing of gains from individual specialization, sustained by larger production, the sharing of a local labor market and finally the sharing of risk. Matching mechanisms, on the other hand, are the improvements of the probability and quality of matching between agents that originate from large (dense) markets, e.g., employees and employers (i.e., labor market externalities), partners in joint projects, or financiers and entrepreneurs. Generally, matching mechanisms can be related to workers, intermediates and ideas. Finally, learning mechanisms are related to the generation, diffusion and accumulation of knowledge in a spatial context (i.e., innovation externalities), e.g., learning about market evolutions, new technologies and new forms of organization and routines (Duranton and Puga, 2004; Duranton, 2008a; Capello, 2009). Similarly, Florida (1995, 531) has argued that

“[t]he shift to knowledge-intensive capitalism goes beyond the particular business and management strategies of individual firms. It involves the development of the new inputs and a broader infrastructure at the regional level on which individual

⁶⁵ The gains of the division of labor are well-known since Adam Smith (Roos, 2002b; Capello, 2009). The idea of specialization by division of labor in a spatial context has also been mentioned by List ([1842] 1909). A few decades later, Young (1928) extended the discussion about increasing returns by addressing Smith’s division of labor concept (see also Rima, 2004; Seiter, 2005; Chandra and Sandilands, 2005).

⁶⁶ Refer to Edwards and Starr (1987), Duranton and Puga (2004), Press (2006a) and Duranton (2008b) for a review and detailed discussion of indivisibilities, specialization and the division of labor. The whole debate on increasing returns is beyond the scope of this study.

⁶⁷ Refer also to Capello (2007, 2009) and World Bank (2009) for an overview.

firms and production complexes of firms can draw. The nature of this economic transformation makes the regions key economic units in the global economy.”

To conclude, the firm’s incentive to concentrate all its production in a single location is, however, not identical to the advantages that originate from proximity to other firms and the advantages of fragmentation in local markets. It is argued that large-scale production promotes returns internal to the firm, which represent a first meaningful incentive for a firm to concentrate production in a single location. Second, firms are considered to (re-) locate production close to a large market in the case of significant costs of transportation. Third, co-location and co-agglomeration in cities and large urban areas are preferred because fragmentation of production induces essential input-output linkages that affect input prices (Gallagher, 2008; Combes *et al.*, 2008; Capello, 2007, 2009).⁶⁸ Spatial proximity is assumed to induce additional external economies which are independent from internal scale economies but originate from the scale of the local market (Ciccone, 2008; Henderson, 2010). Therefore, central classifications of external economies will be reviewed and discussed in the subsequent section, particularly those related to knowledge-intensive industries and innovation.⁶⁹

2.1.4. Agglomeration, Clustering and External Economies

2.1.4.1. Industrial Districts and External Economies

The external advantages of agglomerated activities and environments are considered to represent central determinants of the spatial distribution of production and research activities across regions. It is argued that regional disparities are persistent phenomena because of “second-nature” agglomeration economies (Fujita and Thisse, 1996; Acs, 2002; Duranton, 2008a).⁷⁰

Long ago, Alfred Marshall ([1890] 1920b) has disclosed the advantages of co-location and spatial proximity. In the following, the main arguments are briefly reviewed. Marshall (1920b, 271) argued that

“[w]hen an industry has thus chosen a locality for itself, it is likely to stay there long: so great are the advantages which people following the same skilled trade get from near neighbourhood to one another. The mysteries of trade become no mysteries; but are as it were in the air, and children learn many of them unconsciously. [...] Good work is rightly appreciated, inventions and improvements in machinery, in processes and the general organization of the business have their merits promptly discussed: if one man starts a new idea, it is taken up by others and combined

⁶⁸ See also Krugman and Venables (1996), Holmes (1999) and Harris (2008). In an US context, Glaeser (2005a) suggested that economies in transportation may also explain why industries became concentrated in cities.

⁶⁹ The following section places emphasis on Marshall’s external economies put forward in his *Principles of Economics* ([1890]/1920), Chapter X of Book IV. Several economists equalize Marshall’s arguments with a general Marshallian agglomeration theory (Roos, 2002b, 2008; Capello, 2007; Combes *et al.*, 2008).

⁷⁰ See also Caniëls (1996), Keilbach (2000), Roos (2002b), Press (2006a), Capello (2007) and Fingleton (2007).

with suggestions of their own: and thus it becomes the source of further new ideas. [...] and presently subsidiary trades grow up in the neighbourhood, supplying [the industry] with implements and materials, organizing its traffic, and in many ways conducing to the economy of its material.”

Besides these input externalities, another agglomerative effect, which was addressed by Marshall, is the observed tendency of firms and entrepreneurs to locate near specialized markets for labor, what is nowadays discussed under the label “labor-market pooling” or “labor-market externalities” (Krugman, 1995; Combes and Duranton, 2006; Martin *et al.*, 2008).⁷¹ As Marshall (1920b, 270) argued,

“[a]gain, in all but the earliest stages of economic development a localized industry gains a great advantage from the fact that it offers a constant market for skills. Employers are apt to resort to any place where they are likely to find a good choice of workers with special skill which they require; while men seeking employment naturally go to places where there are many employers who need such skill as theirs and where therefore it is likely to find a good market.”

Marshall additionally addressed the consumption behavior of agents in a spatial context, i.e., local markets and local demand by consumers. This is similar to the new economic geography framework (section 2.1.5.5), where centripetal forces increase with the size of the local market (i.e., pecuniary externality). In the new economic geography, the process of agglomeration is enforced by cumulative causation and circular causality as production factors (and demand) are inter-regionally mobile (Krugman, 1991; Roos, 2002b; Capello, 2007).⁷² Additionally, Marshall pointed to the effects of co-location on the transaction and search costs related to the consumer’s preferences. In this respect, he implicitly discussed the benefits of co-location of specialized suppliers and vertical disintegration, although his remarks are related to consumers and not directly to intermediate industries.⁷³

The aforementioned factors are considered to affect different levels of aggregation; i.e., the firm-/ plant-level level, the regional level, the industry-level. Some effects are surely external to single firms but internal to local industries, whereas Marshall’s attention was primarily on “proximity externalities” in industrial district. Other effects are, however, external to the industry but internal to the (regional) economy as a whole. This makes several agglomeration effects (i.e., technological externalities) compatible with the perfect competition framework (see section 2.1.4.3).

As is frequently argued, literature on clustering and agglomeration uses Marshall’s external economies as a main reference with respect to economies of localization and urbanization and the dynamic effects from agglomeration (Audretsch and Feldman, 1999; Capello, 2007; de Groot *et al.*, 2009).⁷⁴

⁷¹ Refer also to Fujita and Thisse (1996), Roos (2002b), Sonobe and Otsuka (2006), Press (2006a), Capello (2007), Combes *et al.* (2008), Harris (2008), World Bank (2009) and Overman and Puga (2010) for an overview.

⁷² For additional overviews refer to Keilbach (2000) and Press (2006a).

⁷³ “[T]he consumer will go to the nearest shop for a trifling purchase; but for an important purchase he will take the trouble of visiting any part of the town where he knows that there are specially good shops for this purpose” (Marshall, 1920b, 273).

⁷⁴ Krugman used Marshall’s agglomeration economies to overcome perfect competition. He modeled economies of scale internal to the individual firm (plant-level), which is based on the idea of imperfect

Related to the technological externalities debate, a central part in Marshall is devoted to the diffusion of ideas and knowledge in a spatial context, nowadays labeled “Marshallian externalities of the third kind” (Breschi and Lissoni, 2001a,b; Rosenthal and Strange, 2004). In this context, the diffusion of economically useful knowledge is the source of technological externalities, as the

“[n]ew idea, [...] taken up by others and combined with suggestions of their own [...] becomes the source of further new ideas” (Marshall, 1920b, 270).

In *Industry and Trade*, Marshall (1920a, 190) has additionally argued that

“[t]he leadership in a special industry, which a district derives from an industrial atmosphere, such as that of Sheffield or Solingen, has shown more vitality than might have seemed probable in view of the incessant changes of technique. The explanation is perhaps to be found in the fact that an established centre of specialized skill, unless dominated by a guild or trade-union of an exceptionally obstructive character, is generally in a position to turn to account quickly any new departure affecting its work; and if the change comes gradually, there is no particular time at which strong incitement is offered to open up the industry elsewhere.”

Related to the previously mentioned aspects, Marshall attributed central importance to the “industrial atmosphere” in districts, which originates from the presence of skilled people that transform regions (and districts) into leading industrial places. In a more socio-cultural perspective, the Marshallian industrial atmosphere is also interpreted as the advantages that arise from (localized) networks and social proximity in urban areas (Fujita and Thisse, 1996; Capello, 2007, 189). The capacity of agents to co-operate is rooted in the socio-cultural environment which generates increasing returns, the so-called “district economies” (Roos, 2002b; Capello, 2007, 2009).⁷⁵ These economies are based on trust, sense and social proximity, which represent indivisibilities, and spatial proximity is considered a meaningful prerequisite (Capello, 2007, 2009).⁷⁶

To summarize, it is argued that Marshall early contributed with a well-defined classification of external advantages of agglomerated activities and environments (Scitovsky, 1954; Fujita

competition. This is also a reason why non-pecuniary effects are not modeled in early new economic geography models as the novelty is related to pecuniary effects from increasing returns. Equilibrium city size (or more general the manufacturing share in the region) depends on the trade-off between pecuniary externalities (centripetal forces) and the costs of spatial concentration (centrifugal forces) (Feldman, 2000; Keilbach, 2000; Press, 2006a; Capello, 2007; Audretsch *et al.*, 2008; Combes *et al.*, 2008). As Krugman has argued: “*Thus local external economies never disappeared as a concept from economics. Indeed, if you were ask a mainstream economist at any time between, say, 1930 and the last few years why cities exist, or why some industries are so concentrated in space, he or she would surely answer in terms of just such local externalities [technological and pecuniary externalities based upon Marshall]*” (Krugman, 1995, 50).

⁷⁵ Further to this, it is argued that Marshall linked geographical proximity with the transfer mechanisms of knowledge, which improves the level of productivity in all companies (Keilbach, 2000; Press, 2006a; Capello, 2007).

⁷⁶ As Marshall (1920a, 189) has argued: “[...] *personal contact is most needed (1) in trade between allied branches of production, at all events in regard to things which have not yet been brought completely under the dominion of either general or particular standardization; and (2) in all dealings, especially retail, connected with dress, ornaments and other goods, which need to be adapted to individual requirements and idiosyncrasies.*”

and Thisse, 1996; Rosenthal and Strange, 2004).⁷⁷ As a consequence, there exist several interpretations of Marshall's external economies, i.e., building blocks of agglomeration economies in the literature, that place emphasis on different working channels (Duranton and Puga, 2004; Capello, 2009).

2.1.4.2. Interpretations of Marshall's Agglomeration Economies

A popular interpretation of Marshall's external economies is given by Krugman (1991) and has been used in his new economic geography framework and in further framework advancements (see sections 2.1.5.5 and 2.1.6.7). According to Krugman, agglomeration economies can generally be classified into three forces: (i) human capital externalities, (ii) technological externalities and (iii) market interaction (pecuniary) externalities (Krugman, 1991, 1995; Capello, 2007, 2009).⁷⁸ Similarly, Martin *et al.* (2008) classified Marshall's agglomeration economies into (i) labor market externalities, (ii) knowledge externalities and (iii) input externalities. The latter force is also known as pecuniary externality. The incorporation of technological externalities was a general approach in endogenous growth models (see section 2.1.6.6), whereas pecuniary externalities were central features of the new economic geography. The application of both externality types to innovation clusters and industry agglomerations has recently (re-)accelerated. However, "technological spillovers," although recognized, are not included in Krugman's seminal core-periphery framework. In this respect, an illustrative statement on the importance of such spatial external effects and emphases in economic models was offered by Fujita *et al.* (2001, 4), although technological externalities are downplayed.⁷⁹

"[A]lthough all three of Marshall's forces are clearly operating in the real world, the new economic geography models have generally downplayed the first two [knowledge spillovers and markets for skilled labor], essentially because they remain hard to model in any explicit way. Instead they have focused on the role of linkages [backward and forward linkages associated with large local markets]."

⁷⁷ See also Press (2006a), Martin *et al.* (2008), Combes *et al.* (2008), Capello (2007, 2009) and Puga (2010). Fujita and Thisse (1996, 345) concluded that, "[f]ollowing Scitovsky (1954), it has been customary to consider two categories: 'technological externalities' (such as spillovers) and 'pecuniary externalities'. The former deals with the effects of nonmarket interactions which are realized through processes directly affecting the utility of an individual or the production function of a firm. By contrast, the latter refers to the benefits of economic interactions which take place through usual market mechanisms via the mediation of prices. For obvious reasons Marshall was not aware of this distinction, and his externalities turn out to be a mixture of technological and pecuniary externalities. As a consequence, each type of externality may lead to the agglomeration of economic activities."

⁷⁸ Krugman (1992, 36) argued: "First, [...] a pooled market for workers with specialized skills; [...] Second, an industrial center allows provision of nontraded inputs specific to an industry in greater variety and at lower cost [...] Finally, because information flows locally more easily than over great distance, an industrial center generates what we would call technological spillovers." See also Crafts and Venables (2003) for an identical classification and review.

⁷⁹ Another interpretation of Marshall's described economies, very similar to the one of Krugman, is given by Fujita and Thisse (2003, 8), who put emphasis on (1) internal economies, (2) the formation of a highly specialized labor force and the production of new ideas, both based on the accumulation of human capital and face-to-face communication, (3) the availability of specialized input services and (4) the existence of modern infrastructures.

Labor-market externalities, as described by Marshall, represent another salient feature of cities and agglomerations (Crafts and Venables, 2003; Combes and Duranton, 2006; Henderson, 2010). Rosenthal and Strange (2004, 2153) classified the gains and incentives of labor-pooling into two distinct aspects. First, when firms (industries) show an ex ante lack of knowledge about the labor market structure in a region, firms tend to agglomerate in urban areas and cities. Such locations are said to provide dense and heterogenous labor markets, which increase the probability of a better match of specific labor demand and supply. Therefore, growing cities show an increasing diversity of labor supply, which should lead to fulfilling the needs of knowledge-intensive industries. Second, firms with ex ante knowledge of regions' labor markets tend to co-agglomerate (locate) in cities or urban areas, which minimizes search costs, training costs and risks for employees. Furthermore, if industries are hidden by positive demand shocks, firms will generally find it easier to hire additional workers in urban regions and cities (Duranton and Puga, 2004; Gallagher, 2008; Martin *et al.*, 2008).⁸⁰ In a research clustering perspective, one may argue that regional disparities in research activity are (increasingly) dependent on the spatial distribution of human capital (i.e., researchers and creative minded people) which grants migration and network studies a pivotal attention (Florida, 1995; Fujita and Thisse, 1996; Breschi and Lissoni, 2009).⁸¹

In a more general way, Fujita and Thisse (1996) differentiated between market-led mechanisms and the effects that occur outside the anonymous market.⁸² Fujita and Thisse (1996, 345) concluded that

“[i]t is now customary to [distinguish between] two categories: technological externalities and pecuniary externalities. The former deals with the effects of non-market interactions that are realized through processes directly affecting the utility of an individual or the production function of a firm. In contrast, pecuniary externalities are by-products of market interactions [transactions]: They affect firms or consumers and workers only insofar as they are involved in exchanges mediated by the price mechanism. Pecuniary externalities are relevant when the markets are imperfectly competitive, for when an agent's decision affects prices, it also affects the well-being of others.”

In contrast to Krugman (1991), Ottaviano and Thisse (2001) gave much more attention to technological externalities that originate from knowledge transmission at a proximate distance. However, they also placed a special emphasis on the spatial scale of analysis when differentiating between the possible externalities.⁸³

In light of the aforementioned determinants and drivers of clustering and agglomeration, the role of knowledge externalities was (and is) widely discussed in literature, especially in the context of knowledge generation and diffusion in cities (Glaeser *et al.*, 1992; Fujita and Thisse, 1996; Johansson, 2005).⁸⁴ As this study is explicitly focusing on the determinants

⁸⁰ See also Keilbach (2000), Roos (2002b), Capello (2007) and Combes *et al.* (2008).

⁸¹ See also Zucker *et al.* (1998) and Almeida and Kogut (1999).

⁸² For a further discussion refer to Ottaviano and Thisse (2001).

⁸³ Refer also to Lucas and Rossi-Hansberg (2002), Duranton and Puga (2004), Boschma and Frenken (2009a).

⁸⁴ Refer also to Henderson *et al.* (1995), Black and Henderson (1999b), Glaeser (2000), Duranton and Puga (2001), Henderson (2003a), Duranton and Puga (2004) for an overview.

of research clustering and the distribution of patenting activity, the access to information and knowledge and its transmission are assumed to represent pivotal factors of a firm's location decision. Related to this perception, Fujita and Thisse (1996) pointed to the meaningful differentiation between production and creation as these are distinct activities of individuals, whereas the existence of pecuniary externalities in agglomerations is a crucial factor for production processes in the manufacturing industry (and industrial geography). Creative activities of individuals are in particular influenced by their proximity to other people. As a consequence, economic activities in the "knowledge economy" are considered to particularly depend on creativity which is identical to Florida's "creative class concept" (Florida, 1995, 2002c,a; Florida and Tinagli, 2004).⁸⁵ Similarly, Lucas (1988, 39) argued

"[t]hat the 'force' we need to postulate account for the central role of cities in economic life is of exactly the same character as the 'external human capital' I have postulated. [...] What can people be paying Manhattan or downtown Chicago rents for, if not for being near other people?"

Hence, personal communication and knowledge transmission within and between groups of individuals (and epistemic communities) are considered to be vital preconditions for creativity and innovation output in knowledge-intensive industries.⁸⁶

Finally, in a core-periphery perspective, Kilkenny (2010) brought forward the argument that remote low-density areas (rural regions) seem to be competitively disadvantaged due to a significant lack of static and dynamic agglomeration externalities, which gives inter-regional research linkages a pivotal role in regional development.⁸⁷

To sum up, knowledge externalities seem to matter for the development of new routines and new products. Neighboring regions are considered to benefit from spatial proximity to high-level growing regions if there are considerable positive externalities and inter-regional flows of knowledge. Moreover, firms and agents have access to knowledge bases via intra- and inter-regional research linkages and networks which also induce some kind of externalities. The following sections are organized in order to offer a detailed classification and taxonomy of the causes and effects of agglomeration, co-agglomeration and clustering. Special attention is drawn to research clustering, knowledge transmission and the spatial concentration of research and innovative activity.

2.1.4.3. Agglomeration Economies, Spillovers and Networks: A Taxonomy

It is evident from the previous sections that the origins of agglomeration economies and the causes of clustering are indeed multifaceted. The literature generally distinguishes between (i) intra-market externalities (pecuniary externalities) that work via prices, (ii) quasi-market externalities (externalities from a network transactions) and (iii) extra-market externalities (technological externalities) that occur without any monetary compensation

⁸⁵ Refer also to Jacobs (1969) and Glaeser (2005a).

⁸⁶ Similarly, Robert-Nicoud (2004, 4) argued that "[a]gglomeration generates inertia [...], people and firms are there because other people and firms are there too. So people are willing to move out of the agglomeration [relocate] only if a large shrunk of people are willing to do as well."

⁸⁷ Refer also to Partridge and Rickman (1999), Duranton and Puga (2001), Duranton (2008a), de Groot *et al.* (2009).

(Johansson, 2005; Capello, 2007, 2009). Moreover, a general taxonomy can be built upon the following pillars: (i) the source of externalities (proximity vs. network link externality); (ii) the effects and consequences of externalities (efficiency vs. innovation externality); and (iii) the nature of externalities (pecuniary vs. non-pecuniary externality). The industry dimension on agglomeration economies is additionally considered with the concepts of urbanization and localization economies (section 2.1.5). Furthermore, the concept of innovation externalities (section 2.1.6), i.e., the concepts of Marshall-Arrow-Romer externalities (section 2.1.6.2), Jacobs externalities (section 2.1.6.3) and Porter externalities (section 2.1.6.4) are considered. Finally, special attention is given to the generation and transmission of knowledge via anonymous market transactions, via (persistent) inter-regional network linkages and intentional and unintentional knowledge flows in localized networks and industry clusters (section 2.1.7).

The subsequent table 2.1 illustrates a general typology of the aforementioned externalities (Johansson, 2005; Capello, 2007, 2009); it classifies horizontal and vertical externalities against efficiency and innovation externalities.⁸⁸ The taxonomy seems to fit to the research agenda of several epistemic communities; e.g., geographical economics, economic geography, evolutionary economics, evolutionary economic geography and geography of innovation. The different externality concepts are reflected in different models, which will be presented and discussed in the following sections.⁸⁹

2.1.5. Agglomeration, Research Clustering and Pecuniary Externalities

2.1.5.1. Pecuniary Externalities, Local Scale and Efficiency

Pecuniary externalities are of broad interest in explaining the spatial concentration, agglomeration and co-agglomeration, as shown by the majority of new economic geography (NEG) models and approaches in economic geography proper.⁹⁰ They are also sometimes labeled vertical spillovers, welfare spillovers or rent spillovers (Johansson, 2005; Harris, 2008).⁹¹

⁸⁸ The classification also takes into consideration the following contributions: Scitovsky (1954), Puga and Duranton (2000), Duranton and Puga (2004), Jacobs (1969), Acs *et al.* (1997), Acs *et al.* (2002), Ottaviano and Thisse (2001), Kelly and Hageman (1999), Martin and Sunley (2003), Caniëls (2000), Glaeser *et al.* (1992), Glaeser and Resseger (2009), Henderson *et al.* (1995), Audretsch and Feldman (1995), Audretsch and Feldman (1999), Audretsch and Feldman (2004), Audretsch and Keilbach (2008), Glaeser (2000), Feldman (2000), Roos (2002b), Döring (2004), Autant-Bernard and Massard (2007), Autant-Bernard *et al.* (2007), Döring and Schnellenbach (2006), Athreye and Werker (2004), Breschi and Lissoni (2001b), Breschi *et al.* (2005), Press (2006a), Keilbach (2000), Maggioni (2002), de Groot *et al.* (2009), Andersson *et al.* (2005), Greunz (2005), Rosenthal and Strange (2001), Rosenthal and Strange (2003), Harris (2008).

⁸⁹ The following summary of models and concepts is, however, non-exhaustive.

⁹⁰ For an overview refer to Ottaviano and Puga (1998), Neary (2001), Duranton and Puga (2004), Autant-Bernard and Massard (2007) and Capello (2007).

⁹¹ Verspagen (1997, 230) has argued that “*Griliches (1979) termed this form of spillovers ‘rent spillovers’, because they are crucially related to the rents of both the receiving and supplying firm. On a different, more semantic level, Griliches (1992) has argued that as long as goods are being traded between the supplying and receiving party, there are no ‘real’ externalities, in the strict sense of the word, involved. Although one might therefore argue that the term ‘spillover’ is less appropriate in this case, there is no need to abandon the terminology as long as it is clear that rent spillovers*

Table 2.1. Innovation vs. efficiency externalities

Form/type	Innovation externality	Pecuniary/efficiency externality
Proximity externality	Absolute size and/or diversity of local market affects product development (early phases of a product cycle) and knowledge spillovers on innovative output (MAR vs. Jacobs)	Size of local market induces scale economies for producers (distance-sensitive production)
Vertical	Downstream externality from knowledge flows between supplier and customer; proximity externality and/or network transaction externality	Downstream externality affecting the price (supplier, customer)
Vertical	Upstream externality from knowledge flows between input (knowledge) buyer and seller; proximity externality and/or network transaction externality	Upstream externality affecting input costs (of a company)
Horizontal	Knowledge flows between competitors from joint R&D efforts based on a transaction linkage (network linkage) or based on (unintended) spillovers in an agglomeration due to proximity	Co-operation between competitors (transportation, marketing, long-distance export)

Source: illustration based on Johansson (2005, 112); see also Johansson and Quigley (2003), Capello (2007, 2009) and Burger *et al.* (2009).

Pecuniary externalities are based on market interactions and affect firms (or consumers) by means of exchanges involving prices (Ottaviano and Thisse, 2001; Duranton and Puga, 2004; Johansson, 2005).⁹² The interdependence between the supply side (firms, products) and demand side (consumers, market size) is direct due to the spatial range and location of pecuniary externalities (Autant-Bernard and Massard, 2007; Dewhurst and McCann, 2007). NEG models, for example, treat market mechanisms as the origins of centripetal and centrifugal forces (Fujita and Mori, 2005; Robert-Nicoud, 2005; Krugman, 2009). The overall effects of agglomeration externalities depend on the local range of these pecuniary externalities (i.e., proximity externalities). The effect is the same for intermediates and final goods as long as both suffer from transportation costs (Martin *et al.*, 2008; Combes *et al.*, 2008; Audretsch *et al.*, 2008).⁹³

Pecuniary externalities operate via anonymous market interactions. If agents co-locate at a proximate distance, an anonymous market offers everything: providing agents with a large quantity and quality of inputs; efficient backward and forward market linkages;

involve a different process than the pure knowledge spillovers, the other form of R&D spillovers that Griliches noted."

⁹² See also Autant-Bernard and Massard (2007) and Capello (2007, 2009) for classifications.

⁹³ The overall effect is interdependent and spurs agglomeration and the market size, which is denoted as a pecuniary externality or a pecuniary effect (Keilbach, 2000; Autant-Bernard and Massard, 2007; Capello, 2007).

retail firms in the neighborhood that reduce input costs and increase variety. Moreover, firms benefit from shared inputs in a local market, e.g., capital goods, intermediates and labor pooling (Johansson and Quigley, 2003; Duranton and Puga, 2004; Martin *et al.*, 2008). Thus, pecuniary effects can be regarded to enable firms to move to, or to move along, existing production frontiers (Neary, 2001; Harris, 2008; Capello, 2007, 2009). In comparison, non-pecuniary (technological) effects shift production possibility frontiers of firms and/or regions and countries (Romer, 1990b; Feldman, 1999, 2000; Harris, 2008). Furthermore, the concept of pecuniary externalities has been extended to the concepts of urbanization and localization economies, which represents a commonly used classification and focal point of empirical debates, especially in neo-Marshallian studies (see Feldman, 2000; Capello, 2007; DeGroot *et al.*, 2009). These concepts first and foremost represent the “industry perspective” on agglomeration economies. However, the differentiation itself represents a highly discussed area of research which is additionally divided into “static” and “dynamic” externalities (Henderson, 2003a; Autant-Bernard and Massard, 2007; Duranton, 2008a). These externalities are also known as “efficiency” and “development” externalities (Johansson and Quigley, 2003; Johansson, 2005; Capello, 2007, 2009).⁹⁴ Table 2.2 shows the classification of pecuniary (efficiency) externalities into localization and urbanization economies and summarizes the different working channels. The concepts are separately reviewed in the following sections.

2.1.5.2. Localization Economies

“Localization economies” are assumed to usually take the form of Marshallian externalities. The labor productivity level in a certain industry is assumed to depend on the size of the industry and the specialization of the region (Dewhurst and McCann, 2007; Duranton, 2008a; Henderson, 2010). Rosenthal and Strange (2004) suggested that, for typical industries, doubling the local industry size leads to a 2-10% increase in the productivity level of employed workers. Moreover, doubling city size (i.e., the local scale) may also lead to a productivity increase in the same local industry, especially in high-technology industries. Dating back to Marshall’s industrial districts argument, economies of scale due to high specialization, division of labor and increasing industry-wide output are associated with downward sloping average cost curves. Accordingly, industry concentration is assumed to promote external economies for agents, particularly at a proximate distance, and to have, first of all, static effects, i.e., input-costs, delivery costs (Johansson, 2005; DeGroot *et al.*, 2009).⁹⁵

⁹⁴ According to Henderson (2003b, 29), “[t]here appear to be two working interpretations of dynamic externalities. First is that either the history of economic activity in a location affects productivity levels or growth. So this could be past levels of own industry activity (employment) that generate a stock of local industry and location specific “trade secrets.” The second set concerns the effect of “knowledge” (rather than information) spillovers on productivity levels. Knowledge is typically measured as non-industry specific, average education in the city. If average education in a city affects productivity it isn’t clear this is a dynamic effect per se. It could be static in the sense that average education could simply enhance static productivity levels (but not on-going growth rates of productivity), but [...] that is sufficient to enhance overall urban scale and promote endogenous growth.”

⁹⁵ See also Maggioni (2002), Autant-Bernard and Massard (2007), Burger *et al.* (2009) and Henderson (2010).

Table 2.2. Taxonomy of agglomeration economies

Localization economies (intra-industry)	Urbanization economies (inter-industry)
Accessibility to:	Accessibility to:
a specialized labor market	a diversified labor market
a high number of firms in the same industry	a high number of firms belonging to a diversified industry structure
specialized suppliers and service providers	a diversified market for industrial services and inputs
a highly specialized market for final goods (large market size)	a large market for diversified final goods
highly specialized R&D-departments and universities of intra-industry type	a diversified scientific environment with diversified universities and R&D-departments
scale economies from a single localized industry	scale economies from overall city size (also diversified production structure)
localization explains productivity level differentials of cities and regions	urbanization explains productivity level differentials of cities and regions

Source: own illustration.

A forerunning contribution to localization economies was made by Henderson (1974). He argued that an industry-specific externality in production decreases marginal costs of production depending on the level of industry output (i.e., efficiency externality). The distribution (and agglomeration) of firms is then determined by both positive industry externalities and negative effects from spatial concentration (e.g., commuting costs, increasing labor and capital costs). According to his results, cities show tendencies to specialize into industries. Thus, industries with large external economies tend to be predominantly concentrated in cities and urban areas.⁹⁶ Consequently, cities are considered to benefit significantly more from localization externalities than rural and peripheral areas (see also Henderson, 2010). Thus, a core-periphery distribution of industries and R&D-activity might represent a beneficial outcome.⁹⁷ The idea of such localization externalities (although the mentioned effects are pecuniary) has additionally been applied to innovative capacity in a spatial context (Feldman, 1999; van der Panne, 2004; Harris, 2008). However, such externalities are regarded as dynamic effects of co-location when they are related to growth in employment, innovations and new products (see section 2.1.6).

In a new economic geography context, Krugman and Venables (1996) and Aiginger and Pfaffermayr (2004) have argued that European economic integration might induce industry

⁹⁶ Again, the contribution and differentiation of sources of externalities is rather controversial. Refer to Feldman (1999) and Glaeser (2000) for further details.

⁹⁷ Ciccone and Hall (1996), among others, found that county employment densities are crucial in accounting for large differences in labor productivity across U.S. states.

agglomeration and increases in the degree of local specialization, bringing the European case closer to the spatial specialization pattern that economists and geographers identified in the United States. In this respect, they suggested that integration generally induces a geographic consolidation of industries at the national level and increasing regional specialization.⁹⁸

To conclude, the local scale is a major part of the explanation why industrial activities agglomerate in cities and urban areas and why regions differ in terms of their productivity levels (Dewhurst and McCann, 2007). However, urban diseconomies (i.e., costs of collocation) dissipate agglomeration economies and explain why cities and localized industries show limitations in their overall size (Hoover, 1936; Henderson, 1974, 2003a; Duranton and Puga, 2004).⁹⁹

2.1.5.3. Urbanization Economies

“Urbanization economies” are related to the size (urban scale) and industry structure of the city, region or agglomeration in order to explain varying levels in productivity (see table 2.2) (Hoover, 1936; Hoover and Giarrattani, 1999; Henderson, 2003). An obvious economic advantage of big cities is that they offer a large (and heterogenous) market affecting costs and prices (Johansson, 2005; Capello, 2007; Duranton, 2010).¹⁰⁰ Consequently, cities are considered to form and grow in order to exploit agglomeration economies that operate across all co-located activities/industries.

Hoover and Giarrattani (1984, 73) discussed the advantages of urbanization as

“[e]ssentially elements of a large urban agglomeration. Their presence, and the quality and variety of the services they offer, depend more on the size of the city than on the size of the local concentration of any of the activities they serve.[...] Economies generated by activities and services of this sort are external to any single-activity cluster, but they are internal to the urban area. There is a parallel to be drawn here to the relationship between a single-activity cluster and its constituent units. In that instance, economies were realized by the units as the size of the cluster increased; thus economies are internal to the cluster but external to the unit. In the case of urbanization economies, we recognize that economies accrue to constituent clusters as the size of the urban area increases. [...] Technological changes and enhancement of the mobility of labor and entrepreneurship explain why such local specialization has become increasingly rare. By contrast, external economies on the broader basis of urban size and diversity have remained a powerful locational force.”

Similarly, Lucas (1993) discussed urbanization economies in an endogenous growth context, asserting that the main compelling reason for the growth of cities originates from

⁹⁸ The specialization-localization debate will be reviewed in more detail in section 2.2.4 and is summarized in tables in the appendix.

⁹⁹ See also World Bank (2009) and Henderson (2010).

¹⁰⁰ Urbanization economies stem from effects external to the industry but internal to spatial units, such as cities or regions. For further discussions refer to Glaeser (2000), Feldman (2000), Maggioni (2002), Roos (2002b), Johansson (2005), Press (2006a), Autant-Bernard and Massard (2007), Capello (2007) and Dewhurst and McCann (2007).

the existence of increasing returns to scale that shift the productivity level.¹⁰¹ Accordingly, urbanization economies can be empirically challenged by different working channels, depending on the research question, e.g., the employment structure, infrastructure, relative factor prizes, industry-structure, presence of industrial suppliers and service providers (Johansson, 2005; de Groot *et al.*, 2009; Puga, 2010).

However, it has also been argued that cities, metropolises and urban regions may reach absolute population levels and scales that increase external diseconomies of congestion that fully (or even more than) compensate positive agglomeration economies (Duranton and Puga, 2004; Martin *et al.*, 2008; World Bank, 2009).¹⁰²

Finally, Partridge and Rickman (1999) and Burger *et al.* (2008) argued that static externalities from urbanization are different from dynamic urban externalities, the so-called Jacobs externalities (see section 2.1.6.3), as the latter explicitly account for employment growth, productivity growth and the effects from knowledge spillovers on innovative capacities (product development and new routines), whereas the static urbanization externality concept in general focuses on the local scale of production and existing productivity differentials, and the positive effects from population density, input supply structures and local market size on prices and costs. In light of the still prevalent debate and area of regular conflict, recent approaches link the Jacobs externality concept to the process of inter-industry knowledge diffusion and the effects of innovation externalities on innovative capacity (Audretsch and Feldman, 2004). The approach is thus different from the 1970s static view on agglomeration economies and the explanation of persistent productivity differentials (Partridge and Rickman, 1999; Johansson, 2005; Capello, 2009).¹⁰³ Similarly, Capello recently argued that especially neo-Marshallian studies identified regions (and space in general) as the origin of “dynamic” external economies which emerge as positive effects from co-location and affect the firm’s productive and innovation efficiency (i.e., innovative capacity) (Capello, 2007, 185; Capello, 2009). Accordingly, the effects differ from static gains in agglomerations.

2.1.5.4. A Taxonomy of Urbanization and Localization Economies

Table 2.3 summarizes pecuniary (intra-market) externalities that originate from spatial proximity in an urbanization and localization economies context, where the emphasis is on

¹⁰¹ See Roos (2002b), Press (2006a), Capello (2007, 2009) for an overview.

¹⁰² Higher GDP per capita growth rates and other forms of agglomeration economies only dominate up to metropolitan size of maximum 6 to 7 million citizens, which resembles the well-known inverted U-shaped relationship (OECD, 2006, 2009a,f; World Bank, 2009) (see section 5.4). Another crucial debate is about the privatization of benefits from agglomeration and the socialization of associated costs that stem from concentration (OECD, 2009b,a,f). See also Capello (2007), World Bank (2009) or Henderson (2010).

¹⁰³ Partridge and Rickman (1999, 319) argued that “[s]everal empirical regional studies related to geographic concentration of economic activity and economic spillovers emphasize their relationship to employment growth, only indirectly testing the externality-productivity relationship (e.g., Glaeser *et al.* 1992; Henderson, Kuncoro, and Turner 1995; Partridge and Rickman 1996; Henderson 1997). Also, studies of regional productivity differences typically focus on static urbanization and localization economies and not on dynamic externality effects emphasized in the endogenous growth literature (e.g., Moomaw 1983, 1986).”

prices, costs, profits and productivity levels. More generally, the demand-externality is related to the size of the market, which is central in the new economic geography (Krugman, 1991). To conclude, localization and urbanization economies emerged as a conceptualization in the mid 1970s which represents the conventional industry dimension of agglomeration economies (Feldman, 2000; Capello, 2007, 2009). The focus of analysis is solely on the question whether agglomeration economies are related to the scale of a single (and specialized) industry or to the cross-fertilization enhanced by diversity and the scale of other industries (Henderson, 2003a). Consequently, the concept centers the exploitation of indivisibilities within either a specialized or diversified industry environment (Feldman, 1999, 2000; Rosenthal and Strange, 2001; Johansson, 2005). Thus, the presence and strength of the mentioned externalities is related to the emergence and stability of core-periphery structures.

Table 2.3. Pecuniary externalities

Externality type	Transaction type	Mechanism
Demand	Intra-regional demand externality. “Home market effect.”	A large local demand makes it possible for firms to exploit scale economies and hence supply commodities to households at a lower price and with a greater variety.
Vertical	Downstream/delivery-cost externality. Localization and urbanization economies.	Firms can offer inputs/products with lower transaction costs and (potentially) at a lower price due to physical proximity (proximity externality).
	Upstream input-cost externality. Localization and urbanization economies.	Supplier firms in an industry provide inputs with lower transaction costs and (potentially) at a lower price due to physical proximity (proximity externality).

Source: illustration based on Johansson (2005, 119), Johansson and Quigley (2003) and Capello (2007, 2009).

2.1.5.5. Core-Periphery Structures and Endogenous Location

2.1.5.5.1. The Origins of the New Economic Geography

The new economic geography corresponds to the proposed classification of agglomeration economies (see section 2.1.4.3) and represents a formalization of pecuniary externalities that induce core-periphery structures. Paul Krugman is one of the main contributors to geographical economics in the 1990s who has been working for re-establishing spatial

aspects as a pivotal factor in economic theorizing and empirical research (Krugman, 1991, 1992, 2009; Fujita and Krugman, 2003; Fujita and Mori, 2005).¹⁰⁴

According to Krugman (1995), a salient feature of early trade and geography models is the assumption that countries specialize their production on the locally abundant factor, e.g., natural resource advantages (e.g., the Heckscher-Ohlin framework within neoclassical trade theory).¹⁰⁵ It has been argued by Krugman and colleagues that endogenous spatial issues, centripetal forces and circular causalities are rather absent in early trade and geography models (Head and Mayer, 2004; Krugman, 2009; Neary, 2009). As Krugman (2009, 567) provocatively noted:

“[W]hy was geography ignored by trade theorists? A large part of the explanation is the obvious centrality of increasing returns to geographical patterns: nobody really thinks that Silicon Valley owes its existence to exogenously given factors of production or Ricardian comparative advantage [although] God made the Santa Clara Valley for apricots, not semiconductors.”

A central feature of the NEG framework is that it completely abstracts from physical geography, i.e., “first-nature causes” (see chapter 2, section 2.1.2) (Ottaviano and Thisse, 2000; Capello, 2007; Thisse, 2011).¹⁰⁶ The crucial difference between the new economic geography approach and the neoclassical models is the overall relevance of scale in production (Roos, 2002b; Crafts and Venables, 2003; Capello, 2007). Neoclassical (trade) models are solely concerned with relative terms, suppressing scale and size; e.g., consumers’ choices for saving and consumption, firms’ decisions of production structures, and wage-setting are all determined at the margin. According to Krugman (1992), among others, the outcome of such processes are unaltered in an economy with 10, 10,000 or 10,000,000 individuals. Regarding this aspects, Krugman (1992, 14) argued that

“[t]he basic story of geographic concentration [...] relies on the interaction of increasing returns, transportation costs, and demand. Given sufficiently strong economies of scale, each manufacturer wants to serve the national market from a single location with large local demand. But local demand will be large precisely where the majority

¹⁰⁴ Krugman was awarded with the Nobel Prize in Economics in 2008 for his contributions to trade theory and economic geography. For an appraisal see Nobel Prize Committee (2008a), Nobel Prize Committee (2008b), Fujita and Thisse (2009), Feenstra (2009), Neary (2009), Brakman and Garretsen (2009).

¹⁰⁵ Brakman and Garretsen (2009, 2) defined the economic novelty of the NEG literature as follows: “[T]he subsequent NEG literature can in fact be seen as belonging to a much more extensive (and older) literature in regional economics or even economic geography at large, where spatial interdependencies are at the heart of the analysis. The performance of a region depends crucially on the developments in and characteristics of neighboring regions. Regions are therefore not freely floating islands in NEG. This non-trivial role of spatial linkages amounts to saying that it is above all between location economic geography that matters in (old and) NEG.” See also Ottaviano and Thisse (2000, 3).

¹⁰⁶ See also Krugman (1991), Krugman (1995) and Krugman (2000). Fujita *et al.* (2001, 4) mentioned the importance of incorporating the spatial dimension into economic theory and empirical research. They argued that “[t]he defining issue of economic geography is the need to explain concentrations of population and of economic activity: the distinction between manufacturing belt and farm belt, the existence of cities, the role of industry clusters. Broadly speaking, all these concentrations form and survive because of some form of agglomeration economies, in which spatial concentration itself creates the favorable economic environment that supports further or continued concentration.”

of manufacturers choose to locate. Thus there is a circularity that tends to keep a manufacturing belt in existence once it is established.”

Thus, scale effects (i.e., increasing returns) in production are considered to significantly matter in the new economic geography and a core-periphery distribution might be the outcome of relocation activities and large distributional effects via self-feeding and self-enforcing mechanisms.¹⁰⁷ Krugman’s model is based on the Dixit and Stiglitz (1977) contribution of product differentiation but it also offers a formalization of Myrdal’s circular and cumulative causation (Krugman, 1995; Crafts and Venables, 2003; Capello, 2007).¹⁰⁸ Nevertheless, NEG is considered to go beyond forerunning contributions because agglomeration is not the only possible outcome.¹⁰⁹ Krugman (1991) also distinguished the new economic geography from previous land-rent models that were based on, inter alia, von Thünen (1966) and Alonso (1964), among others (Fujita and Krugman, 2003; Fujita, 2010; Thisse, 2011).¹¹⁰ NEG adherents generally argued that the work of classical contributors, e.g., Johann Heinrich von Thünen (Thünen, 1966), are unsuited to explain the emergence and breakdown of core-periphery structures (and intra-industry trade) due to the lack of agglomeration economies (Krugman, 1995; Roos, 2002b; Combes *et al.*, 2008). In the majority of land-use models, the existence of a core region (or central market) is exogenous and the main attention is on accessibility and transportation costs, which makes this optimization criterion central to urban economics (Capello, 2007; Fujita, 2010; Thisse, 2011). The NEG framework and model alternatives are related to several agglomeration economies mentioned in Marshall’s *Principles of Economics* (see section 2.1.4.2). A detailed critical discussion, theoretical subordination and comparison of early location theories and contributions is, however, beyond the scope of this project.¹¹¹

As the NEG frameworks are mostly identical, except the origins of centripetal and centrifugal forces, the subsequent section briefly reviews the new economic geography framework in its simplest form (i.e., the Krugman (1991) model). Afterwards, a brief summary of al-

¹⁰⁷ Krugman (1995, 36) has argued that “[i]n order to talk even halfway about economic geography it is necessary to invoke the role of increasing returns in some form.”. Similarly, Weber (1922, 123) already discussed agglomeration effects and locational advantage similar to Krugman’s NEG as a “[V]orteil, also eine Verbilligung der Produktion oder des Absatzes, die sich daraus ergibt, dass die Produktion in einer bestimmten Masse an einem Platz vereinigt vorgenommen wird.”

¹⁰⁸ Myrdal (1957) addressed circular causation similar to Hirschman (1958). Circular causation and cumulative effects are considered to lead to increasing superiority of countries that already have superior productivity and a high level of income, while inferior countries will suffer from inferior income levels. Myrdal described some backwash effects that promote inequality and emerge from internal and external economies (economies of scale and growth of knowledge by innovation). See Combes *et al.* (2008).

¹⁰⁹ Essential for Krugman’s framework is that a fraction of the mobile income is spent in the region in which it is generated. NEG approaches are said to be built upon qualitative ideas of Perroux’s (1955) “growth poles,” on Myrdal’s (1957) contributions to “circular and cumulative causation,” and finally on Hirschman’s (1958) concept of “forward and backward linkages” (Krugman, 1995; Crafts and Venables, 2003; Capello, 2007; OECD, 2009a).

¹¹⁰ See also Krugman (1995), Roos (2002b), Robert-Nicoud (2005), Fujita and Mori (2005), Capello (2007), Combes *et al.* (2008), OECD (2009a) and Dauth (2010).

¹¹¹ The interested reader should consider, e.g., Roos (2002b), Roos (2004), Capello (2007), Cruz and Teixeira (2007), Combes *et al.* (2008), OECD (2009a) and Thisse (2011) for a comprehensive overview and discussion of agglomeration theories.

ternative core-periphery models will follow with special emphasis regarding modifications, extensions and conclusions.¹¹²

2.1.5.5.2. Industry Agglomeration, Core-Periphery and Footloose Labor

Krugman's (1991) new economic geography (NEG) framework is regarded as the starting point of a new generation of spatial economic models (Krugman, 1991, 1995, 2009; Capello, 2007; Combes *et al.*, 2008).¹¹³ Increasing returns, transportation costs and migratory movements are the pivotal factors which determine the dynamics of centripetal and centrifugal forces and the emergence of core-periphery structures.¹¹⁴ The core-periphery model instruments the trade-off between positive pecuniary externalities (i.e., agglomeration economies, see section 2.1.5) and transportation costs.¹¹⁵

As skilled and unskilled labor are the only production factors, which are assumed to be partly mobile, the modeling equilibrium essentially depends on the migration behavior of workers. The model simplifies by excluding capital and intermediates. It consists of two sectors; an agricultural and manufacturing sector. Workers in the agricultural sector do not feature inter-regional or at least inter-sectoral mobility (i.e., the centrifugal force). In opposition, workers within the manufacturing sector (and their expenditures) are inter-regionally mobile, which represents the centripetal force. The representative agent is modeled to follow a CES utility function, which exhibits a two-stage process of expenditure allocation, i.e., expenditures for the agricultural (homogeneous) good and expenditures for varieties of the manufacturing sector. The production side is defined by constant returns to scale in the agricultural sector and increasing returns to scale in the manufacturing sector (Krugman, 1991, 1995; Capello, 2007; Combes *et al.*, 2008).

Regarding endowments, every region has a fixed amount of labor in the agricultural and manufacturing sector. The traditional good underlies no transportation costs (i.e., the channel for factor prize equalization), whereas manufacturing goods exhibit costs of transportation. The equilibrium location of workers/ consumers and firms is determined by several forces that strongly affect the dynamics of the model in terms of stability and adjustment mechanisms (Krugman, 1991, 1995; Capello, 2007; Combes *et al.*, 2008).

Firms optimize economies of scale in production by their location decision, which represents the incentive to relocate production to the larger regional market; i.e., the "market-size-effect" or "home market effect." The market expansion affects the local profits and represents a strong incentive for firms to relocate production according to absolute terms

¹¹² The following section only summarizes the main conclusions. For comprehensive overviews and formal representations of NEG models refer to, e.g., Roos (2002b), Fujita and Krugman (2003), Robert-Nicoud (2005), Fujita and Mori (2005), Capello (2007), Eckey (2008), Combes *et al.* (2008) and Thisse (2011).

¹¹³ For an overview refer to Roos (2002b), Litzenberger (2007), Eckey (2008) and OECD (2009a).

¹¹⁴ In general, the NEG is widely classified as an extension of the new trade theory, although Krugman personally defined the NEG as a general framework which includes the new trade theory as a special case.

¹¹⁵ Krugman (1995, 62) finally stated that "[t]he clustering of production that results from this dynamic process can be seen as the consequence of a kind of pecuniary external economy, not really inconsistent with Marshall's description."

(Fujita and Krugman, 2003; Fujita and Mori, 2005; Krugman, 2009). A firm's decision to relocate production induces two processes that essentially affect regional disparities. First, there is a competition effect: the market entry of firms squeezes the market share and profits of existing firms in the local market. Second, the spatial distribution is affected by a demand or market-size effect: the increasing size of the local market affects the profits of firms and their local labor demand. The increasing number of varieties and labor demand bring about higher local wages and attract mobile skilled workers; thus, the circular causality induces an additional increase in local expenditures via migratory movements. As skilled workers are the only mobile factor of production, inter-regional movements induce expenditure shifting, followed by production shifting. The higher the number of consumers in a location, the more firms have to employ an increasing workforce to supply goods in the local market. The more varieties are produced, the higher is the level of real income and the more workers are attracted to the region. Accordingly, demand shifting induces production shifting and the relocation of manufacturing goods induces again demand and expenditure shifting (centripetal force) but also higher competition in the labor and goods market in the growing core region (centrifugal force). A *perpetuum mobile* is clearly visible (Krugman, 1991, 1992, 2009; Capello, 2007; Combes *et al.*, 2008; OECD, 2009a). However, the fixed amount of immobile agricultural workers functions as a strong centrifugal force against the agglomeration process because immobile workers represent an immobile source of demand for manufactured goods in the periphery. Low levels of transportation costs will, however, not stop the relocation of skilled workers and the emergence of an agglomerated manufacturing industry (Krugman, 1991, 1992, 2009; Henderson, 2003a; OECD, 2009a).

Nevertheless, the emergence of industrial core-periphery structures depends on the net effect, meaning that the centripetal force (demand effect) has to surpass the centrifugal force (competition effect). The strength of the competition effect depends positively on the substitution elasticity among the goods produced by manufacturing firms and the costs of transportation. The intensity of the demand effect depends on the realized economies of scale which increase profits and the income share spent on manufacturing goods (Krugman, 1991, 1992, 1995, 2009; Capello, 2007). Accordingly, the original core-periphery model is central in explaining the formation of core-periphery structures detached from endowments.

To conclude, the stability of a core-periphery pattern is highly influenced by transportation costs and the presence of pecuniary externalities. The demand effect always exceeds the competition effect in case that (i) varieties are difficult to substitute, (ii) scale economies are intense, (iii) the share of income spent by consumers on manufacturing goods is large and (iv) transport costs are at a modest level or decreasing due to integration (Krugman, 1991, 1992, 1995, 2009). Accordingly, the strength of the competition effect and demand effect are considered to change the geographic distribution of industries and the size of local markets in a meaningful way (Krugman, 1991, 1992, 2009; Capello, 2007). Small variations of the initial distribution of labor crucially determine the spatial distribution of the manufacturing industry and the expenditures of consumers (function of initial conditions or historical accident). Without the above mentioned assumption of migratory movements of manufacturing workers, the core-periphery model would be unable to produce core-periphery structures (Krugman, 1991; Roos, 2002b; Capello, 2007). Thus, the implementation of inter-regional mobility of workers is a key factor in explaining spatial

expenditure shifting and thus circular and cumulative causation known from early cumulative development models (Krugman, 1992, 2009; OECD, 2009a; Thisse, 2011).¹¹⁶ In retrospect, new economic geography is considered to have benefited considerably from several past workhorse contributions in economic theory, economic geography and regional science (Fujita and Krugman, 2003; Crafts and Venables, 2003; Combes *et al.*, 2008).¹¹⁷

For comparison purpose, the main findings of selected alternative NEG models, which offer alternative centripetal forces, are briefly reviewed in the subsequent section.¹¹⁸

2.1.5.5.3. Alternative Core-Periphery Models

Krugman and Venables (1995b) introduced a model that puts aside migratory movements of workers; it consists of two regions that are identical in endowments, preferences and technology. The manufacturing sector produces final goods and intermediates under increasing returns to scale technology. In case of high transportation costs, the manufacturing industry is equally distributed across the regions. In case of low transportation costs (below a certain threshold level), the region with the initially larger manufacturing share will induce a relocation process and attract producers due to strong forward and backward industrial linkages (demand and cost linkages). First, final good producers benefit from stronger industry concentration of intermediate producers, which induces forward linkages (i.e., cost linkages). Second, producers of intermediates will prefer to produce at a proximate distance to large final good producers, which induces backward-/demand-linkages (i.e., the centripetal force). Real income in the core region is increasing due to these forward and backward linkages. However, in case of falling transportation costs, the wage differential between the periphery and the core region will induce relocation of firms back into the periphery. The model is pivotal in explaining input-output structures in the manufacturing industry.¹¹⁹

Venables (1996) introduced an alternative framework to the Krugman-type core-periphery model without migratory movements. The model incorporates pecuniary externalities which originate from industry input-output linkages that induce cost effects. The model consist of three sectors (in opposition to two sectors in Krugman and Venables (1995b)). One sector produces a tradable good (perfectly competitive sector); the other two sectors

¹¹⁶ Furthermore, Krugman (1991, 497) argued that “[i]n an economy characterized by high transportation costs, a small share of footloose manufacturing or low economies of scale, the distribution of manufacturing production will be determined by the distribution of the primary stratum of peasants. With lower transportation costs, a higher manufacturing share or stronger economies of scale, circular causation sets in, and manufacturing will concentrate in whichever region gets a head start.” Refer also to Nobel Prize Committee (2008a,b).

¹¹⁷ See also Capello (2007), OECD (2009a) and Neary (2009). As Fujita and Krugman (2003, 142) have concluded: “*Dixit-Stiglitz, icebergs, evolution and the computer. Yet the slogan captures the essence of the intellectual tricks that we and other new economic geography theorists have used in order to cope with the technical difficulties involved in trying to deal with the subject. Everyone recognizes that these are strategic simplifications, which is to say, intellectual cheap tricks; but they do allow us to get past the technical issues and tell the stories about the real economics.*”

¹¹⁸ For an overview refer to OECD (2009a).

¹¹⁹ For a comprehensive overview see Keilbach (2000), Roos (2002b), Litzenberger (2007), Combes *et al.* (2008) and OECD (2009a).

are vertically linked and show a monopolistically competitive structure and one sector produces an intermediate good. The industries are located in both regions and the firms supply their output to both markets. The level of linkages and transportation costs determines the production decision of firms. In the case of high transportation costs, firms have an incentive to locate close to consumers and thus to produce in both locations. In the case of low transportation costs, firms also prefer to produce in both locations, which induces decreasing regional disparities since factor prices are equal in both locations. In the case of intermediate transportation costs, the model shows emerging clustering forces which give rise to multiple equilibria, determined by factor price differences. Some industries show symmetric distribution in response to regional factor price differences; other industries, however, agglomerate. To summarize, the cost effect in the model is associated with an increase in firms' profits through an expansion of the local market for intermediates. This centripetal force works against the local competition effect (centrifugal force). If firms use the same intermediates, the model of Venables predicts the following: (i) a decreasing intermediate good price for downstream firms; (ii) an increasing market size for upstream ones. The contribution is central in explaining the emergence of an intermediate industry and the strength of pecuniary externalities.¹²⁰

Krugman and Venables (1996) modified Venables (1996). The authors placed emphasis on the process of European integration. Their model includes two industries in two regions. Final and intermediate goods are produced in both industries and intermediates are used in the production process. The production technology is characterized by monopolistic competition. Migratory movements of workers are absent and transportation costs exist for manufacturing goods. The model emphasizes the dynamics of economic integration between several regions, each containing several industries. In case of high transportation costs, the regions will generally maintain the full range of industries. Backward and forward linkages are not strong enough to lead to core-periphery structures. In case of intermediate transportation costs, industry agglomeration can only be observed if the initial distribution of industries is skewed. In case of low transportation costs, regions with a strong initial (exogenous) industry endowment benefit from a locational advantage that evolves due to forward and backward linkages (cumulative circular causation). In this case, each region concentrates onto a single industry.¹²¹

2.1.5.5.4. Critical Remarks and Discussion

The NEG literature contains a large number of alternative frameworks which explain the spatial distribution of activities at different geographical levels, e.g., international specialization, the distribution of employment and productivity at the national, regional and city level (Neary, 2001; Roos, 2002b; Fujita and Krugman, 2003).¹²² The impressive amount of models is based upon heterogeneous (alternative) ways in which inter-firm relations generate externalities that induce centripetal and centrifugal forces. In some cases the externalities originate from the demand-side, in others from input-output linkages at the supply-

¹²⁰ For an overview refer to Roos (2002b), Litzenberger (2007) and OECD (2009a).

¹²¹ Refer also to Keilbach (2000), Roos (2002b), Litzenberger (2007), Combes *et al.* (2008) and OECD (2009a).

¹²² See also Capello (2007), Combes *et al.* (2008) and Neary (2009).

side. Nevertheless, all these models implement pecuniary externalities.¹²³ Accordingly, the models solely differ in the way economists and geographers allow for varying modes of mobility of people, capital goods or intermediates. The purpose of first-generation NEG models was to explain regional specialization, agglomeration (i.e., industrialization) and the distribution of industries (and agents) across regions, depending on spatial distance, market-size (pecuniary) effects and costs of transportation.¹²⁴ Non-pecuniary externalities, such as knowledge flows or externalities (section 2.1.7), have not played any role.¹²⁵

Furthermore, a salient feature of all new economic geography models is that the location choice of firms is solely determined by profit maximization behavior whereas the location decision of households crucially depends on utility maximization. The activities of agents are interrelated and induce cumulative circular developments that give rise to centripetal and centrifugal forces in line with antecedent contributions; i.e., Myrdal's virtuous circle of cumulative development and Kaldor's formalized model of cumulative circular causation (Krugman, 1995, 2009, 2010; Capello, 2007, 228, 236; Thisse, 2011). The basic argument, according to early new economic geography adherents, was to develop a general theoretical framework, that also includes aspects of trade theory, with special focus on pecuniary (and proximity) externalities, which enter the system via market mechanisms depending on prices (Krugman, 1991, 1995; Capello, 2007). Opposed to technological externalities, market-led mechanisms do not affect utility or production directly (Ottaviano and Thisse, 2001; Roos, 2002b; Harris, 2008).¹²⁶

Although there exists a meaningful amount of modifications of the new economic geography, the majority of (older) contributions have not considered knowledge spillovers as a major driver of agglomeration (Krugman, 1995, 2009; Martin, 1999; Capello, 2007). Krugman was highly pessimistic with respect to centripetal forces stemming from knowledge spillovers.¹²⁷ Krugman (1992, 54) argued that

“[k]nowledge flows are invisible; they leave no paper trail by which they may be measured and tracked, and there is nothing to prevent the theorist from assuming anything about them that she likes. So while I am sure that true technological spillovers play an important role in the localization of some industries, one should not assume that this is the typical reason - even in the high technology industries themselves.”

¹²³ The models which include R&D are briefly discussed in section 2.1.6.

¹²⁴ In contrast to first-nature causes that refer to the concept of comparative advantage (i.e., natural advantage, resources, endowments, infrastructure, climate, past location choice), the NEG models especially use second-nature causes of agglomeration that induce cumulative causations due to pecuniary externalities.

¹²⁵ For a critical debate on spillovers refer to Fujita and Thisse (1997), Krugman (2000), Fujita and Krugman (2003), Robert-Nicoud (2005) and Krugman (2009, 2011).

¹²⁶ Krugman (1995, 52) argued that “*[w]hile it has been possible to make the sources of agglomeration safe for neoclassical economics by assuming that they are pure technological externalities, this strategic evasion has been costly in terms of both credibility and researchability. [Consequently,] you have no deeper structure to examine, no way to relate agglomeration to more micro-level features of the economy.*”

¹²⁷ In this context, the spatial share of innovative firms and the effects of firm size on invention and productivity are essential in terms of intensity and spatial scope of MAR, Porter or Jacobs externalities and the cluster life cycle. Unfortunately, firm size is still not incorporated in the early NEG models.

Therefore, the new economic geography was mainly focusing on the trade-off between pecuniary externalities (centripetal force) and transport costs (centrifugal force). In this respect, first-generation NEG models consciously suppressed technological externalities. However, the influence and significance of knowledge externalities in the context of knowledge-intensive industries became increasingly issued (Fujita and Thisse, 1996; Audretsch and Feldman, 1996); especially by economic geographers, geography of innovation adherents and researchers in an innovation system tradition (Duranton and Rodríguez-Pose, 2005; Behrens and Thisse, 2007; Rodríguez-Pose, 2010). Additionally, Krugman (2011) has put his 1990 statement into perspective.¹²⁸

Another shortcoming of the presented new economic geography framework(s) is that social and relational proximity, in the context of knowledge-intensive industries, do not perform a central role in the conceptualization of agglomeration economies. This matter of fact distinguishes the NEG from the locational advantages in innovative milieus, network approaches and concepts in an evolutionary economics tradition (see section 2.1.7.3). Accordingly, NEG solely applies pecuniary externalities (see section 2.1.5) but not technological externalities (see section 2.1.6). A final critique concerns the lack of an R&D industry in early NEG models. As R&D activity is not explicitly modeled, regional disparities of research activities have to be considered to represent a reflection of the spatial distribution of the manufacturing industry (i.e., the distribution of the intermediate and final good industry). Thus, it has to be assumed that the distribution of R&D solely follows the spatial distribution (relocation) of the manufacturing industry. Accordingly, the framework clearly suppresses R&D activities and knowledge-intensive tasks, which seems to reduce its applicability to knowledge-intensive industries (Krugman, 2009, 2011). To address this issue in a European context, the distribution of knowledge-intensive tasks is measured directly by analyzing the spatial concentration of European research (and patenting) activity at the regional level (see chapter 3).

2.1.6. Industry and Research Clustering and Innovation Externalities

2.1.6.1. Non-Pecuniary Externalities

The agglomeration economies, which have been described in the previous sections, examine the role of space as a promotor of locational advantage that enters the system by means of a more efficient use of resources and lower transaction and production costs, which induce higher levels of productivity and profits at the firm-level. However, spatial proximity not only improves static efficiency of production. Economists and geographers have additionally stressed the importance of non-pecuniary effects, i.e., technological externalities, in the context of research clustering, R&D networks and co-patenting activity (Feldman and Audretsch, 1999; Audretsch and Feldman, 2004; Johansson and Quigley, 2003). This consideration predominantly concerns the relationship between spatial proximity and innovative and creative capacities of the firm and individuals, i.e., innovation externalities (Capello, 2007, 193; Capello, 2009).

¹²⁸ Similarly, Fujita and Thisse (1996, 345) argued that “[a]n economic agglomeration is created through both technological and pecuniary externalities, often working together.”

A seminal contributor to the technological externalities debate was Scitovsky (1954). He concluded in the 1950s that non-pecuniary externalities apply when agents are interdependent.¹²⁹ However, interdependence between agents does not necessarily have to occur via prices, i.e., via anonymous market transactions.¹³⁰ His main focal point was on the question of non-rivalry, non-excludability and compensation. A few decades later, Griliches (1992b, 36) has related non-pecuniary externalities to R&D activities and knowledge spillovers as

“[w]orking on similar things and hence benefiting much from each others research. [...] True knowledge spillover are ideas borrowed by the research teams of industry *i* from the research results of industry *j*. [...] To measure them directly in some fashion, one has to assume either that their benefits are localized in a particular industry or range of products or that there are other ways of identifying the relevant channels of influence, that one can detect the path of the spillovers in the sands of data.”

Accordingly, technological externalities are considered to influence the economic efficiency in terms of new routines or innovative capacity and innovation output of the firm and to increase product diversity (Johansson, 2005; Capello, 2007).

Moreover, it is frequently argued that non-pecuniary externalities represent effects disembodied from capital goods, new products, intermediates and service inputs and to be decoupled from direct input-output linkages (Fujita and Thisse, 1996; Duranton and Puga, 2004; Capello, 2009). However, the technological externality approach (i.e., knowledge spillover approach) has been heavily criticized as it implements a “black box” of unexplained technological progress into the production system (Fujita and Krugman, 2003; Breschi and Lissoni, 2001a; Breschi *et al.*, 2005).¹³¹

With respect to regional innovation systems (Cooke *et al.*, 1997; Doloreux and Parto, 2005) and research clusters, an essential factor is R&D activity, as it has a twofold effect within the region. The first effect has a direct nature and leads to new blueprints/patents and new products (see also sections 2.1.6.6 and 2.1.6.7). The benefits are then appropriated by the inventor who has, under the assumption of existence of an intellectual property protection system, a temporary monopoly position and rents. The second effect comes from knowledge codification (i.e., the technical documentation/blueprint) in the patent application process. This effect has an indirect nature in the sense that this kind of knowledge is available for competitors under specific circumstances. They can accumulate the knowledge which positively influences their innovative capacity (Capello, 2007, 189). However, due to the property right protection competitors cannot commercialize the same pieces of knowledge

¹²⁹ According to Scitovsky (1954, 144), non-pecuniary externalities originate from “[...] inventions that facilitate production and become available to producers without charge.”

¹³⁰ Scitovsky, among others, has differentiated between rent spillovers (via traded goods) and technological spillovers (no compensation). Rent spillovers originate from a market transaction, whereas technological externalities (pure knowledge spillovers) are assumed to occur outside the market, e.g., knowledge spillovers from just being there. For older discussions see Griliches (1979), Grossman and Helpman (1991b), Coe and Helpman (1995), Coe *et al.* (1997), Verspagen (1997) and Keilbach (2000).

¹³¹ Ottaviano and Thisse (2001, 160), for example, argued that “[t]echnological externalities are ‘black boxes’, that is, ‘reduced forms’ that capture the crucial role of complex non market institutions whose role and importance are strongly stressed by geographers and urban planners.”

as the patent system generally provides a legal mechanism to enforce excludability.¹³² Nevertheless, the overall effect is a technological externality and an upgrading of the region-wide, perhaps industry-wide, stock of knowledge and a positive effect on the innovative capacity (i.e., innovation externality) (Johansson, 2005; Capello, 2007).¹³³

Directly related to the previous points is the debate whether knowledge always fulfills the attributes of non-rivalry and non-excludability (see, e.g., Romer, 1990b). The public good character has been heavily criticized (Lissoni, 2001; Breschi and Lissoni, 2001b,a; Krugman, 1995).¹³⁴ Several research streams have implemented the idea of externalities but modified to localized knowledge spillovers, localized networks and tacit knowledge (see section 2.1.7). In fact, the non-rivalry assumption of knowledge mainly works as perpetual-motion in endogenous growth and economic geography models (see sections 2.1.6.6 and 2.1.6.7). Endogenous growth models which are heavily built upon technological externalities normally lead to hypotheses towards economy wide under-investments in R&D and knowledge production (see section 2.1.6.6).¹³⁵ Due to the effects of R&D externalities on aggregate growth, productivity and innovation output, the degree of rivalry and excludability crucially determines normative conclusions and policy recommendations. These debates are essentially dependent on the spatial level of analysis as externalities are determined by strong distance decay effects, networks and industry structures (see also sections 2.1.7 and 2.2).

2.1.6.2. Marshall-Arrow-Romer Externalities and Specialized Clusters

A by-product of the discussions on agglomeration economies, associated with the knowledge spillover approach, is the introduction of the “Marshall-Arrow-Romer (MAR) externalities” concept (Audretsch, 1998; Partridge and Rickman, 1999; Carlino *et al.*, 2001).¹³⁶ It is argued that local firms benefit from externalities that originate from a high concentration of firms of the same industry (localization). These externalities can be regarded as a dynamic type of localization economies (dynamic agglomeration economies) which are linked to inventive capacity and innovation output of firms in the same industry (Feldman, 2000;

¹³² Non-pecuniary effects (externalities) determine the individual utility or production function directly (Combes *et al.*, 2008). This aspect is a crucial determinant in the new economic geography variants of Martin and Ottaviano (1999), Baldwin and Forslid (2000a), Baldwin *et al.* (2001b), Baldwin and Martin (2004) as will be discussed in detail in section 2.1.6.7.

¹³³ According to the mainstream literature, the diffusion of knowledge in such models is not accompanied by (full) monetary compensation.

¹³⁴ Following Romer, non-rivalry means that different firms (or regional units) can take advantage from new pieces of knowledge without diminishing the flow of knowledge for competitors (Romer, 1986, 1990b). Even if firm A diminishes the long-term economic benefit from the piece of knowledge for competitors B, C, and D, all of them gain by absorbing (technological) knowledge/blueprints without compensation.

¹³⁵ Griliches (1992b, 43) has put special emphasis on R&D spillovers and has concluded that “[...] *there has been a significant number of reasonably well done studies all pointing in the same direction: R&D spillovers are present, their magnitude may be quite large, and social rates of return remain significantly above private rates.*”

¹³⁶ The MAR concept is considered to originate from contributions of Marshall [1890](1920), Arrow (1962) and Romer (1986). Refer also to the remarks of Feldman (1999), Keilbach (2000), Combes (2000b), Paci and Usai (2000a), van der Panne (2004), van der Panne and van Beers (2006), Capello (2007) and de Groot *et al.* (2009).

Johansson, 2005; Capello, 2007).¹³⁷ Accordingly, MAR-externalities imply that the spatial concentration of firms of a specific sector promotes growth rates of innovation output (and implicitly industry employment and productivity growth) (van der Panne, 2004; Johansson, 2005).¹³⁸

In Henderson (1974), localization economies in cities are considered as a pure form of the above presented Marshallian externalities; industry-specific productivity of workers is assumed to increase with the industry employment share. Moreover, a relatively small technological distance between individuals and firms implies low barriers for knowledge spillovers and is seen as a condition for sustained growth (innovation externality) (Greunz, 2003a; van der Panne, 2004; Döring and Schnellenbach, 2006). This would lead to the testable hypothesis, that regions which are characterized by higher sector-/industry-specific localization of firms, and thus similar production technologies, should *ceteris paribus* tend to have higher income and productivity growth rates and/or innovation output than regions with lower intra-industry localization (Griliches, 1979; Boschma and Frenken, 2009a).¹³⁹ Accordingly, Marshall-Arrow-Romer externalities are sometimes linked to knowledge spillovers and innovative capacity and sometimes to productivity or employment growth (Beaudry and Schiffauerova, 2009).¹⁴⁰

Similarly, Feldman (2000) concluded that firms, if they belong to the same (or at least similar) industry, in which complementary assets are essential, could realize greater gains (i.e., growth) in productivity.¹⁴¹ Moreover, she argued that MAR-externalities are generally associated with strong distance decay effects (proximity externalities).

A final consideration in this context concerns the industry and cluster life cycle and the existence of high- and low-tech regions (Audretsch and Feldman, 1996; Audretsch, 1998; Malecki, 2010). Audretsch and Feldman (1996, 254) have matched the concept of knowledge transfer with the stage of the (spatially clustered) industry under observation. They concluded that

“[p]erhaps most striking is the finding that during the mature and declining stages of the life cycle increases in the geographic concentration of production tend to lead to greater and not less dispersion of innovative activity. It may be that new ideas need new space, at least during the mature and declining stages of the industry life cycle. In any case, the positive agglomeration effects during the early stages of the industry life cycle apparently are less important during the latter life cycle stages.”

¹³⁷ Empirical studies in the neo-Marshallian tradition also use productivity growth or employment growth as proxies for such dynamic agglomeration economies (see also Roos, 2002; Harris, 2008; Neffke et al., 2009).

¹³⁸ To repeat a point made earlier, static localization economies solely explain disparities in (regional) productivity levels and the effects on prices and costs via market transactions (Glaeser et al., 1992; Audretsch and Feldman, 1994, 1999; Van der Panne, 2004; Johansson, 2005).

¹³⁹ Henderson (2003a) finds that intra-sectoral specialization tends to have a positive effect on productivity.

¹⁴⁰ See also Glaeser (2000), Feldman (2000) and DeGroot et al. (2009).

¹⁴¹ For complementary contributions that discuss this approach refer to Romer (1990b), Harhoff (1995), Feldman (1999), Keilbach (2000), Caniëls and Verspagen (2001), Neffke *et al.* (2009) and Neffke *et al.* (2011).

It is argued in several studies that concentrated industries are in most cases mature industries and technology fields that are organized in large scale production. MAR externalities are predominantly present in such mature industries (Feldman, 2000; Audretsch and Feldman, 2004).¹⁴² Accordingly, mature industries are considered to have enjoyed from cross-fertilization and high growth rates of inventions at early stages of the life cycle (Audretsch *et al.*, 2008).¹⁴³ Nevertheless, an important shortcoming of the MAR-spillover concept is that it predominantly centers the origin of the externalities in an industrial perspective, i.e., intra-industry effects. However, the working channels (carriers) of such knowledge spillovers remain a “black box” and object for critique and further research (Feldman, 1999, 2000; Breschi and Lissoni, 2001a).

2.1.6.3. Jacobs Externalities and Diversity in Cities

“Jacobs externalities” are treated as a particular type of urbanization externalities.¹⁴⁴ They represent dynamic inter-industry effects that originate from a significant diversified production structure and are in most cases linked to inter-industry knowledge spillovers (Partridge and Rickman, 1999; Johansson, 2005; de Groot *et al.*, 2009).¹⁴⁵ Related to innovative capacity and innovation output, they are also labeled “innovation externalities” (Johansson and Quigley, 2003; Capello, 2007, 193). Accordingly, innovation externalities are dynamic economies which appear in the system as new routines (process innovations) or new products and an increasing product diversity (product innovation) (Johansson, 2005).¹⁴⁶

In the late 1960s, Jacobs (1969, 71) suggested that

“[o]ur remote ancestors did not expand their economies by simply doing more of what they already been doing [...]. They expand their economies by adding new kind of work. So do we. Innovating economies expand and develop. Economies that do not add new kinds of goods and services, but continue only to repeat old work, do not expand much nor do they, by definition, develop.”

Following her arguments, cities have to frequently upgrade their industries (see also Audretsch and Feldman, 1999; Duranton and Puga, 2001).¹⁴⁷ Otherwise, a monotonous urban industry structure is considered to induce a stagnant settlement. As she has argued,

¹⁴² See also van der Panne and van Beers (2006), de Groot *et al.* (2009) and Neffke *et al.* (2011).

¹⁴³ Griliches (1979, 104) presented the computer industry as an example: “[*The computer industry*] has had a tremendous real productivity growth, most of it unmeasured in its official indices, and most of it unappropriated within the industry itself [...] because of rather intensive competitive pressures.”

¹⁴⁴ See Taylor (2006) for an overview and appreciation of Jane Jacobs.

¹⁴⁵ See also Combes (2000a), Keilbach (2000), Carlino *et al.* (2001), Henderson (2003a), Autant-Bernard and Massard (2007), Glaeser and Resseger (2009) and Dauth (2010).

¹⁴⁶ This idea of cross-fertilization of industries has already been mentioned by Mansfield, who has linked the spillover approach to knowledge as a relevant input. He has concluded that “[...] *techniques invented for one industry turning out to be useful for others as well.*” (Mansfield, 1968, 19). Similar ideas of inter-industry technology flows have already been argued by Scherer (1982).

¹⁴⁷ See also Behrens and Robert-Nicoud (2008) and Henderson (2010).

“[a] very successful growth industry poses a crisis for a city. Everything – all other development work, all other processes of city growth, the fertile and creative inefficiency of the growth industry’s suppliers, the opportunities of able workers to break away, the inefficient but creative use of capital – can be sacrificed to the exigencies of the growth industry, which turns the city into a company town. [...] Monopolies gratuitously harm cities and suppress what their economies are capable of achieving [...] extortionate prices, harmful though they most certainly are, are the least of disadvantages of monopolies, for monopolies forestall alternate methods, products and services” (Jacobs 1969, 124-125).

As firms’ (and regions’) innovative capacities are assumed to be stimulated by inter-industry spillovers, the idea of cross-fertilization has been related to the regional settlement structure, which means that the industry dimension of agglomeration economies is combined with a geographic dimension (Audretsch and Feldman, 1999; Carlino, 2001; Capello, 2009). Large urban regions are considered to be more efficient and to gain in efficiency (productivity), to innovate faster (innovation rate) and to grow faster (employment growth) (Johansson and Quigley, 2003; Johansson, 2005; Capello, 2007, 195). Thus, cities and urban areas are regarded to raise innovative capacities because they act as arenas for the confluence of innovative factors (Fujita and Thisse, 1996; Duranton and Puga, 2001; Johansson and Quigley, 2003). According to the Schumpeterian paradigm, new economically relevant knowledge emerges from creating new combinations of existing ideas. Related to this view, Glaeser (2000, 83) considered cities to be centers of excellence for the creation and transmission of ideas and figured that

“[c]ities will grow when they are producing new ideas or when their role as intellectual centers is increasing.”

Glaeser *et al.* (1992) investigated how industrial diversity of a city - and not solely its size and the size of its industries – can give rise to growth promoting agglomeration economies.¹⁴⁸ The authors argued that, in contrast to static externalities, dynamic externalities have implications for industry growth rates in cities.¹⁴⁹

Similarly, Audretsch and Feldman (1999) and Audretsch *et al.* (2008) linked higher potentialities for invention and innovation to urban, diversified industry structures but not to specialized ones. Their conclusions are based upon the empirical result that the number of new US product announcements of diversified spatial units exceeds those of industries located in cities, which are specialized into a few industrial activities.¹⁵⁰

The Jacobs-externality approach is also in line with Florida’s “creative class” hypothesis, where creative people are considered to locate in diversified locations and creative places

¹⁴⁸ In a later work, Glaeser (1996, 230) has pointed out the idea that “[g]rowth hinges on the movement of ideas, naturally led to a re-exploration of the economic role of cities in furthering intellectual flows.”

¹⁴⁹ Glaeser *et al.* (1992, 1128) additionally argued that “[dynamic externalities] are different from the more standard location and urbanization externality theories that address the formation and specialization of cities (Henderson 1986) but not city growth.”

¹⁵⁰ In a similar context Kelly and Hageman (1999) stated that the location of industry R&D activities is much more determined by other industries’ R&D activities than industries’ own production.

to (re-) combine pieces of knowledge and to establish an entrepreneurial society (Florida, 1995, 2002c,a).¹⁵¹

More recently, based on the above presented concepts, classifications and debates, researchers in a geography of innovation tradition are challenging the “relatedness” of industries (Boschma and Frenken, 2009b; Boschma and Iammarino, 2009; Neffke *et al.*, 2011). These studies test the hypothesis that knowledge predominantly spills over between related technology fields (i.e., related variety), which adds a cognitive dimension to the industrial and spatial dimension of agglomeration economies.¹⁵²

To conclude, Jacobs externalities are generally linked to the benefits from industrial cross-fertilization and are in most cases associated with distance decay effects (proximity externality). Accordingly, it is argued that cities serve as central places for upgrading a region’s innovative capacity because knowledge is assumed to spill over between industries at a proximate distance. Hence, accumulated knowledge of a specific industry can (partially) be applied in other (or related) industries.¹⁵³

With a glance on the technological diversification and presence of different technology-specific research clusters in European capital and metro regions and urban and rural areas, this study applies EPO patent applications at the regional level to contribute to the “specialization-diversity” debate (see chapter 3).

2.1.6.4. Porter Externalities and the Competitive Advantage of Regions

In comparison to the inter- and intra-industry knowledge spillover debate, economists (and geographers) have discussed the effects of competition on the rate of innovation and growth; some argue that monopoly structures encourage innovation; others argue that competitive markets show higher rates of innovation (Carlino, 2001; Carlino *et al.*, 2001; Capello, 2007).¹⁵⁴ Porter argued in several studies, in line with the MAR-externalities concept, that knowledge spillovers and strong competition in geographically concentrated and specialized industries stimulate growth (Glaeser *et al.*, 1992). In this context, externalities are associated with cities and urban areas and originate from competition between proximate firms. The approach is based upon Porter’s “competitive advantage concept” and the “Diamond approach,” which mainly consists of four determinants (Porter, 1990, 1998a,b).¹⁵⁵

According to Porter (1990, 71), the approach centers

¹⁵¹ In this respect, the creative class approach resembles a sort of human capital theory.

¹⁵² The “diversity-specialization-debate” is addressed in the empirical literature review (section 2.2) and challenged in the empirical analyses with special focus on research clustering and patenting activity (sections 3 and 3.5).

¹⁵³ For further details refer to Jacobs (1969), Glaeser *et al.* (1992), Audretsch and Feldman (1999), Breschi and Lissoni (2001), Scott and Storper (2003), Athreye and Werker (2004), Greunz (2005).

¹⁵⁴ According to Carlino (2001, 19), “[w]hen local economies are competitive, the innovations of local firms are rapidly adopted and improved by neighboring firms. In contrast, local monopolists tend to rest on their laurels rather than risk innovation.”

¹⁵⁵ For a critical discussion refer to Glaeser *et al.* (1992), Maggioni (2002), Martin and Sunley (2003), Martin and Sunley (2005).

“(i) factor conditions (e.g., the nation’s position in the factors of production, such as skilled labour or infrastructure, necessary to compete in a given industry; (ii) demand conditions (e.g., the nature of home demand for the industry’s product or service; (iii) related and supporting industries (e.g., the presence or absence in the nation of supplier industries and related industries that are internationally competitive); (iv) firm strategy, structure and rivalry (e.g., the conditions in the nation governing how companies are created, organised, and managed, and the nature of domestic rivalry.”

Porter (1996, 87) adapted the Diamond concept, which has been introduced at the level of countries, to the regional level and suggested that

“[r]egional clusters grow because of several factors: concentration of highly specialized knowledge, inputs and institutions; the motivational benefits of local competition; and often the presence of sophisticated local demand for a product or a service.”

In rethinking the effect of location on competition, he argued that local competition is mostly limited to competition for natural resources, employees and inputs, e.g., highly-skilled employees (Porter, 2000). But effects from local competition on the international competitiveness of firms is hard to theorize (Martin and Sunley, 2003). Similarly, Glaeser *et al.* (1992) argued that fierce local competition may produce significant incentives to innovate faster. According to this, Porter externalities are very similar to the MAR-case presented above; the discussions, however, should focus on the underlying market structure.¹⁵⁶

To summarize, Porter externalities are intra-industry externalities. Opposed to monopoly power, the presence of pure competition and rivalry in a cluster (or region) propels creation, adoption and diffusion of information and knowledge and the development of new products. According to this approach, the incentives to innovate are greatest when markets work under strong competition.¹⁵⁷ Unfortunately, competition and market structures cannot be explored in the pan-European context in this study due to a significant lack of firm-level data.

2.1.6.5. A Taxonomy of Innovation Externalities

The above presented different sources and working channels of technological externalities are summarized in table 2.4. The main focus is on knowledge spillovers and information externalities that originate (i) from anonymous market-led activities as an unintended by-product, (ii) from routinized and sustained transaction linkages between well-known partners at a proximate or long-distance (i.e., R&D co-operations, co-patenting networks), or (iii) from MAR- and Jacobs externalities (knowledge spillovers) in agglomerations (proximity externality). With respect to the latter, a relevant source of knowledge externalities is related to unintended spillovers from knowledge providers in dense agglomerations.

¹⁵⁶ Glaeser *et al.* (1992, 1127-1128) argued that “[k]nowledge spillovers in specialized, geographically concentrated industries stimulate growth. (Porter) insists, however, that local competition, as opposed to local monopoly, fosters the pursuit and rapid adoption of innovation.”

¹⁵⁷ For a discussion see also Audretsch and Feldman (1999), Audretsch and Feldman (2004) and Feldman and Kogler (2010).

The MAR- and Jacobs externality approach emerged in the mid 1980s and 1990s and reflects a combined industrial and geographic dimension on (dynamic) agglomeration economies that primarily differentiates between inter- and intra-industry effects in a spatial context (Audretsch and Feldman, 1999; Capello, 2009). However, the main focus of the approach is on scale and diversity but not explicitly on the working channels and micro-foundations of knowledge transmission (Breschi and Lissoni, 2001a). Although it is a multidimensional approach that includes the industry and geographic dimension, it gives no role to synergies, to research networks, to innovation and learning or to socio-cultural or cognitive aspects.

Nevertheless, inter- and intra-industry innovation externalities may also originate from tacit knowledge transmission in localized social (informal) networks and from long-distance research collaborations, which is in line with the “collective learning approach” (McCann *et al.*, 2002; Johansson, 2005; Wilhelmsson, 2009).¹⁵⁸ Therefore, section 2.1.7 places the emphasis on these shortcomings.

2.1.6.6. Endogenous Growth Theory and Research Clustering

2.1.6.6.1. Knowledge Stocks and Knowledge Spillovers

In order to explain persistent national and regional growth disparities and the emergence and persistence of research clustering, the relationship between research activities, knowledge stocks and innovation processes are taken into account in the literature. Early endogenous growth (NGT) models are mainly built upon technological externalities and thus correspond to the proposed taxonomy of agglomeration economies and externalities (see sections 2.1.4.3 and 2.1.6).¹⁵⁹

An influential contribution to the endogenous growth literature represents the work of Paul Romer (1986, 1987, 1990b,a). Romer himself explained the idea of regional disparities as rooted in a Smith-Marshall-Young-Kaldor tradition (Rima, 2004; Chandra and Sandilands, 2005; Solow, 2007).¹⁶⁰ What has been essential for the cluster literature, in the context of knowledge-intensive industries, is the combination of ideas about spatial interaction with theoretical aspects of endogenous growth (Capello, 2007; Eckey, 2008; OECD, 2009a). Following the early contributions of Romer (1986), ideas (or knowledge) generally do not correspond to the law of diminishing returns as opposed to labor or capital inputs (see section 2.1.7). In Romer’s original NGT version (1986), the stock of knowledge in the economy is intertwined with the capital accumulation process, but the “public” capital

¹⁵⁸ The diffusion of knowledge in social networks is also addressed in section 2.1.7 and the empirical review in section 2.2.6. Refer to Johansson and Quigley (2003), de Groot *et al.* (2009), Breschi and Lissoni (2009), Capello (2009).

¹⁵⁹ For a comprehensive overview refer to Capello (2007), Eckey (2008) and OECD (2009a).

¹⁶⁰ Romer (1986, 1004) argued that “[t]he idea that increasing returns are central to the explanation of long-run growth is at least as old as Adam Smith’s story of the pin factory. With the introduction by Alfred Marshall of the distinction between internal and external economies, it appeared that this explanation could be given a consistent, competitive equilibrium interpretation. The most prominent such attempt was made by Allyn Young in his 1928 presidential address.”

remains uncompensated. That being the case, the technological progress and interdependencies between new ideas, technological knowledge and capital accumulation induce endogenous growth (Romer, 1986; Capello, 2007).

Table 2.4. Innovation externalities

Externality type	Transaction type	Mechanism
Industry structure in agglomerations	Spillovers based on proximity; different innovation spillovers in an agglomeration; MAR- and Jacobs externality (see sections 2.1.6.2, 2.1.6.3 and 2.1.7.3).	Size and structure of the agglomeration; inter- and intra-industry knowledge externalities stimulates the innovation processes and product development of firms.
Market vs. networks (section 2.1.7.7)	Upstream knowledge spillovers. Unintentional spillovers as by-product of anonymous market transaction.	Information and/or knowledge spills over as by-product of interaction between an (knowledge) input-buying firm and its suppliers.
	Downstream knowledge spillovers. Unintentional spillovers as by-product of anonymous market transaction.	Information and knowledge spillovers occur as a by-product of interactions between an (knowledge) input-selling firm and its customer.
	Upstream knowledge spillovers. Routinized, persistent inter-firm (network) transaction linkages induce knowledge externalities.	Information and/or knowledge spillovers from a vertical transaction linkages (formal network); directed spillovers stimulate innovation output of the buyer.
	Downstream knowledge spillovers. Routinized, persistent inter-firm (network) transaction linkages induce knowledge externalities.	Information and knowledge spillovers from a vertical transaction linkages (formal network); directed spillovers stimulate innovation output of the seller.
Competition	Competition between proximate companies in a specialized cluster (Porter externality, see section 2.1.6.4).	Due to physical proximity competing firms imitate competitors in order to move towards best-practice, improve routines and develop new products.

Source: illustration based on Johansson (2005, 122), Johansson and Quigley (2003) and Capello (2007, 2009).

Knowledge is assumed to enter the production sphere in two ways (Romer, 1986; Capello, 2007, 242). First and foremost, newly developed technological knowledge is utilized by the firm that has invested in its development to obtain productivity effects and new products.

This knowledge can be protected from being imitated. Second, the new pieces of knowledge that have been protected by the legal system increase the stock of public available knowledge as the technological knowledge is codified in the patent application. Thus, designs become available for other researchers in the form of public patent documentations (i.e., blueprints). By studying the blueprint, pieces of knowledge have a high propensity to spill over to other researchers (and regions/clusters) and will increase their productivity. Moreover, one could think of cross-fertilization of firms in other industries (see sections

2.1.4.3 and 2.1.6). The “diversification-specialization debate” exactly builds upon this argument (Beaudry and Schiffauerova, 2009; de Groot *et al.*, 2009). The question then centers the issue of the spatial and technological proximity of knowledge (i.e., technological relatedness). Several authors discuss the threshold level of spatial and technological (and cognitive) distance (Boschma and Frenken, 2009b; Neffke *et al.*, 2009, 2011).¹⁶¹

Regarding the main mechanisms, most contributions to the endogenous growth theory build upon the concept of technological externalities, which is specified by non-rivalry and (partial) non-excludability, e.g., in a blueprint-producing R&D sector (Arrow, 1962b; Romer, 1990b; Jones, 2004).¹⁶² Introducing externalities converts decreasing returns into constant or increasing ones.

In a regional context, regions with high population densities and a crucial size of their populations of researchers are expected to reach high levels of innovative output (innovation externality) and efficiency via new routines (efficiency externality). Moreover, it is assumed that researchers generally build dense and developed social networks that increase the scope for the exchange of information, ideas and technological knowledge (Breschi and Lissoni, 2009). These prerequisites could then stimulate knowledge exchange and technological progress in the spatial unit (Gordon and McCann, 2000; Iammarino and McCann, 2006).¹⁶³ These thoughts are reflected in the “proximity versus network debate,” which focuses on innovation output and productivity growth (Johansson, 2005; Capello, 2007).

2.1.6.6.2. Technological Externalities and Specialization

Several endogenous growth models interpret the source of increasing returns as rooted in fixed costs and/or technological externalities.¹⁶⁴ Accordingly, besides the pure knowledge spillover approach (Romer, 1986), increasing returns are linked to the concept of fixed costs, which implements a form of indivisibilities (non-convexities) and specialization (Romer, 1987, 1990b,a, 1991; Rima, 2004; Chandra and Sandilands, 2005).¹⁶⁵ Therefore, these models combine the mechanisms presented in sections 2.1.4.3, 2.1.5 and 2.1.6.

¹⁶¹ As has been argued by Castellacci (2008, 985), “[t]he general proposition that innovation and intersectoral knowledge spillovers are important for the international competitiveness of manufacturing industries is a major point of agreement between new growth theories and evolutionary economics. The two approaches, however, differ substantially in terms of the conceptualization of the innovative process and the analysis of its economic impacts.”

¹⁶² Regional knowledge bases can be non-rival because they can be utilized by agents without limiting their use by additional agents (non-rivalry). Moreover, non-rivalry goes in most cases hand-in-hand with non-excludability (Romer, 1990b). This circumstance distinguishes knowledge and information from capital goods and equipment, which can normally only be used in one location (at a certain time).

¹⁶³ This view will be challenged empirically in sections 3.5 and 4.3.5.

¹⁶⁴ For a detailed review of the NGT refer to Seiter (1997).

¹⁶⁵ As mentioned by Romer, the concept of Young’s increasing returns is rather built upon the division of labor; this concept combines tendencies of specialization and the expansion of the market, opposed to increasing returns by assuming fixed costs due to economies of scale. Romer (1989, 198) has argued that “[t]he degree of specialisation, or equivalently, the number of different firms that are available at any point in time or location, is limited by the presence of fixed costs [...] Although Marshall and Young choose to describe specialization in terms of competitive equilibrium, with externalities, it is now clear that a more rigorous way to capture the effects they had in mind is in a model with fixed costs. In an equilibrium with nonnegative profits, price must exceed marginal costs to be able

Based on his early ideas, Romer (1990b) has contributed with a model of endogenous growth, which includes fixed costs (non-convexities), knowledge spillovers and a monopolistic market structure. The propelling drivers in the model are (i) horizontal product innovations, (ii) monopolistic competition and (iii) R&D activities and sector-wide learning effects on researchers' productivity (see also Rima, 2004; Chandra and Sandilands, 2005).¹⁶⁶ The framework does not explicitly contain capital goods but builds upon high-skilled labor (human capital) and blueprints in the production process. Thus, knowledge is assumed to enter the system via human capital (rivalry) and blueprints (non-rivalry). The model represents a three-sectoral system. It consists of a perfectly competitive final good sector (manufacturing good) that uses intermediates; the intermediate sector uses the new designs.¹⁶⁷ To implement a sort of learning process, productivity in the R&D sector is assumed to grow proportionally with the accumulated number of blueprints, i.e., the stock of designs, which leads to positive technological externalities. Knowledge spillovers are thus assumed to drive productivity gains in the R&D sector (sector-wide learning curve).¹⁶⁸ This is the so-called "standing on shoulders effect," which enables endogenous growth in these models (see also section 2.1.6.7). The cumulative process shows some kind of scale effect. The higher the knowledge stock of a region, respectively the stock of blueprints in a region, the higher are the associated productivity gains in the region-specific research sector. If the stock of knowledge is a function of the number of researchers in a region, then agglomerated regions (cities, metropolises) should show higher rates of innovation (Eckey, 2008, 132).¹⁶⁹ The number of firms (which is equal to the number of individuals) is determined by the regional population; the number of firms, entry rates and the scale of operation is thus not endogenous. There is no entry because labor supply (i.e., the number of researchers) is fixed (Eckey, 2008).¹⁷⁰

2.1.6.6.3. Conclusions and Critical Remarks

Similar to the above described model, Grossman and Helpman (1991b, 1993) have shown that localized spillovers can lead to geographic disparities and research clustering. The assumption of (partial) non-excludability of knowledge suggests that R&D activities can induce technological externalities (i.e., knowledge spillovers and their productivity effects)

to recover these fixed costs, so the model must therefore contemplate some forms of market power."
For comprehensive overviews refer to Roos (2002b), Rima (2004), Chandra and Sandilands (2005), Capello (2007), Eckey (2008), Harris (2008) and OECD (2009a).

¹⁶⁶ It is, however, essential to understand that the model of Romer (1990b) includes no machinery sector or capital goods in the production function. Most capital theories introduce technological progress via capital good embodied technological change by means of increasing productivity.

¹⁶⁷ The assumption of an R&D sector is picked up in several path-breaking models in new economic geography and endogenous growth theory. Finally, the NEGG model in this paper also has an R&D sector that produces designs.

¹⁶⁸ Romer (1986) also used externalities; however, his initial paper of 1986 does not include monopolistic competition and deals with an aggregated production function and global knowledge spillovers.

¹⁶⁹ Consequently, several models showed scale effects, where an increasing population of entrepreneurs or higher population growth rates would lead to higher productivity gains/regional growth rates.

¹⁷⁰ The simultaneous treatment of agglomeration and growth is not the primary concern. For this purpose, agglomeration and growth need to be combined via the introduction of knowledge and its diffusion in space. Industrial specialization, clustering and spatial diversity then highly depend on knowledge exchange and knowledge externalities.

(see section 2.1.7). However, the primary interest of the authors is grounded on explaining endogenous growth but not explicitly agglomeration economies and research clustering (and centripetal and centrifugal forces).¹⁷¹ Grossman and Helpman (1993, 16) argued that

“[b]y technological spillovers we mean that (1) firms can acquire information created by others without paying for that information in a market transaction, and (2) the creators or current owners of the information have no effective recourse, under prevailing laws, if other firms utilize information so acquired. [...] The technological spillover that result from commercial research may add to a pool of public knowledge, thereby lowering the cost to later generations of achieving a technological breakthrough of some given magnitude. Such cost reductions can offset any tendency for the private returns to invention to fall as a result of increases in the number of competing technologies.”

Endogenous growth models have been heavily criticized. Jones (1999) argued that regional growth in the endogenous growth theory is problematic as it is driven by the implementation of externalities that originate from the stock of accumulated ideas (blueprints) and discoveries due to non-rivalry (see also Keilbach, 2000; Jones, 2004).¹⁷² The stock of ideas is assumed to be directly proportional to the economy’s research effort, which, in turn, is considered to be a function of the total population, i.e., researchers or the creative class (Florida, 1995, 2002c; Jones, 2004; Glaeser, 2005a). Therefore, a considerable number of endogenous growth models are accused to suffer from the so-called “scale effect” (Jones, 1999). It is the link between ideas and returns to scale that gives rise to a basic scale effect in idea-based growth models (Romer, 1986, 1990b; Grossman and Helpman, 1991b; Aghion and Howitt, 1992). The growth rate of blueprints (and the economy) is proportional to the amount of research activities undertaken in the economy which is itself dependent on the growth rate of the population. Accordingly, it is argued that an increase in the size of the regional population, other things being equal, raises the number of researchers and therefore increases the growth rate of per capita income.¹⁷³

Unfortunately, the transfer mechanisms of spillovers remain a “black box.” The models generally abstract from the manifold transfer channels as will be highlighted in section 2.1.7. Much of the criticism has also centered on the non-excludability assumption (Capello, 2007; Freund, 2008). In many cases, economically useful technological knowledge fulfills the attribute of partial excludability, because it is possible to prevent other agents from using technologies (e.g., epistemic communities). Excludability is reflected by technological patterns (tacit knowledge, secrecy) but also by the legal system in an economy. Accordingly, knowledge can be made partially excludable by patent systems. However, depending on the technology case, some pieces of knowledge always remain inaccessible because codification is complex and some additional parts of knowledge have a tacit nature (section 2.1.7.2).

In conclusion, although the economization of knowledge is protected by legal systems (patent systems), spillovers of knowledge may lead to productivity effects in the develop-

¹⁷¹ See also Baldwin and Martin (2003), 19, footnote.

¹⁷² Romer (1990b, 98) argued in his 1990 paper that “[the model here suggests that what is important for growth is integration not into an economy with a large number of people but rather into one with a large amount of human capital.”

¹⁷³ Jones (1998, 11) argued that “[t]he size of the economy affects either the long-run growth rate or the long-run level of per capita income.”

ment of further products and processes (section 2.1.6.7).¹⁷⁴ Further to this, if the potential output of the researchers, who are studying blueprints in the patent documents of their rivals, could violate existing intellectual property rights in the future is rather a technical and legal issue (i.e., the IPR debate). After all, it is clear that patent documents contain codified knowledge (see section 2.1.7), which is available for those who can translate and use it, thus narrowing knowledge transmission to a technology- and sector-specific process and flows within epistemic communities. The translation of blueprints imposes considerable costs and presupposes specific knowledge and skills (partial excludability) only existent in epistemic communities (Steinmueller, 2000; Cowan *et al.*, 2000; Lissoni, 2001). This assumption is consistent with the “absorptive capacity concept” (Cohen and Levinthal, 1990). Related to these thoughts, scientific/technological knowledge is considered to be rather a club good as only fractions of researchers (and firms) can access, translate, modify and recombine such pieces of knowledge (Freund, 2008). Growth poles and centers of technological excellence will persist if the local stock of technological knowledge, which is strongly connected to the number of researchers, is unequally distributed across space. Moreover, the clustering of research activities may persist under the assumption of spatially localized knowledge externalities (proximity externalities), which is strongly related to some key properties of innovative milieus (section 2.1.7.3). An initial non-symmetric distribution of knowledge stocks (i.e., blueprints, researchers, research laboratories) and/or strong distance decay effects of knowledge transfer (i.e., pure externalities and partially compensated flows) may be able to explain the persistence of core-periphery structures, research clustering and regional growth differentials (Capello, 2007; Sachs and McCord, 2008; Henderson, 2010). According to these thoughts, endogenous growth models can be used to explain income and growth differentials and persisting regional disparities in research activities, but they are not suited to explaining the emergence of regional core-periphery structures, at least without migratory movements or researchers, changing distance decay effects of knowledge transmission or other centripetal forces that induce cumulative circular causation.¹⁷⁵

The spatial distribution of knowledge stocks and researchers is a crucial factor for regional development. Therefore, the distribution (and clustering) of knowledge stocks and disparities in research and patenting activity in Europe will be explored in this study by analyzing the concentration of EPO patenting activity at the regional level (see chapter 3). Persistent core-periphery structures in patenting activities should then be reflected in significant differences regarding regional growth rates (see chapter 5).

2.1.6.7. Research Clustering and Knowledge Flows in Core-Periphery Models

2.1.6.7.1. Agglomerations, Blueprints and Technological Externalities

In the standard NEG framework, second-nature causes of agglomeration and clustering solely capture pecuniary causes and effects of agglomeration, e.g., vertical linkages, in-

¹⁷⁴ The literature then issues a “free lunch” from positive technological externalities.

¹⁷⁵ The role of innovative capacities, knowledge stocks and research clustering with respect to GDP growth rates of European regions will be discussed in chapter 5.

creasing returns, transport costs and distance sensitive production, and mobility of workers.¹⁷⁶ Recent contributions focus on the concentration of production and R&D activities, which induce alternative centripetal forces (i.e., R&D spillovers) and determine relocation and regional growth.¹⁷⁷ Clustering of research activity can be traced back to several factors, e.g., accesses to (i) market information, (ii) codified and tacit knowledge, (iii) skilled employees (and human capital in general), (iv) patenting and researcher networks (see section 2.1.7.5), and (v) specialized suppliers in highly fragmented production and supply chains. Accordingly, research activities show indeed spatial concentration in several industries, since firms and entrepreneurs are inclined to co-locate in those regions where required inputs, tasks and processes co-agglomerate (Feldman, 1994b; Gallagher, 2008). The discussed spatial nature of knowledge (see section 2.1.7) has directly entered the new economic geography literature and established a second generation of models by means of an explicit recognition of knowledge transmission as a pivotal centripetal force.¹⁷⁸ Fujita and Krugman (2003, 161) concluded that

“[t]here recently appeared several multiregional growth models such as Martin and Ottaviano (1999), Baldwin et al. (2001) and Fujita and Thisse (2003) in which a core-periphery model is grafted onto a Grossman-Helpman-Romer-type model of endogenous growth. [...] the proximity of people is certainly helpful in the diffusion and generation of knowledge (in particular, through face-to-face communications).”

In this respect, Baldwin and Martin (2004) and Gosens and de Vaal (2010), among others, point out the importance of face-to-face contacts for knowledge transmission (section 2.1.7.2) and localized knowledge flows (section 2.1.7).¹⁷⁹ Accordingly, agglomeration of manufacturing industries, R&D activity and regional growth in blueprints (i.e., capital goods) seem to be positively related. That being the case, agglomeration is considered to have a positive effect on regional growth (i.e., growth in blueprints). Knowledge stocks and manufacturing industries co-locate in regions, which induces research clustering.¹⁸⁰ As a consequence, regional disparities remain and non-equity of research distribution is a possible and maybe stable outcome.¹⁸¹ The centripetal force which originates from R&D concentration and localized knowledge spillovers may be quite strong. Given the assumption of constant (non-decreasing) returns to learning in the aggregate production function of regions, knowledge spillovers in agglomerations can be interpreted as an elementary source of sustained regional growth (Glaeser *et al.*, 1992; Fujita and Thisse, 1996, 2003).

¹⁷⁶ Pecuniary externalities are transferred and stimulated via the market mechanism. However, they are different from technological externalities as the latter explicitly focus on non-rivalry and non-excludability of knowledge as an input.

¹⁷⁷ Baldwin and Martin (2003, 28) suggested that “[...] growth affects geography which itself affects growth and agglomeration is driven by the appearance of growth poles and sinks.”

¹⁷⁸ According to the OECD, “[k]nowledge can be regarded as an economic output in the form of a production blueprint but knowledge is also an input required to produce new blueprints. [...] In this sense, it recalls a corn-economy in which corn produces corn” (OECD, 2000, 21).

¹⁷⁹ They refer to the existence of some kind of “home-bias.”

¹⁸⁰ In other words, “[g]rowth, through innovation, spurs spatial agglomeration of economic activities which in turn leads to a lower cost of innovation and higher growth so that a circular causation between growth and the geographic concentration of economic activities sets in” (Martin and Ottaviano, 2001, 948).

¹⁸¹ These results are in line with the findings from the spatial variants of endogenous growth models developed by Romer (1990b,a) and Grossman and Helpman (1991a), among others.

Furthermore, the regional disparities of knowledge spillover effects between the center and the periphery explain diverging growth paths in blueprint production and the intensity of R&D clustering. According to this conceptualization, the implementation of knowledge externalities and sectoral learning processes can be regarded as the foundation of a second generation new economic geography framework, the “new economic geography growth” (NEGG) or “growth-cum-geography models” (Baldwin and Krugman, 2004).

However, the NEGG models show some central differences regarding centripetal and centrifugal forces. The subsequent table 2.5 summarizes the forces that influence the emergence and stability of core-periphery structures and the concentration of research activity.¹⁸² In general, the new economic geography can be divided into three classes of models.¹⁸³ The seminal contribution was made by Krugman (1991) with his core-periphery framework that allows for labor mobility and expenditure relocation (see section 2.1.5.5). Later on, the core-periphery framework was enriched by vertical linkage (VL) models that focus on centripetal forces originating from input-output linkages, by footloose capital (FC)/capital accumulation (CC) models that center R&D externalities that induce cost linkages and by footloose entrepreneur (FE) models that place the emphasis on migratory movements of agents (Cerina and Pigliaru, 2005; Cerina and Mureddu, 2009).

In the following, selected models that challenge the regional distribution and structural dynamics of research and patenting activity are briefly presented and discussed.

2.1.6.7.2. Growth-Cum-Geography Models and R&D Location

Baldwin and Forslid (2000a) introduced a cum-growth-geography framework based on R&D spillovers. Spillovers can either be intra- or inter-regional (but also somewhere in between). Blueprint (capital) mobility between the regions and repatriation of profits is impossible. A high level of transportation costs (i.e., a low level of integration) is always a stable equilibrium with no core-periphery emergence; however, it is accompanied by lower regional growth rates. The authors showed that a change in transportation costs (at the break point) leads to a “growth take-off” stage if one region accumulates relatively more blueprints (i.e., knowledge). The regional growth rate increases until a new equilibrium is reached. At higher levels of transportation costs, the model predicts full industry agglomeration in only one region; accompanied by higher growth rates (i.e., growth in blueprints) but also increasing regional disparities between the two regions, which again induces normative issues and a trade-off between equity distribution of industrial activity and aggregate

¹⁸² It should be realized that the last row centers the spatial range of technological externalities or knowledge spillovers that are crucial in NEGG models. The other factors, however, also influence core-periphery stability.

¹⁸³ The conceptualization of different geographical scales in models demonstrates that agglomerations are regarded to be influenced by varying centripetal and centrifugal forces. Thus, all these forces form and modify the spatial complex system of economic activity. The essential contribution of NEG models is then to devise a modeling approach that can give essential ideas and information about the centripetal forces that pull the economy together and the opposed centrifugal forces that push things apart (Fujita and Krugman, 2003). As Combes *et al.* (2005, 330) concluded, “[...] there is no inherent contradiction between the urban system approach and NEG: the latter is trying to explain broad trends at large spatial scales while the former attempts to explain spikes of economic activity.”

Table 2.5. Cumulative causation and forces of agglomeration

Centrifugal Forces	Centripetal Forces
a small regional market and small initial manufacturing share	thick markets, home-market effect (i.e., large expenditure share) and expenditure shifting
immobile factors of production (i.e., inter-regional immobility of, e.g., labor, entrepreneurs, patents)	mobility of entrepreneurs, consumers, firms, patents/blueprints (factor mobility)
competition effect (falling price index in the agglomeration)	initial (exogenous) higher level (skewness) of factor endowments (first-nature)
land rents, commuting, congestion costs	intra-regional vertical linkages (intermediates, resources, skilled labor input)
global knowledge spillovers (public good, no distance decay); inter-regional social ties; inter-regional co-inventor linkages	local knowledge spillovers (strong distance decay effects); intra-regional social ties; intra-regional co-inventor linkages

Source: own illustration based on Baldwin *et al.* (2001b), Roos (2002b), Baldwin and Martin (2004), Cerina and Pigliaru (2005), Cerina and Mureddu (2009) and Gosens and de Vaal (2010).

growth. To conclude, the model shows that regional growth rates are affected by research and industry clustering.¹⁸⁴

In Baldwin and Forslid (2000b), a Krugman-type geography framework is merged with an endogenous growth model. The monopolistically competitive sector (increasing returns) uses labor and capital inputs (i.e., blueprints). The production of blueprints exhibits technological externalities in terms of sector-wide (localized) learning effects; thus, industry agglomeration and research clustering are considered to be growth enhancing. Accordingly, localized knowledge spillovers and the growth of blueprints are considered to enforce the agglomeration process. Skilled workers (and their expenditures) show migratory movements between the regions due to varying present values of the underlying utility function, which induces expenditure shifting (centripetal force) (see also Martin and Ottaviano, 1999). To conclude, endogenous growth emerges from sector-wide learning effects in the R&D sector and core-periphery is additionally driven by migratory movements, which differentiates this model (and others) from early endogenous growth models. The model demonstrates that localized knowledge spillovers and research clustering generally support the emergence and stability of core-periphery structures (independent from the level of transportation costs), whereas global spillovers can also induce a process of dispersion. Regarding these predictions, it seems to be of great importance to measure research clustering in Europe.

Martin and Ottaviano (2001) introduced a core-periphery model in which labor is assumed to be inter-regionally immobile. Labor inputs are used to produce a homogeneous consump-

¹⁸⁴ For an overview of NEGG models also refer to Roos (2002b) and Litztenberger (2007).

tion good, a differentiated good and blueprints.¹⁸⁵ The authors merged the NEG with a Rivera-Batiz and Romer (1991) endogenous growth model. As usual in these frameworks, aggregate growth and the costs of blueprints are considered to be dependent on the total number of past research activities within the R&D sector. Blueprints are protected infinitely by a patent whose initial property belongs to agents in the region where the research effort was identified. Patents can be sold and are initially equally distributed among regions. The cost of R&D will be lower in the region where more firms are located due to localized knowledge spillovers. Both regions will engage in research activity if the manufacturing industry is equally distributed. That being the case, there are no incentives to relocate production of the increasing returns sector because the demand for varieties as well as their profits are the same in both regions. If the distribution is not equal, R&D activity also shows a core-periphery structure. If research activity is concentrated in one region, firms will tend to relocate to the core (agglomeration) where the local expenditure level is higher. Accordingly, agglomeration is an increasing function of growth (i.e., “forward linkage”). Furthermore, higher concentration of industries in one region is regarded to affect the R&D learning curve and thus to reduce the costs for additional blueprints (R&D externalities), which attracts more researchers (and firm entries) until profits are zero. Growth is modeled as an increasing function of agglomeration (i.e., “backward linkage”).¹⁸⁶ If the initial distribution is asymmetric, the only stable steady state is the one in which all research activity is concentrated in a single region. This implies that production and R&D activities are geographically concentrated, even if research is still more agglomerated than manufacturing activity (see, e.g., Audretsch and Feldman, 1996).

Fujita and Thisse (2003) introduced an alternative core-periphery framework, which is similar to the one introduced by Baldwin and Forslid (2000b). The authors reported very similar conclusions concerning the agglomeration-and-growth relationship. A Krugman-type geography framework was extended to incorporate endogenous growth via blueprint accumulation (see also previous models). The R&D sector makes use of skilled labor to create new blueprints; the blueprints are then used in the manufacturing sector as a capital input. Similar to Baldwin and Forslid (2000b), the migration behavior of skilled agents is taken into account. Fujita and Thisse showed that industry co-location (and research clustering) leads to higher growth (in varieties). Moreover, if several centripetal forces are strong enough, even those firms are better off which remain in the periphery, although absolute discrepancies between the core region and the periphery increase (i.e., in industrialization, employment structure, wages).¹⁸⁷

Concerning the possibility of cross-fertilization and inter-industry productivity effects, Cerrina and Mureddu (2009) modified the framework of Baldwin *et al.* (2001a) by allowing inter-sectoral technological externalities (see also section 2.1.6.3). Their framework allows for spillovers from the R&D sector to the service sector. As a result of these inter-sectoral knowledge spillovers, the effects and welfare implications are even more unclear, compared

¹⁸⁵ The homogeneous good is produced under constant return to scale and perfect competition and transportation costs are nil. The manufacturing good, in opposition, is produced under increasing returns to scale and monopolistic competition and transportation induces costs (Martin and Ottaviano, 2001).

¹⁸⁶ The symmetric equilibrium (manufacturing share being equal) is only stable for positive equilibrium growth rate, when the regions start in a symmetric distribution.

¹⁸⁷ Indeed, this resembles a strong welfare conclusion similar to the ones included in the former NEGG models.

to the standard case without cross-fertilization. Assuming an initial core-periphery structure with an agglomerated industry in one region, the authors presented different effects. The core region is generally better off and benefits from two dynamic gains from clustering: (i) an increase in the nominal growth rate of blueprints due to localized knowledge spillovers; (ii) a decrease in the costs of services due to (localized) inter-sectoral knowledge spillovers (i.e., productivity effects). At the same time, the deindustrializing region experiences two effects: (i) a dynamic gain given by the increase in the nominal growth rate of manufacturing goods, which are transported to the periphery; (ii) a dynamic loss due to the fact that the stock of capital goods (i.e., blueprints) in the periphery does not grow anymore. Moreover, service prices are fixed as services do not benefit from localized productivity spillovers because inter-sectoral spillovers are localized in the core region. The authors assumed that these losses in the periphery may be counterbalanced by the gains in the services in the core region. Thus, agglomeration is at least welfare enhancing at the aggregate level.¹⁸⁸

A final consideration concerns the implementation of social ties and networks. Gosens and de Vaal (2010) have built on the Fujita and Thisse (2003) “growth-cum-geography model” to analyze the implications of migratory movements and inter- and intra-regional social ties. Inter-personal linkages are considered to be a crucial factor for tacit knowledge exchange within and between regions (see section 2.1.7.2). They introduced a relationship between migration, knowledge spillovers and the concept of codified and non-codified (tacit) knowledge.¹⁸⁹ Codified knowledge is accessible and applicable to other researchers in the community and thus spills over quite easily, whereas non-codified knowledge may remain tacit and local due to several reasons, e.g., for lack of absorptive capacity and/or social ties.¹⁹⁰ According to Gosens and de Vaal (2010), migration is a key factor to benefit from knowledge from other regions. Moreover, inter-regional and intra-regional social ties lower the costs of exchanging tacit knowledge and ease knowledge spillovers, meaning that the region of immigration essentially profits from tacit knowledge of immigrant researchers when social ties to arriving researchers grow considerably.¹⁹¹ The authors concluded that agglomeration of high-skilled researchers and thus research clustering in one region is not a straightforward outcome as the region of immigration and the region of emigration are both affected by existing knowledge networks. Accordingly, if immigrants continue their social relationships with the region of emigration, their newly accumulated tacit knowledge will spill over from the region of immigration to the region of emigration. This idea is identical to the arguments discussed in section 2.1.7.4.¹⁹²

¹⁸⁸ Considering the deindustrializing region, the real growth rate in case of the symmetric equilibrium can be higher compared with the core-periphery equilibrium if the dynamic loss in the services sector overcomes the dynamic gain in manufacturing. However, the standard NEG interpretation finds that the core and the periphery enjoy the same dynamical gains of agglomeration.

¹⁸⁹ For a critical survey refer to Lissoni (2001) and Breschi and Lissoni (2001b).

¹⁹⁰ According to the authors, tacit knowledge exchange is related to social interaction within the labor force, while productivity effects from codified knowledge is related to the number of manufacturing varieties in the region.

¹⁹¹ Important empirical studies are, e.g., Agrawal *et al.* (2006) and Saxenian (2006).

¹⁹² This reasoning resembles Saxenian’s “new argonauts” that propel knowledge exchange between the United States and Asian countries (Saxenian, 2006).

2.1.6.7.3. Critical Remarks and Discussion

NEGG models can be applied to work out general mechanisms that induce relocation and geographic clustering of knowledge bases, researchers and patenting activity (i.e., research clustering). These frameworks have strong similarities to the geography of innovation literature (Audretsch and Feldman, 2004; Boschma and Frenken, 2009b; TerWal and Boschma, 2009) and the regional systems of innovation (RIS) approach (Cooke *et al.*, 1997; Cooke, 2008), although the methodological realization is different. All these research lines generally address clustering and challenge the observed spatial structures of innovative activity, research clustering and regional disparities relating to knowledge-intensive activity.

The aforementioned core-periphery frameworks offer important insights into the distributional dynamics of research clustering. Opposed to early NEG models (see section 2.1.5.5), recent contributions are additionally emphasizing the relationship between research clustering strength, agglomeration and growth of the R&D sector. The modeling structures, as presented in table 2.5, are different to early NEG models. Demand- and supply-side linkages, which emerge from pecuniary externalities in early NEG models, are replaced and/or complemented by alternative core-periphery mechanisms, i.e., non-pecuniary (technological) externalities.¹⁹³ In line with endogenous growth models, the details on knowledge transfer mechanisms remain a “black box.” Nevertheless, the main conclusion of NEGG models is quite similar to endogenous growth models: localized knowledge spillovers (and flows), which induce productivity effects in the R&D sector, sustain core-periphery structures. Therefore, it can be concluded that the spatial distribution of research activity, the distance decay of knowledge spillovers and the structure of inter-regional research networks, i.e., patenting networks, play a crucial role for regional development as major fractions of knowledge are distributed via (R&D-) network linkages. Unfortunately, network linkages still represent a minor framework alternative and an ignored channel of knowledge diffusion.

As has been emphasized by recent studies, inter- and intra-regional research networks may be well reflected by researchers’ co-patenting activities (see section 2.2). Regarding theoretical considerations of research networks, network mechanisms and knowledge flows via linkages represent a meaningful shortcoming of the above described models. The following section briefly summarizes major theoretical aspects of inter-personal and inter- and intra-regional research collaboration linkages and networks.

To conclude, from an empirical point of view, there is a great need for analyzing the distributional dynamics of European research activities at the regional level and to explore the structural dynamics of co-patenting network linkages between European regions. Therefore, the analysis of the distribution of research clusters and inter-regional co-patenting networks in chapters 3 and 4 is regarded as to challenge the aforementioned shortcomings in a European context.

¹⁹³ The main sources and references to the NEGG model are Baldwin and Forslid (1999), Martin and Ottaviano (1999), Baldwin and Forslid (2000b), Baldwin *et al.* (2001b), Baldwin *et al.* (2001a), Baldwin and Martin (2003) and Cerina and Pigliaru (2005).

2.1.7. Agglomerations, Networks and Knowledge Transmission

2.1.7.1. Knowledge Flows, Network Linkages and Spillovers

Besides the broader concept of agglomeration economies presented in the previous sections (sections 2.1.4.3, 2.1.5 and 2.1.6), the survey is now related to the specific factors that are considered to represent the pivotal determinants of knowledge transmission, research clustering and the distribution of research activities. An important consideration concerns the theoretical conceptualization of the working channels of knowledge transmission in the context of spatial and relational proximity in milieus and the exchange of knowledge via inter-regional (trans-territorial) networks (Breschi and Lissoni, 2001b,a; Capello and Faggian, 2005). A crucial aspect in this regard consists of the attributes and properties of knowledge (Lissoni, 2001; Capello, 2009).

From a conceptual point of view, Tödting *et al.* (2010), among others, have proposed a comprehensive classification of knowledge-sourcing strategies that differentiates between the possible knowledge acquisition channels at the firm level (see table 2.6). Similarly, Johansson and Quigley (2003) and Johansson (2005, 133) differentiated between agglomeration economies and the external economies of networks, whereby agglomeration economies and network economies are different but sometimes overlapping. They concluded that spillovers, which originate from networks and transaction linkages (quasi-market), are different from unintentional spillovers that emerge from anonymous market activities. Moreover, they argued that the advantages of established (formal and informal) networks and proximity externalities can geographically overlap in agglomerations. The subsequent table 2.6 summarizes the mechanisms.

Table 2.6. Mechanisms of knowledge acquisition

	static (knowledge transfer)	dynamic (collective learning)
formal/ traded relation	anonymous market relations; contract research; consulting; licenses; buying of intermediate goods and knowledge from knowledge suppliers	co-operation/formal networks; link transaction; R&D co-operations with agents at a proximate or distant location; shared use of R&D facilities making repeated and similar transactions with identifiable and distinct partners
informal/ un-traded relation	externalities/spillovers; recruitment of specialists; monitoring of competitors; participation in fairs, conferences; reading of scientific literature, patent specifications	milieu/informal networks; informal contacts between agents; social networks in agglomerations; proximity sensitive

Source: illustration from Tödting *et al.* (2010, 6); see also Johansson and Quigley (2003), Storper and Venables (2004), Johansson (2005) and Capello (2009) for similar concepts.

First and foremost, spillovers of knowledge may originate from unplanned interactions, especially in the context of highly populated areas and city agglomerations (see the pre-

vious section). This argument has shifted the attention of researchers towards models of urban growth, which are based on agglomeration economies (Glaeser *et al.*, 1992; Fujita and Thisse, 2003; Malecki, 2010). In this respect, knowledge spillovers constitute an important factor of these agglomeration economies and thus influence co-agglomeration and research clustering. Henderson (1999), e.g., concluded that most external economies stem from information externalities (identical to knowledge spillovers).¹⁹⁴ Accordingly, firms, research institutes and even single researchers within the system produce economically useful knowledge, which can unintentionally spill over to other agents without (full) financial compensation (see section 2.1.6.1).

However, firms that are involved in market transactions have the possibility to take additional advantage of unintended knowledge spillovers. Moreover, the co-operation of firms in sharing the costs (and risks) of an investment may result in a meaningful exchange of valuable knowledge. Nevertheless, this cannot be considered as a pure knowledge spillover, since it is first and foremost an exchange of information (or knowledge) crafted on a market transaction (and monetary flow) (Breschi *et al.*, 2005; Johansson, 2005). Consequently, pecuniary (market-led) flows of knowledge have to be separated theoretically from non-compensated flows (i.e., spillovers that are pure technological externalities) and less-compensated knowledge spillovers (rent spillovers) (Verspagen, 1997).¹⁹⁵ However, such a differentiation is difficult regarding empirical studies.

As no consensus or established approach exists to differentiate between pure spillovers and flows, the empirical analysis in this study is restricted to the identification of research collaboration linkages between agents and regions in a pan-European context, i.e., co-patenting linkages (see chapter 4). It is argued that such linkages represents the only practical measure of knowledge transfer when analyzing hundreds of regions.¹⁹⁶ The extent to which collaboration linkages, e.g., co-patenting linkages, induce spillovers is not challenged in this thesis.

2.1.7.2. Tacit versus Codified Knowledge and the Embodiment Concept

Literature distinguishes between three essential properties of knowledge as an economic good (Nonaka and Takeuchi, 1995; Lissoni, 2001; Foray, 2004): (i) parts of knowledge are non-excludable, which makes it difficult to control or to prevent others from using it; (ii) parts of knowledge are non-rival, which means that other agents can use it, even simultaneously, and therefore it is inexhaustible. However, there is also a discussion related to the

¹⁹⁴ For similar arguments refer to Fujita and Thisse (1996), Black and Henderson (1999b), Black and Henderson (1999a) and Glaeser (2008).

¹⁹⁵ Griliches (1992c) distinguished between “rent spillovers” and true “technological spillovers” (see also Verspagen, 1997). Market spillovers are a synonym for rent spillovers. For an understanding of the conceptualization of rent spillovers, the thesis follows the arguments of Griliches and Jaffe in assuming that some knowledge enters the production function of firms with less compensation, which means that some knowledge is internalized by other firms for a lower price (quality price model). Besides this conceptualization, knowledge spillovers can also enter the production (or utility) without any compensation, which then represents technological externalities.

¹⁹⁶ See Ejermo and Karlsson (2006) for a similar argumentation.

appropriability of knowledge (Cohen and Levinthal, 1990; Capello, 2007; Malecki, 2010);¹⁹⁷ (iii) knowledge is cumulative in nature; although old knowledge becomes partly obsolete as best practice technologies and processes advance, some parts of the knowledge base can remain essential. Accordingly, the three mentioned characteristics seem to be essential when discussing economies of agglomeration and the co-location of agents with respect to knowledge generation and transfer, especially in knowledge-intensive industries.

Nonaka and Takeuchi (1995) have introduced a conceptual framework based upon tacitness and codifiability of knowledge, which helps to classify the transformation of knowledge and implicitly its diffusion into different categories:¹⁹⁸ (i) combination, which is the transfer/transformation of explicit (codified) knowledge to explicit knowledge; (ii) internalization, which is the transfer/transformation of explicit knowledge to implicit (tacit) knowledge; (iii) externalization, which represents the transfer/transformation of implicit knowledge to explicit knowledge via codification; (iv) socialization, that encompasses the transfer/transformation of implicit knowledge to implicit knowledge (Nonaka and Takeuchi, 1995).¹⁹⁹ Channel (iv) is especially of pivotal interest in recent debates on inventor mobility, e.g., the mobility of engineers (Almeida and Kogut, 1999; Breschi and Lissoni, 2009) as will be discussed in the empirical review (see sections 2.2.5 and 2.2.6). The empirical contribution on co-patenting linkages within European inventor networks is, however, mainly focusing on channel (i), although co-inventorship activity is considered to rely on significant parts of implicit knowledge. Moreover, absorption by other agents needs specific technological knowledge and skills.

The approach just described has similarly been proposed by Polanyi (1966). He introduced the differentiation between tacit (implicit) and codified (explicit) knowledge. Stickiness of knowledge is mainly based upon three assumptions: (i) difficulties in exchanging knowledge over long distances, (ii) a context-specific nature that needs common social, organizational and even institutional set-ups, and (iii) the necessity of organized learning processes. Stickiness and thus a substantial increase in the need for geographical, technological, and organizational proximity for economic interaction, and an increasing need for face-to-face contacts (i.e., “handshakes”), may in particular be useful to explain persistent research clustering and agglomeration of innovative activity (von Hippel, 1994; Audretsch, 1998; Feldman, 2000).²⁰⁰ In the same line of reasoning Gertler (2003, 79) argued that

“[w]hen one combines these two features of the innovation process - the centrality of sticky, context-laden tacit knowledge and the growing importance of social interaction - it becomes apparent why geography now matters so much.”

¹⁹⁷ Appropriability and the concept of absorptive capacity are related to knowledge accumulation. Cohen and Levinthal (1990, 129) argued that “*research on memory development suggests that accumulated prior knowledge increases both the ability to put new knowledge into memory, what we would refer to as the acquisition of knowledge, and the ability to recall and use it.*”

¹⁹⁸ According to Nonaka and Takeuchi (1995, 59), “[t]acit knowledge is personal, context-specific, and therefore hard to formalize and communicate.”

¹⁹⁹ For further discussions of codification processes from implicit to explicit knowledge refer to Cowan *et al.* (2000), Feldman (2000), Fischer (2001), Scherngell (2007), Jensen *et al.* (2007), Cooke (2007).

²⁰⁰ von Hippel (1994, 432) has argued that “[w]hen information transfer costs are a significant component of the cost of the planned problem-solving work, it is reasonable that there will be a tendency to carry out innovation-related problem-solving activity at the locus of sticky information.”. See also Breschi *et al.* (2005) and Cooke (2007).

Tacitness of knowledge is context-specific. Some people may find it simple to articulate such (pieces of) knowledge, others, however, do not (Cowan *et al.*, 2000; Lissoni, 2001; Johansson and Quigley, 2003). In this respect, epistemic communities (of science) have developed their own language, institutional set-up and communication codes for codifying, transmitting and securing scientific knowledge and for reinforcing tacitness and reducing externalities (Steinmueller, 2000; Lissoni, 2001; Balconi *et al.*, 2004). Accordingly, knowledge can be considered a freely available good within each epistemic community (club good). Related to the degree of codifiability of knowledge, the subsequent table 2.7 summarizes the different modes of knowledge diffusion.²⁰¹ The table particularly centers the type of knowledge (tacit versus codified) and possible working channels of knowledge transmission.

Table 2.7. Modes of transfer of tacit and codified knowledge

Acquisition mechanism	Codified knowledge/ public good	Codified knowledge/ private good	Tacit knowledge
non-market acquisition/ informal networks	learning and absorption of specific knowledge by studying documents, data, blueprints; education and graduation from organizations	externalities from reverse engineering; strategic brain drain; studying patent descriptions	externalities from job hopping; learning by doing, watching, interacting; inventor networks
market acquisition and/or formal networks	-	purchase of technology (anonymous market); licensing of technologies protected by patents; software R&D assignments; M&A	acquisition of researchers and engineers as carriers of tacit knowledge; established, stable and repeated co-operations and R&D networks as carriers of tacit knowledge

Source: illustration taken from Franz (2010, 8); see also McCann *et al.* (2002), Johansson and Quigley (2003), Johansson (2005), Scherngell (2007) and Jensen *et al.* (2007) for similar concepts.

To conclude, possible transfer channels (and carriers) of knowledge spillovers are summarized in table 2.8 for a complementary review. According to the table, the working channels can be classified with respect to the “embodiment” issue. The table distinguishes between knowledge embodied in people and knowledge enclosed in goods. It is worth noting that the empirical analysis draws attention to the distribution of research activity, where the focus is on the distribution of patenting activity, inventors and inter-regional co-patenting networks, but not explicitly on people, their social networks or their migratory movements.

²⁰¹ For further discussions and definitions of tacit knowledge refer to Feldman (1994b), Audretsch (1998), Feldman (1999), Ottaviano and Thisse (2000), Lissoni (2001), Asheim and Gertler (2005), Döring and Schnellenbach (2006), Scherngell (2007), Jensen *et al.* (2007) and Franz (2010).

Table 2.8. Transfer channels of knowledge via agents, goods and documents

Embodied in agents	Embodied in products/documents
mobility of labor; especially mobility of highly skilled people via job hopping	technology white book and scientific publications
mobility of labor via entrepreneurship and spin-offs	patent documents, patent application, patent licensing
mobility of labor via conferences, expositions	vertical linkages/technology transfer via reverse engineering of intermediates (rent spillovers)
(formal) inventor networks and informal social networks	horizontal linkages/technology transfer via reverse engineering of final goods (rent spillovers)

Source: illustration based on Feldman (2000), Lissoni (2001), Johansson and Quigley (2003), Johansson (2005), Scherngell (2007) and Capello (2009).

2.1.7.3. Agglomerations, Innovative Milieus and the Proximity Hypothesis

Networks are considered to differ from agglomerations although they may have some overlaps (Burger *et al.*, 2009). The formation and efficiency of an agglomeration arises from its quasi public good character (non-rivalry, non-excludability). Agents, households and firms within an agglomeration share the benefits of spatial proximity; only spatial distance makes it a “quasi club good” if agglomeration economies show strong distance decay effects. In contrast, an economic network between agents represents some kind of “private capital” which originates from individual investments that are shared solely by network participants. Economic networks emerge from collective decisions which are made by groups which run private institution. However, agglomerations and industry clusters rely mostly on public institutions (Johansson and Quigley, 2003; Johansson, 2005).

According to Johansson (2005), networks are generally established in order to facilitate the exchange of assets within and between organizations, regions and countries to reduce transaction costs. The transaction cost approach (TCA) is helpful to determine whether markets, organizations or a combination is more efficient in coordinating exchange of assets. Intangible economic networks represent transaction agreements and routinized arrangements between agents and firms; they differ from the anonymous market and physical networks (see also Williamson, 1975, 1979; Johansson and Quigley, 2003; Wilhelmsson, 2009). An economic network can be regarded as an organization of interlinked agents which combines features of the market and the firm. The network internalizes some interaction costs and is built on several agreements, similar to standard market contracts. Accordingly, networks exist in order to reduce transaction costs. Regarding research and co-inventor networks, it is generally argued that long-distance research collaborations are costly. When transactions are generally distance-sensitive, persistent transaction linkages can overcome spatial distance and reduce costs. However, there are always fixed costs associated with the process of establishing a network between agents and/or firms. The transaction costs may be lower inside an agglomeration, but long-distance linkages also

reduce costs if they are persistently used (McCann *et al.*, 2002; Johansson and Quigley, 2003; Johansson, 2005). Accordingly, network linkages can emerge within agglomerations in different forms, e.g., industrial complexes and social networks, but also between regions and agglomerations (McCann *et al.*, 2002; Johansson and Quigley, 2003; Burger *et al.*, 2009). The co-patenting analysis in chapter 4 builds upon this idea, as R&D collaboration is regarded as a meaningful channel for knowledge flows (Ejeremo and Karlsson, 2006; Burger *et al.*, 2009).

Contributions to regional knowledge networks and the innovative milieu since the late 1970s combined an “industrial,” “spatial” and “cognitive” dimensions of agglomeration economies (Capello and Faggian, 2005; Capello, 2009). An interesting debate in the context of spatial proximity was related to the distance decay effects of knowledge transfer due to the aforementioned properties of knowledge. Although geography was included in the “spatial” and “industrial” concepts, the micro-foundations of knowledge transmission remained a “black box” (Lissoni, 2001; Breschi and Lissoni, 2001a; Storper and Venables, 2004). However, a salient feature reported by many empirical studies is that greater distance tends to decrease the frequency of economic activities and interactions among observations, especially with respect to knowledge transmission and research activity. For this reason, intellectual tasks are considered to be influenced enormously by geographic distance (Maggioni *et al.*, 2007; Maggioni and Uberti, 2009; Hoekman *et al.*, 2009). That being the case, the observed patterns of spatial knowledge diffusion are said to originate from the different properties and attributes of knowledge as described above. In light of this, scholars regularly make use of the tacit knowledge concept in order to explain and categorize the relationship between spatial proximity and knowledge transmission. Thus, the tacit knowledge concept is linked with the social network approach (Lissoni, 2001; Breschi and Lissoni, 2003; Storper and Venables, 2004).²⁰² Such (social) networks are generally related to the work of, e.g., Granovetter (1973) and can be regarded as a response to the hierarchies model of Williamson (1975) (see also Johansson, 2005; Capello, 2009). The social network approach argues that mutual trust relations between agents in different organizations are at least as important as decision-making hierarchies within the individual organizations (McCann *et al.*, 2002).

Opposed to the commonly applied a-spatial public good character of knowledge in early endogenous growth models (Romer, 1986; Jones, 2004), the French “proximity school” considers localization as a relevant factor due to the costly transmission of knowledge across space as it is embedded, non-codified and not explicitly stated. For this reason, it is not easily transferable and its exchange is extremely costly and sensitive to the social context, which is itself a local phenomenon (localized social networks). Such localized interdependencies create a milieu effect (Camagni, 1991b,a; Capello, 2009). The approach explicitly supports the observed phenomena of spatial concentration and clustering of research activity (Paci and Usai, 2000b; Balconi *et al.*, 2004; Maggioni *et al.*, 2007). The local “stickiness” of parts of knowledge is assumed to support localized intra-regional knowledge-intensive interaction (Nonaka and Takeuchi, 1995; Lissoni, 2001; Johansson and Quigley, 2003).²⁰³

²⁰² Similarly, Lundvall (2007, 103) suggested that “[a] key difference between firms, sectors, regional and national systems is the role played by respectively codified and tacit knowledge in the innovation process.”

²⁰³ Refer also to Scherngell (2007), Lundvall (2007) and Powell and Giannella (2010).

Regarding spatial distance between epistemic communities, it is argued that it is difficult to communicate and collaborate over considerable distances, as distance generally increases costs of establishing and maintaining knowledge access (Balconi *et al.*, 2004; Hoekman *et al.*, 2009). Long-distance transaction and its coordination are generally more time-consuming, cost-intensive and hinder a productive dialogue compared to collaborations at a proximate distance. According to that, the efficiency of knowledge exchange at a distance is a function of codifiability, teachability and complexity (Breschi and Lissoni, 2003; Storper and Venables, 2004; Capello, 2009). Related to these interdependencies, Storper and Venables (2004), Bathelt *et al.* (2004) and Maskell *et al.* (2005), among others, argued that local systems are determined by several dimensions of proximity. They emphasized that localized learning processes are heavily influenced by learning by interacting (vertical), learning by monitoring (horizontal) and some neighborhood-effects and “local buzz” (social dimension), which makes the city a central place. Similarly, Glaeser *et al.* (1992, 1126) argued that

“[i]f geographical proximity facilitates transmission of ideas, then we should expect knowledge spillovers to be particularly important in cities. After all, intellectual breakthroughs must cross hallways and streets more easily than oceans and continents.”

Obviously, the above presented concept of “knowledge tacitness” is used and extended by different schools of thought; e.g., economic geographers (Boschma and Frenken, 2009; Hoekman *et al.*, 2010), economists (Fujita and Thisse, 1996; Ottaviano and Thisse, 2001; Baldwin and Martin, 2004; Gosens and de Vaal, 2010) and innovation scholars (Audretsch, 1998; Audretsch and Feldman, 1999; Feldman, 1999, 2000; Breschi and Lissoni, 2003).

The presented assumptions and concepts lead to the conclusion that the region represents a central place of knowledge production, recombination and sharing (and of knowledge diffusion in general).²⁰⁴ This idea is considered to be especially relevant with regard to research activity that is in general spatially concentrated in large cities and urban regions (Fischer, 2001; Cooke, 2001; Henderson, 2010).²⁰⁵

Another working channel of knowledge exchange at a proximate distance are spin-offs, which are considered to be located in the neighborhood of their parent organizations (or competitors), which increases spatial concentration and thus research clustering (Zucker *et al.*, 1998; Audretsch *et al.*, 2005; Ponds *et al.*, 2010). According to Audretsch and Feldman (2004, 2733), spin-offs locate in proximity to existing clusters as

“[s]uch start-ups typically do not have direct access to large R&D laboratory. Rather, these small firms succeed in exploiting the knowledge and experience accrued from the R&D laboratories with their previous employers.”

To conclude, spatial proximity affects network formation and place makes a difference (Glückler, 2007). Spatial proximity between agents and the emergence of milieus facili-

²⁰⁴ Storper (1997, 44) concluded that the region itself represents “[a] site of important stocks of relational assets.”

²⁰⁵ This has also been issued by Lagendijk (2001, 81) who argued that “[d]ue to the changes in industrial organisation, notably the rising importance of networking and learning, the region has come to be seen as a highly appropriate level for knowledge production.”

tate both unintended knowledge spillover and intended knowledge exchange (in localized networks). Moreover, co-location is considered to enable “collective learning” within the boundaries of the territory (Capello and Faggian, 2005; Johansson, 2005; Capello, 2007). In this respect, network economies and agglomeration economies may overlap in urban areas and innovation clusters as soon as informal relationships (social networks) are present. If the agents are located in a single location and the effects of local interdependencies are low, then there is no clear-cut distinction between the relationships based upon network linkages and the formal contracts of an anonymous market transaction. In general, it is suggested that spillovers in agglomerations and spillovers in networks lead to a more rapid development in technology, innovative capacity, innovation output and productivity (Johansson and Quigley, 2003; Capello, 2007, 196). However, network linkages differ from anonymous market interactions in case of long-distance interactions as will be discussed in the following section.

2.1.7.4. Long-Distance Linkages and R&D Collaboration Networks

Another relevant type of economic and social relations represents trans-territorial cooperation agreements, i.e., inter-regional network linkages. Continuous and stable networks originate from the complexity of strategic alliances between agents (von Hippel, 2005; Ejermo and Karlsson, 2006; Powell and Giannella, 2010). It is generally assumed that transaction networks facilitate knowledge exchange between agents. Formal inter-regional network linkages are considered to function as a substitute for spatial proximity in the R&D process (proximity externalities in agglomerations) and in the knowledge-transmission process, respectively (Foray and Steinmueller, 2003; Johansson and Quigley, 2003; Porter *et al.*, 2005). According to Johansson (2005), advantages emerge from both transaction and innovation externalities if the network linkages show continuity (see section 2.1.6.5) what Capello (2009) calls the “synergy dimension” of agglomeration economies.

Related to the analysis of research networks and patenting activity, Maggioni *et al.* (2007, 475) recently argued that

“[i]t is almost impossible to disentangle the tacit from the codified elements of knowledge flows running across European regions. It is reasonable however, to assume that, since tacit knowledge needs face-to-face contacts and these contacts are inversely related to geographic distance, long-distance relations imply a greater role played by codified knowledge than the relationships between nearer regions.”

Therefore, a pivotal role is attributed to inter-regional research linkages and the emergence of trans-territorial networks as they are said to complement the locational advantage in agglomerations and milieus. This study follows this argument in analyzing European co-inventorship linkages in a spatial and technological perspective. For clarification purpose, table 2.9 offers a taxonomy of transaction-link based externalities. These externalities represent idiosyncratic inter-firm relations, which provide benefits that emerge from outside the ordinary (anonymous) market, i.e., a quasi-market setting (Johansson, 2005, 120). It is argued that a research network shares the extra-market properties of a club (Capello, 2009). Opposed to market anonymity, link transactions represent repeated and similar transactions between identifiable (non-anonymous) and distinct partners and build upon

Table 2.9. Network linkages and externalities

Externality type	Type of transaction	Principle mechanism
Network	Supply-chain externalities and complex network (transaction) externalities	Agents belonging to a network form a kind of club, through which they have accessibility to joint assets that facilitate transactions.
	Knowledge externalities within networks via transaction linkages	Knowledge spillovers are possible between agents that belong to the same network.
Vertical	Upstream or input- cost link externality. Established, repeated transactions.	A persistent (network) link between an input supplier and a customer reduces transaction costs; linkages may be distance sensitive (setup costs); positive transaction externality for the customer.
	Downstream or delivery-cost link externality. Established, repeated transactions.	A persistent (network) link between an input supplier and a customer reduces transaction costs; linkages may be distance sensitive (setup costs); positive transaction externality for the supplier.

Source: illustration based on Johansson (2005, 121); see also Johansson and Quigley (2003) and Capello (2007, 2009).

prior interactions. Moreover, investments in network linkages (i.e., sunk costs) affect future interactions and are thus profitable if linkages are expected to be used permanently (Johansson and Quigley, 2003; Johansson, 2005; Bahlmann *et al.*, 2009).²⁰⁶ The partners in inter-regional networks are always selected single economic units (researchers, firms) and geography represents only one dimension that affects the identification and selection of potential partners (Capello, 2007, 198-199).

To conclude, an established and stable network can reduce the “effective” distance between agents located in different regions in reducing transaction costs. In the case of infeasible co-location, networks have potentialities to act as a substitute for co-location and co-agglomeration and offer advantages similar to innovative milieus, especially if the progress in communication technologies is fast and the organizational structures improve in the course of time. Transaction linkages via networks have positive effects (Johansson, 2005). First, they are defined by reducing coordination and search costs and the set-up of interactions with identical agents induces sunk costs. Second, they are non-anonymous and repeatable, which reduces uncertainty. Third, knowledge externalities can occur as a by-product of network transactions in a proximate distance or long-distance relationship (innovation externalities).

²⁰⁶ Refer to the transaction cost approach of Williamson (1979).

2.1.7.5. Localized Networks versus Inter-Regional Network Linkages

As has been argued in the previous sections, the relationship between agglomeration economies, local interaction, innovative capacity and economic growth represents an established and growing field of research. With respect to proximity and networks (sections 2.1.7.3 and 2.1.7.4) it is suggested that agglomerations have potentialities to develop new knowledge and technologies faster and to show higher productivity growth (Ellison and Glaeser, 1997; Johansson and Quigley, 2003; TerWal and Boschma, 2009).²⁰⁷ Information and knowledge diffuse quite quickly among agents who belong to the same social and/or formal network, i.e., the same transaction network and/or epistemic community, especially when they co-locate at a proximate distance (proximity externality). However, it has also been argued by economists and geographers that well-functioning (formal and informal) networks between agents may be able to substitute for spatial proximity in the context of research activities and the processes of intended (and unintended) knowledge diffusion (Johansson and Quigley, 2003; Bergman, 2009; Burger et al., 2009).

However, the presented frameworks and remarks on agglomeration economies in the former sections solely focus on intra-regional factors. Spatial interaction is implemented as a “black box” of spillovers, if at all. Regarding this issue, Harris (2008, 22) complained that

“[r]esearch on agglomerations/clusters has focused on the internal characteristics and mechanisms in those places and diverted attention from the necessary distinct, even global, linkages that competitive places require.”

Spatial distance is commonly considered a general barrier to interaction and knowledge diffusion, meaning that many frameworks have not taken into account inter-regional linkages and research collaborations via network pipelines. Increasing attention in recent theoretical (and empirical) contributions to economic geography (TerWal and Boschma, 2009; Neffke *et al.*, 2009; Boschma and Frenken, 2010) and geographical economics (Fujita and Thisse, 1996, 2003; Gosens and de Vaal, 2010) is drawn to the question of whether geography is still the dominant factor for productivity and competitiveness and for regional development and economic growth (see section 2.1.7.3). Inter-regional linkages may represent a substantial factor for regional innovative capacity and growth (see section 2.1.7.4).

Geographers differentiate between the “space of places” and “space of flows” (Castells, 1996; Burger *et al.*, 2009).²⁰⁸ The former concept supports the idea that location and intra-regional factors matter for knowledge transfer and innovative capacities, whereas the latter concept centers on the assumption that networks are the pivotal factor. In light of this discussion, agglomeration economies, inter- and intra-regional networks and long-distance research collaborations are considered pivotal factors that likewise operate and affect the geography of innovation. This theoretical consideration has meaningful effects on research methodologies and agendas with respect to (i) firm-level network analysis, (ii) intra-cluster and intra-regional studies, (iii) inter-cluster and inter-regional studies and

²⁰⁷ In this respect, the debates also cover the questions whether sectoral specialization or a more diversified regional structure is fruitful for knowledge generation, diffusion and growth in employment, productivity, and research output in general (section 2.1.6). Moreover, researchers are interested in the question if distance decay effects of knowledge diffusion may have essential influence (sections 2.1.7.1 and 2.1.7.2).

²⁰⁸ See also Boschma and Lambooy (2002) and TerWal and Boschma (2009).

(iv) research on agglomeration economies (TerWal and Boschma, 2009; Burger *et al.*, 2009; Maggioni and Uberti, 2009). Besides being a crucial theoretical debate, it is moreover an empirical discussion to which this thesis will contribute (see chapters 3 and 4).

From a theoretical perspective, Breschi and Lissoni (2001a, 2003) criticized the existing foundations of knowledge transmission by arguing that it is not geographical proximity itself (and distance decay) that generates localized knowledge diffusion (i.e., spillovers) and thus research clustering. They argued that the central driving force is networks of agents and firms, i.e., the mobility of entrepreneurs and inventors across firms and regions in specific technology fields, which may tend to be geographically localized (section 2.1.7). This consequently might cause knowledge externalities to exhibit strong distance decay effects and knowledge flows and collaborations to have a limited spatial distance because the underlying knowledge infrastructure, i.e., inventor and research network, is assumed to be confined to the boundaries of the cluster (or region) (Breschi and Lissoni, 2001b; TerWal and Boschma, 2009; Breschi and Lissoni, 2009).²⁰⁹ According to this point of view, clusters, innovative milieus and industrial districts are considered to enclose mostly all relevant parts of the research network (see section 2.1.7.3). However, such an inward perspective is likely to ignore a meaningful fraction of linkages which reaches beyond regional borders (Boschma and Lambooy, 2002; TerWal and Boschma, 2009; Burger *et al.*, 2009).

2.1.7.6. City Networks and Inter-Regional Research Collaborations

Fading out the local boundaries of innovative milieus (and regions, respectively), there is significant evidence in the literature that inter-regional linkages may represent increasingly important factors with respect to knowledge generation, transfer and diffusion (Bathelt *et al.*, 2004; Capello, 2007; TerWal and Boschma, 2009) - at least since the last wave of globalization has induced additional fragmentation and offshoring of R&D activities (Dicken, 2000; Belitz *et al.*, 2006; Legler and Krawczyk, 2006).²¹⁰ Thus, knowledge is assumed to be intentionally transmitted in research networks, which are structured via contractual agreements (see section 2.1.7.4). Accordingly, the ICT revolution is said to have created knowledge infrastructures, such as pipelines that allow for trans-border knowledge flows, and which facilitate the search, combination and recombination of different types of knowledge and information beyond the boundaries of a location (Steinmueller, 2000; Johansson and Quigley, 2003; Bathelt *et al.*, 2004).²¹¹

In economic geography, several researchers have discussed a globalization driven “death of distance” and the transformation of the globe into a “flat world” (Cairncross, 2001; Dicken, 2000; Maggioni and Uberti, 2009).²¹² On the other extreme, the traditional agglomeration economies literature, as presented and discussed in the previous sections, clearly leaves out the possibility of significant knowledge flows between research clusters via persistent

²⁰⁹ For an overview refer to Capello (2007), Burger *et al.* (2009) and Bergman (2009).

²¹⁰ For a detailed overview refer to Capello (2007).

²¹¹ Additionally, some authors see the benefit from global knowledge pipelines in overcoming trajectories and potential lock-in (Asheim and Isaksen, 2002; Kilkenny, 2010).

²¹² In 1995, the Economist raised meaningful doubts that geographic location is still a central factor for the innovation process in a world full of email, fax machines and the internet (“The Death of Distance,” The Economist, 30 September, 1995). See also Audretsch (1998).

inter-regional co-inventor networks. In view of this, many researchers argue that distance and clustering are persistent phenomena, even in the internet era (Gertler, 2003; Scott and Storper, 2003; Crafts and Venables, 2003).

An interesting concept, related to the just-described network linkages and research collaborations, is the conceptual paradigm of city networks that can be considered an alternative interpretation of existing transaction linkages within and between metropolitan regions (Capello, 2007, 78). Cities could be regarded as spatial entities in an urban system of horizontal and vertical relationships. Urban systems are formed by networks which consist of specialized but complementary (production) centers and specific input-output relations which lead to inter-regional transactions. Economies of scale depend on sectoral specialization and fragmentation of tasks. Horizontal transaction linkages between different places create synergy networks between cities. Such transaction networks enable economies of scale as markets are interconnected, i.e., network externalities emerge for network members (Capello, 2007, 79). Furthermore, innovation networks between cities, i.e., research networks (see section 2.1.7.4), are considered to connect regions. Such inter-regional co-inventor networks emerge from persistent research linkages at the firm level (Balconi *et al.*, 2004; Maggioni and Uberti, 2009). Economic relations between metropolises/cities based upon cooperative (research) linkages may enable some kind of economies of scale that do not depend on the size of the regional economy. However, the efficiency of the linkage depends on the economic and technological features of the network (and set-up costs) (Johansson, 2005). Persistent inter-regional linkages could generate economies (or externalities) of specialization (via division of labor), co-operation, synergy and/or innovation (Capello, 2007; Maggioni and Uberti, 2009). In the context of R&D activities, urban systems connect knowledge hot spots via network linkages that represent (persistent) knowledge pipelines (Bathelt *et al.*, 2004; Powell and Grodal, 2005; Bahlmann *et al.*, 2009).

Belitz *et al.* (2006) discussed the emergence of inter-regional research collaborations under the well-known label “the internationalization of industrial R&D.” They argued that companies generally intensify their foreign research activities as they need access to the forefront knowledge that is located in global centers of excellence, i.e., research clusters. Moreover, Belitz *et al.* (2006, 59) concluded that

“the more knowledge-intensive technology fields are, the closer are research activities to the scientific forefront of knowledge.”

Research networks are considered to be increasingly important as they contribute to research output of superior quality (Stephan, 1996; Wilhelmsson, 2009). Accordingly, tendencies of inter-regional and international network formation and research clustering are said to co-exist.

In light of the debate on R&D internationalization, Malecki (2010) similarly argued that R&D is no longer confined to firms’ R&D laboratories (see also Powell and Giannella, 2010). Today, research takes place within dispersed networks, both internal and external to the single firm and region (Bergman, 2008; Burger *et al.*, 2009). Moreover, Malecki stated that global networks of production and innovation contain widespread connections among sources of knowledge (Ernst, 2002; Ernst and Kim, 2002), which is in line with the “new ecology of R&D movement,” “open innovation models” and “collective invention approaches” (Johansson and Quigley, 2003; Chesbrough, 2003; Powell and Giannella,

2010). Collective invention enables the access to information (and knowledge) and the upgrading of technological skills at the same time. Accordingly, the (inward) R&D-based regional knowledge production function seems to be vanishing and represents an increasingly incorrect approximation of reality (Coombs and Georghiou, 2002; Malecki, 2010). The internationalization of production induces at the same time an internationalization of R&D tasks. It is argued that the fragmentation and specialization of R&D activities has led to a more international generation and exploitation of technological and scientific knowledge in a co-evolutionary process (Belitz *et al.*, 2006; Frietsch and Schmoch, 2006; Malecki, 2010).

Bathelt *et al.* (2004) argued that knowledge, which enters the cluster via global research pipelines, is likely to spill over to other agents. Accordingly, the actors' regional research network is the key in understanding knowledge diffusion. As a consequence, the "global knowledge pipeline story" is interpreted as an essential progress in the common cluster literature, as it turns the view of clusters as bounded regions into a (dynamic) network perspective (Bathelt *et al.*, 2004; Bahlmann *et al.*, 2009; Burger *et al.*, 2009).²¹³ Similarly, Bresnahan *et al.* (2001) pointed out the necessity of inter-regional linkages for the rise and development of clusters (see also Breschi and Malerba, 2001).

TerWal and Boschma (2009) argued that the inflow of a large variety of knowledge through inter-regional research linkages compensate historical lock-ins and relative specialization into mature industries. Similarly, Boschma and Iammarino (2007) suggested that inter-regional research collaborations and inflows of knowledge might particularly enhance and upgrade regional knowledge bases (see also Asheim and Isaksen, 2002; Bathelt *et al.*, 2004; Bahlmann *et al.*, 2009).

Different benefits of research collaborations have been discussed in the literature: (i) better access of firms to information and knowledge (i.e., knowledge bases); (ii) intense linkages and co-operation between agents leading to the accumulation of skills; (iii) higher response capacity, stimulating effects and sources of creativity; (iv) reduction of risk and moral hazard; (v) reduction of search and transaction costs; (vi) trust-based relationships and formal linkages, social cohesion; and (vii) enhancing the potential visibility of the single agent (Fraunhofer, 2009).²¹⁴

Mattsson *et al.* (2008) grouped the above-mentioned advantages and benefits into four categories: (i) financial reasons (e.g., access to funding and sharing facilities); (ii) social factors (e.g., networking and acknowledgements within communities); (iii) a preference for working in teams and not in isolation; and (iv) improving technical, analytical and theoretical knowledge and political factors (including framework programs to ease collaboration). Powell and Giannella (2010) discussed these benefits under the label "collective invention."

An increase in inter-regional research collaboration, i.e., co-inventor linkages, could be related to an advancing regional integration that is based upon falling transportation costs, increased mobility of researchers and employees, footloose entrepreneurs, communication technologies that facilitate codified knowledge transfer and the transformation of tacit

²¹³ Johansson and Quigley (2003) label this development the "agglomeration economies vs. networks debate."

²¹⁴ See also Hotz-Hart (2000), Bergman (2009) and Burger *et al.* (2009).

knowledge to more codified forms. Accordingly, the spatial distance of network relations between agents is considered to have increased over time as the knowledge base of an industry becomes increasingly codified (Lissoni, 2001; Gertler, 2003; TerWal and Boschma, 2009).²¹⁵

It is also argued that the different stages in a cluster and/or industry life cycle may be interrelated with the frequency and intensity of inter- and intra-regional knowledge flows via co-inventor networks. In this respect, it is suggested that inter-regional co-inventor linkages are essential for both cases, for regions dominated by mature industries and/or emerging regions that have to build upon external knowledge. Agents in regions benefit from inter-regional flows of knowledge and regions experience a significant upgrade of their specific knowledge base (Bathelt *et al.*, 2004; Singh, 2005; Powell and Giannella, 2010). Nevertheless, it is argued that there is a meaningful difference between a “weightless” and “spaceless” economy.²¹⁶

2.1.7.7. Agglomeration vs. Networks: Critical Remarks

With respect to the above-listed carriers and working channels of knowledge, Audretsch and Feldman (2004) and Capello (2007, 2009), among others, discussed the lack of a clear microeconomic conceptualization (foundation) of transfer and diffusion channels in the majority of knowledge spillover studies. Similarly, Breschi and Lissoni (2001a) reviewed recent studies and offered a critical discussion of the knowledge spillover approach in general and the applied econometric approaches. Although knowledge spillovers are said to perform a pivotal role in the seminal theoretical frameworks, especially in the 1990s’ and 2000s’ workhorse models of endogenous growth (section 2.1.6.6 and 2.1.6.7), there is still a serious gap in the literature from a theoretical (and empirical) point of view. This is especially a severe issue in knowledge production function approaches, which introduce spatial lags of R&D activity or innovation output. However, such approaches do not give any indication about the knowledge diffusion channels, which turns them into a “black box” (Breschi and Lissoni, 2001a; Döring and Schnellbach, 2006).²¹⁷

Boschma and Frenken (2006) distinguished between different working channels of knowledge spillovers: (i) imitation, (ii) spinoff firms, (iii) social networks, (iv) labor mobility and (v) R&D collaborations via collaborative networking (see also Burger *et al.*, 2009). In this respect, several authors consider networks as meaningful sources of knowledge spillovers and flows (Bergman, 2009; TerWal and Boschma, 2009). However, regarding knowledge-intensive industries, it seems rather impossible and counterproductive to separate the agglomeration economies debate from network approaches; in particular when agglomeration economies are assumed to stem from knowledge transmission via intra- (and inter-) regional

²¹⁵ A high degree of proximity may increase the probability of agents getting connected to others; however, it is expected that the effects of network linkages on innovative activity are rather ambiguous (TerWal and Boschma, 2009; Boschma and Frenken, 2009a).

²¹⁶ Geppert and Stephan (2008, 209) argued that “[t]he internet and knowledge society may increasingly become weightless, but there is no indication that it is also becoming spaceless.”

²¹⁷ For further discussions refer to Feldman (2000), Audretsch and Feldman (2004), Capello and Faggian (2005) and Feldman and Kogler (2010).

research networks (see chapter 2, section 2.1.7.5). From a conceptual point of view, knowledge sourcing via the market (buying from knowledge suppliers) and knowledge transfer in inter-regional research co-operations via research networks (transaction link externalities) represent an alternative to the locational advantage in agglomerations.

A region's innovative capacities are affected from two sides. On the one hand, collective learning processes and knowledge transmission, which are mainly based upon local interaction and the transmission of tacit knowledge in local networks, are seen as pivotal factors of co-location and research clustering. Researchers assume that knowledge externalities indeed happen due to spatial proximity (proximity externalities), institutional thickness of the regional system and a significant tacitness of knowledge (Johansson, 2005; Cooke, 2007; Tödtling *et al.*, 2010). On the other hand, inter-regional flows of knowledge originate from anonymous market transactions and from continuous inter-regional research networks (network linkages) that connect global knowledge hot spots (Capello, 2007). Moreover, the existence of trans-territorial networks supports the idea of a technology-field-specific minimum degree of openness and "absorptive capacity" of regional systems and clusters.²¹⁸

First and foremost, elite researchers (and their research locations) take advantage from inter-regional research linkages, who work at the cutting edge (in epistemic communities) (Hoekman *et al.*, 2010). Under the assumption that elite researchers and research centers are much more spatially concentrated, higher shares of inter-regional linkages are expected to exist and emerge within this group of researchers but not within less advanced ones (Capello, 2007; Frenken *et al.*, 2007; Hoekman *et al.*, 2010). Elite researchers, who are mainly located in dense urban areas, may primarily build collaboration linkages with other leading research centers but not with less advanced ones, which then form an urban system of city networks (Capello, 2007, 2009). However, backward research locations may also profit from inter-regional collaboration networks as they become connected to other knowledge hot spots and research clusters (Bathelt *et al.*, 2004; von Hippel, 2005; Maggioni *et al.*, 2007). With respect to the costs associated with such research collaboration linkages, two major improvements that stem from technological progress are observed: (i) decreasing transportation costs (and travel times) and (ii) a significant improvement in information and communication technologies; both developments are assumed to have hampered the effects of spatial distance on inter-regional and international research collaborations (and economic integration in general). In addition, stable network linkages are different from anonymous market transactions as they induce set-up costs.

However, even today, research activities may still face the issue of search and coordination costs in a geographical context (Hoekman *et al.*, 2010). Agents (and research centers) have to bridge geographic distances, which makes research collaboration activities sensitive to physical distance (section 2.1.7.3). As the embeddedness of researchers (and their laboratories and facilities), their mobility, different institutional settings and linguistic areas, differing labor markets and technological specialization (among factors) generally show

²¹⁸ Absorptive capacity is a core component of regional systems; however it is assumed to vary between regions and countries (Cohen and Levinthal, 1990). This idea is also formulated by Camagni (1991b, 8), among others, who stated that "[t]echnological innovation [...] is increasingly a product of social innovation, a process happening both at the intra-regional level in the form of collective learning processes, and through inter-regional linkages facilitating the firms access to different, though localised, innovation capabilities."

a local nature, most research collaborations are said to happen at a proximate distance (Maggioni *et al.*, 2007; Breschi and Lissoni, 2009; Paci and Usai, 2009). From an institutional economics point of view, it is also argued that regions that belong to different countries are institutionally different and more reluctant to collaborate in research activities (Hoekman *et al.*, 2009). These arguments are completely in contrast to the suggested “death of distance” argument (Castells, 1996; Cairncross, 2001).²¹⁹ It can be argued that the intensity of inter-regional collaborations is a function of costs and that collaborations are negatively affected by spatial distance. To optimize costs, researchers have a strong incentive to collaborate with other groups of researchers at an institutionally and spatially proximate distance, i.e., within an epistemic community within a cluster or region. In a European context, one should expect to find highly localized networks.

Moreover, it can be concluded from the above-described concepts, models and debates that agglomerations and the co-location of research activity are pivotal when the knowledge transfer follows unintended patterns (technological externalities) or happens intentionally in spatially concentrated networks. However, knowledge transmission is also said to happen intentionally via inter-regional research linkages irrespective of spatial distance. Although it is impossible to separate clearly tacit from codified knowledge flows, it is, however, reasonable to assume that knowledge transfer is inversely related to spatial distance. Furthermore, long-distance relations imply a greater role played by codified pieces of knowledge.

In summary, the theories described in the previous sections have highlighted central issues related to research clustering, agglomeration economies and inter-regional research networks. The empirical analysis in this study aims to follow explicitly the aforementioned arguments and concerns. In the first part, the empirical analysis in this study will shed light on the regional disparities and spatial concentration of patenting activity in Europe at the regional level (chapter 3). In the second part, the analysis will also emphasize the structures and dynamics of inter-regional research collaboration linkages, i.e., European co-patenting networks at the regional level (chapter 4). On account of this, co-inventor network analysis, among other approaches, can apply EPO patent applications as relational data, as will be discussed in the following part of the survey.²²⁰ The subsequent section 2.2 briefly presents empirical results relating to research clustering, regional R&D spillovers and inter-regional co-patenting networks.

2.2. A Survey of the Empirical Literature

2.2.1. The Co-Evolution of Different Strands of Empirical Research

The empirical literature on the geography of innovation, research clustering and knowledge transmission can be generally classified into six streams: (i) research concentration and clustering studies, which focus on regional disparities and the distribution of research activities; (ii) the knowledge production function approach (KPF), which analyzes the

²¹⁹ See also Dicken (2000) and Giddens (2000).

²²⁰ Alternative data sources for network analysis are, e.g., co-publication data (Hoekman *et al.*, 2009; Ponds *et al.*, 2010) and European Framework Programme data (Maggioni *et al.*, 2007).

input-output relationship between R&D and patenting activity in a geographic context; (iii) studies on localization and urbanization economies and regional development; (iv) the patent citation or “paper-trail” approach, which explores the “real” knowledge spillovers and the geographic and/or technological relatedness of forward and/or backward patent citations; (v) studies on the mobility of individuals and their social networks, especially of researchers, engineers and other highly skilled individuals in a spatial context; and finally (vi) studies on inventor networks, research collaborations and co-patenting networks, which use data on intra- and inter-regional research linkages from co-patenting data.

The major contribution of the mentioned research streams is to approach and work out empirical issues related to the distribution of research activity, the causes and effects of research clustering, the functional boundaries of local systems and clusters and the peculiarities of inter- and intra-personal and inter- and intra-regional knowledge transmission. It can be argued that the strands of empirical research combine an “industrial,” “geographic,” “technological,” “socio-cultural” and “cognitive” dimension of research clustering, agglomeration economies and knowledge transmission.

The following is a detailed empirical literature review of the mentioned strands of research in the context of European research clustering, R&D spillovers, the localization of patent citations, local inventor networks and inter-regional network linkages. Although the empirical analyses in this thesis place the emphasis on the regional disparities of patenting activity and the identification of research clustering across the many European regions (chapter 3), an additional part of the study will be related to the analysis of inter-regional co-patenting linkages and thus to relational aspects of research and patenting activity (chapter 4). Therefore, the following empirical review discusses existing results, methodological issues and technical problems of alternative approaches. Finally, the review offers several arguments in favor of a pan-European clustering study and the identification of inter-regional co-patenting linkages.

2.2.2. Regional Disparities, Urbanization and Research Clustering

The majority of studies are primarily concerned with the effects of concentration and co-location but not with the general trends in the global distribution of research activities. It is generally assumed that the distribution of research activity is highly skewed because it was always skewed. However, researchers should pay more attention to measuring the spatial distribution and dynamics of research activity before empirically approaching the potential effects of specialization and/or concentration. What is more important? Knowing that skewed distributions may have certain effects or knowing that the distributions are skewed but that regional disparities/ concentration may show some meaningful dynamics? Accordingly, the analysis of regional disparities of innovative activity and research clustering seems to be of central importance. Furthermore, the analysis should combine an “industrial,” “geographic” and “technological” dimension. Regarding this aspect, the empirical analyses in chapters 3 and 4 are primarily concerned with the distribution of patenting activity across the 819 European TL3 regions since the 1980s, the identification of research clusters and the structural analysis of inter-regional co-patenting linkages. Thus, the focus is on the distribution of knowledge-intensive tasks and the embeddedness of regions.

Regarding the theoretical base of concentration and disparity studies, it is necessary to distinguish four broad families of theoretical models that address the spatial distribution of research activity, as has been presented in the theoretical part of this study, especially in section 2.1: (i) the traditional neoclassical approaches predict convergence and dispersion; (ii) models with external scale effects, spillovers and different forms of externalities predict persistent disparities, depending on the initial distribution; (iii) models with internal scale economies and pecuniary externalities predict core-periphery structures or equity, depending on the initial distributions and the strength of centripetal and centrifugal forces; and finally (iv) models that include (ii) and (iii) differentiate between severe core-periphery structures and equity distribution, depending on the initial distributions and the strength of centripetal and centrifugal forces (Brühlhart, 2001; Baldwin and Martin, 2004; Harris, 2008).²²¹

From an empirical perspective, a strong motivation for analyzing the structure and dynamics of the distribution of European inventorship activity from patent data is based upon the fact that innovation data, and regional data in general, are said to show a strong and persistent non-normal distribution (i.e., skewness, kurtosis) and spatial autocorrelation (Fotheringham *et al.*, 2002; Scherngell, 2007; Anselin, 2007).

Several seminal studies already pointed out the non-normal, highly skewed distribution of gross domestic product (GDP) per capita, gross value added (GVA) and employment within and across European regions (Combes and Overman, 2004; Frenken and Hoekman, 2006; Paas and Schlitte, 2007, 2008). Moreover, a meaningful number of regional studies has highlighted stable agglomeration patterns in selected cities and urban regions or single countries. Kim (1995), for example, found that the correlation of the coefficient of regional localization for 2-digit industries at the US state level is around 0.64 between 1860 and 1987. Similarly, Dumais *et al.* (2002) identified stable agglomeration patterns at the 3-digit level for US-industries. With respect to plant location, Fujita and Ishii (1999) analyzed the location of R&D activities (mass-production vs. trial plants) and found that diversified trial plants are mainly located in central Japanese metropolitan areas, e.g., Tokyo, Kyoto. In opposition, plants for mass-production are mainly located in rural areas or in at least smaller cities, where urbanization externalities (and Jacobs externalities) are less prevalent.²²² Moreover, it has been demonstrated that the distribution of research (patenting) activity was already highly skewed in the past centuries. Pred (1966) examined US patent data for the mid-nineteenth century and found that innovative activity in cities was four times greater compared to the national average of patenting activity. Similarly, Higgs (1971) found that the number of US patents (between 1870 and 1920) was positively related to the urbanization level (see also Carlino, 2001). At the national level, Degner and Streb (2010) recently showed that foreign patenting activity in Germany was dominated by leading (and neighboring) countries, e.g., the United Kingdom and the United States, and that foreign patenting activity of countries varied with respect to the different waves of technological progress and diffusion of general purpose technologies.

Related to the recent decades, Puga (1999, 304) exposed that the European regions with the highest manufacturing employment density (27 NUTS regions) account for approximately

²²¹ The interested reader can take a closer look on the progress in the research lines (ii), (iii) and (iv) in the detailed literature review in chapter 2.1.

²²² Refer to Duranton and Puga (2001) for further interpretation.

50% of all manufacturing employment in the Union and for 45% of its population but only for 17% of the Union's areal surface. In comparison, the 14 US states with the highest manufacturing employment density also account for approximately 50% of the country's manufacturing employment, but only for 13% of areal surface and 21% of US population. Accordingly, employment and production seem to be more concentrated in the US. Regarding innovative activity, Audretsch and Feldman (1996) analyzed the spatial concentration of US production and innovation activities at the state-level. Their study was seminal in showing that innovation is, on average, more concentrated compared to production. In a European context, Maurseth and Verspagen (2002) argued that several European regions could be characterized as high-technology clusters, whereas Europe, i.e., the ERA, also includes low-technology dominated regions (especially in Southern Europe and the NMS). Similarly, Audretsch and Fritsch (2002) reported the existence of four different technological growth regimes for 74 Western German planning regions between 1983 and 1998.²²³

Several studies have made extensive use of patent statistics in order to analyze the dynamics of research and patenting activity in a spatial, sectoral and technological context. Concerning distributional particularities of innovative activity across European regions in the 1990s, especially in the ERA, in particular Caniëls (1996, 1997, 2000) and Breschi (2000) represent seminal contributions. The authors emphasized the highly skewed distribution of patenting activity, although at a very aggregated regional level (NUTS1/2). Paci and Usai (2000b) similarly contributed to the agglomeration of innovation and production debate, although they focused on a smaller set of countries and larger spatial aggregates.²²⁴ Asheim and Gertler (2005) concluded that knowledge, and innovative activity in general, are geographically clustered, and that the tendencies towards geographic concentration have become more distinct over time. Florida (2005) also argued that the world, and the geography of knowledge, is "spiky," which reinforces the stylized fact that knowledge bases and research activity seem to be remarkably concentrated in space. Moreno *et al.* (2005a) found that specialized European innovation clusters, i.e., European NUTS1/2 regions, exist and that specialization is still increasing. Their empirical result is in direct opposition to common findings of studies on production clusters, which normally argue that production is continuously undergoing geographic dispersion.²²⁵ Similarly, Paci and Usai (2009) used a population of 175 NUTS regions and demonstrated that EPO patent citations show strong core-periphery structures, with a deep gap between core-regions in central-northern Europe and the European periphery. These findings will be challenged by the empirical analysis of the geographic distribution of EPO patenting activity in chapter 3. Related to this debate, Castellacci and Archibugi (2008) argued that the explanation of the variance in the distribution of knowledge among 131 nation states can be reduced to two major factors: (i) differences in technological infrastructures and human skills, i.e., absorptive capacity, and (ii) differences in the creation and diffusion of codified knowledge.²²⁶ The latter point will be empirically challenged in chapter 4.

²²³ Audretsch and Keilbach (2004) similarly explored the effects of entrepreneurship capital for German regions.

²²⁴ These studies only explored European patenting at a very aggregated regional (and national) level.

²²⁵ In this respect, Usai (2008) argued that one possible interpretation for concentration is that firms' strategic innovation activities may be to a large extent influenced by spatially localized interactions.

²²⁶ See Malecki (2010) for a similar point of view.

However, a severe issue of empirical investigations of core-periphery structures and spatial dynamics is the question of aggregation from a sectoral and a spatial perspective. Geographical economics and economic geography always have the problem of defining and defending the relevant industrial and geographical scale of analysis (Amiti, 1999; Ciccone, 2002; Arbia and Petrarca, 2010). Ideally, real-world industries and regions correspond to their theoretical counterparts (Brakman *et al.*, 2005). In practice, there is a trade-off between industrial detail and regional detail. Some researchers choose three-digit manufacturing industries, which are available at the national level (NUTS0/TL1). Other researchers instead prefer one-digit industries, which are also available at a more detailed regional level. The geographical scope of the new economic geography literature is, according to Brakman *et al.* (2005), by and large restricted to regional levels of analysis (NUTS2, NUTS3, TL2 and TL3 level). Brakman *et al.* (2005, 7) also suggested that “[...] *there is something to gain from sacrificing even more industrial detail for the sake of regional detail.*” The methodologies and empirical analyses applied throughout this study directly follow their line of reasoning.²²⁷

Unfortunately, the availability of spatially disaggregated European data is disillusioning. Combes and Overman (2004, 2847), among others, recently complained that

“[a]fter reviewing the literature, and given our first hand knowledge, the only conclusion that we are able to reach is that the European data are a mess. It is not clear where blame for this situation lies. It is clear that part of the problem stems from the institutional framework within which most EU governmental statistical agencies work. In particular, the fact that they often have no mandate to facilitate the re-use of data collected to fulfill their institution roles. Even where they do have a mandate, data are often expensive and incentives to ensure efficient delivery appear to be limited. [...] To summarise, the data situation is not good at the national, regional, or urban levels in the EU, although individual countries may provide excellent data sources.”²²⁸

Accordingly, regional studies have to deal with several statistical issues, e.g., incomplete data coverage, selection biases, small sample size or inconsistent spatial and sectoral classification (Combes and Overman, 2004; Brühlhart and Traeger, 2005; Scherngell, 2007). Consequently, most studies which center regional disparities of production, knowledge-intensive industries or research and patenting activity are either conceptualized at the

²²⁷ On account of this, this study explores 43 technology fields based on EPO patent applications by priority date. Additionally, the study explores structural dynamics of 6 large high-technology fields (laser, aviation, computers and automated business equipment, micro-organism and genetic engineering, communication technology and semiconductors). The patent classification system (IPC)-technology field concordance is applied to an own relational EPO patent database at the very disaggregate spatial level of OECD Territorial Level 3 (TL3) regions, which explicitly approaches the issue of functional spatial units.

²²⁸ For an identical critique refer to Arbia *et al.* (2005).

national level²²⁹, or they are mainly organized at the level of large regional aggregates²³⁰, or restricted to single countries²³¹. The trans-regional structures and dynamics of clustering remained unexplored in most studies, especially the distribution and clustering of knowledge-intensive tasks, i.e. patenting activity. Regarding pan-European and worldwide patent statistics, the OECD and EUROSTAT generally provide comprehensive statistics, reports and overviews (OECD, 2007a, 2008, 2009a). Nevertheless, the officially available reports are determined by a significant lack of disaggregated technology field calculations, a lack of disaggregated spatial classification systems and heterogeneous statistical methodologies. Moreover, the reports are in most cases restricted to short periods.

To conclude, to the author's knowledge, no single pan-European empirical study exists that analyzes the spatial distribution of research and patenting activity at the regional TL3 level for all 819 regions of the EU-25, Norway and Switzerland for a comprehensive number of technology fields or industries for the last three decades. Regarding this deficit, the empirical analysis of the distribution of patenting activity in Europe in chapter 3 is a first essential objective of this study and aims to help to sharpen the cognition and to enrich the understanding of spatial structures, regional disparities and ongoing dynamics of research and patenting activities in Europe. In this respect, the empirical analysis will be dedicated to analyzing whether technology fields in Europe show decreasing disparities within the last three decades. Moreover, a harmonized, multidimensional research clustering index will be introduced, which represents the base for global cluster statistics and for the identification of leading innovative places in Europe.

2.2.3. The Regional Knowledge Production Function

2.2.3.1. The Origins of the Knowledge Production Function

As has been demonstrated in the last sections of the chapter, the distribution of innovative activity represents a central issue. Obviously, the analysis of potential effects of research clustering on innovative capacity and output (patents) represents a second step. The knowledge production function (KPF) represents a pivotal empirical approach which combines the "industrial," "geographic" and "technological" dimension of agglomeration economies and regional knowledge production. In applying the KPF approach, the main exercises aimed at measuring the spatial scope of spillovers.

²²⁹ See, e.g., Archibugi and Pianta (1992), Amiti (1999), Brühlhart (2001), Midelfart-Knarvik *et al.* (2003), Midelfart-Knarvik *et al.* (2004), Aiginger and Pfaffermayr (2004), Greif and Schmiedl (2006), Legler and Krawczyk (2006). In addition, the majority of contributions at the level of European regions center GDP and GVA distribution, employment and unemployment dynamics (Frenken and Hoekman, 2006; Paas and Schlitte, 2007; Brakman and van Marrewijk, 2008). The distribution of US R&D labs is analyzed by, e.g., Carlino *et al.* (2010).

²³⁰ See, e.g., Combes and Overman (2004), Scherngell (2007), Rodríguez-Pose and Fratesi (2007), Brakman and van Marrewijk (2008), Brakman *et al.* (2009), Paci and Usai (2009).

²³¹ See, e.g., Maurel and Sédillot (1999), Keilbach (2000), Greif (2001), Dekle (2002), Litzenberger and Sternberg (2006), Fingleton *et al.* (2007), Dewhurst and McCann (2007), Breschi (2008), Fornahl and Brenner (2009). Exceptions are Frenken and Hoekman (2006) and Paas and Schlitte (2007). Combes and Overman (2004) give a comprehensive overview regarding shortcomings of existing regional studies.

The knowledge production function is based on the work of Griliches (1979) and Griliches and Pakes (1980a), among others.²³² A first issue with regard to the KPF is the choice of the level of aggregation: the plant-level/firm-level, the sector- and industry-level, the regional level (functional and administrative units). Audretsch (1998), Foray (2004) and Malecki (2010), among others, described the KPF approach as a “comfortable world” of standardized models, in which only some agents, institutions and sectors are included in the production of knowledge. The KPF approach is considered to end up with a “black box” of knowledge production and diffusion (section 2.1.7).²³³

Following the original contribution of Griliches (1979), the KPF can be written (and finally estimated) in logarithmic form as in equation 2.2.1:

$$Q_i = \alpha + \beta_1 C_i + \beta_2 L_i + \beta_3 RD_i + \beta_4 Z + \varepsilon_i \quad (2.2.1)$$

Firm i 's output (Q_i) is linked to the traditional inputs capital (C_i) and labor (L_i), but also to internal R&D activities (RD_i), and additionally to spatial spillovers (Z) that exhibit an effect on firm's output. Such externalities can originate from spatial, technological (sectoral/industrial) and/or social proximity. ε_i finally represents a random disturbance term and α is a constant term.

In the KPF tradition, the firm level is perhaps one of the most explored levels of research (Audretsch and Feldman, 2004).²³⁴ Early production function approaches have been mostly dedicated to the individual level (firm- or plant-level) (Griliches, 1979; Griliches and Pakes, 1980b; Griliches *et al.*, 1984). Jaffe (1986) is one of the most cited studies, who has applied technological distance via patent data to the firm-level and regions. The approach is based upon the idea that industries foremost apply intra-industry knowledge, meaning that there is an implementation and absorption of technologically related knowledge.²³⁵ Differing regional levels of aggregation lead to varying point estimates (and differing inference and causalities). This issue is well related to the modifiable area unit problem (MAUP) due to aggregation and zoning (Arbia and Petrarca, 2010). The spatial effects of knowledge spillovers, either intra- or inter-industry, or intra- or inter-regional, can vary largely with the spatial level.²³⁶ It is worth noting that, according to several studies, the KPF model seems to hold for regions but becomes less compelling at the level of the firm or plant (Bergman and Usai, 2009; Malecki, 2010). Finally, a notable advantage of the KPF approach is that

²³² Refer to Griliches and Pakes (1980b), Griliches *et al.* (1984), Hall *et al.* (1986), Griliches (1992b), Griliches (1990), Audretsch and Feldman (1996), Acs *et al.* (1997), Audretsch (1998), Feldman (1999), Keilbach (2000), Porter and Stern (2000), Feldman (2000), OECD (2009a), and Feldman and Kogler (2010) for further information and an overview.

²³³ A comprehensive overview is given by Feldman (1999), Scherngell (2007), Bergman and Maier (2009), OECD (2009a), Foray and Lissoni (2010), Feldman and Kogler (2010).

²³⁴ According to Griliches ([1992] 1998, 252), the empirical background is related to innovation externalities as “[t]he more difficult to measure and the possibly more interesting and pervasive aspect of R&D externalities is the impact of the discovered ideas [...] on the productivity of the research endeavour of others.” See also Jaffe (1986), Feldman (1994a), Audretsch and Feldman (1996) and Acs *et al.* (1997).

²³⁵ Additional firm-level studies are contributed by Mansfield (1986). For an overview refer to Scherer (2005).

²³⁶ KPF analysis at the disaggregated micro level of plants/firms, establishments, or even lines of business, however, render the model of the knowledge production function less compelling.

it can be conceptualized at the agent-level, the plant-/firm-level, the city-level, but also the level of districts, counties, regions or countries.²³⁷

2.2.3.2. The Regional Knowledge Production Function

Several authors have modified the original knowledge production function by focusing on regions, which represents the “spatial dimension” of R&D clustering and agglomeration economies (Jaffe, 1989; Acs *et al.*, 1997; Acs, 2002).²³⁸ It is a standard approach to apply formal R&D data at the spatial level. Unfortunately, such data largely ignore the complex processes of technological diffusion and knowledge accumulation, whereby tacit knowledge (section 2.1.7) is built up. This approach also overlooks, e.g., formal and informal institutions, history (Audretsch and Feldman, 2004; Malecki, 2010).

The basic knowledge production function (equation 2.2.2) is modeled including an innovative output ($INV_{i,t}$) and a vector of inputs, whereas the most important one is R&D (i.e., R&D expenditures or employment, $RD_{i,t}$). The KPF can, in general, be considered to be an unrestricted Cobb-Douglas production function (Verspagen, 1993; Usai, 2008).²³⁹

The regional knowledge production function has been heavily criticized as it models only global spatial processes (global mean regression) without the explicit recognition of region-specific (internal) set-ups. Moreover, the approach is simplifying the microeconomic issues (foundation) of the knowledge diffusion process, as it can only incorporate puristic regional spillover effects, i.e., global spatial processes. However, the pivotal advantage of the production function is its application to a large number of spatial units by means of small costs of modifying the econometric design (Audretsch and Feldman, 2004). Additionally, opposed to KPF regressions, survey-based research methodologies can hardly be generalized (Acs, 2002; Usai, 2008; Malecki, 2010).

$$INV_{i,t} = RD_{i,t}^{\alpha} e_{i,t} \quad (2.2.2)$$

Innovative output ($INV_{i,t}$) can be approximated by product introductions, new established processes or, more general, by patent applications or granted patents of different patent offices (e.g., EPO, JPO, USPTO, WIPO).²⁴⁰ Issues are caught by the stochastic error term

²³⁷ It has been verified only for large macro areas (regions, countries). However, the KPF model becomes less convincing at the level of the firm due to the weak relationship found between R&D inputs and innovative output. In this respect, the application of GIS based data and distance models seems to add complexity and efficiency to econometric research (Audretsch and Feldman, 2004). Note, however, that one essential issue of spatial (dis-)aggregation is the modifiable area unit problem, which essentially influences the raise and decline of modeled spatial effects (and inference).

²³⁸ It was mainly Jaffe (1986, 1989) who contributed with insights related to university research spillovers on private firms. See also Keilbach (2000), Usai (2008) and Freund (2008) for an overview.

²³⁹ For a detailed discussion and additional information refer to Griliches and Pakes (1980a), Jaffe (1989), Coe and Helpman (1995), Audretsch and Feldman (1996), Acs *et al.* (1997), Audretsch and Feldman (1999), Bottazzi and Peri (2000), Anselin (2000), Varga (2000), Acs *et al.* (2002), Bottazzi and Peri (2003), Greunz (2003b), Greunz (2003a), Greunz (2004), Greunz (2005), Moreno *et al.* (2005c), Moreno *et al.* (2005a), LeSage *et al.* (2007), Scherngell *et al.* (2007), Crescenzi *et al.* (2007b), Crescenzi and Rodríguez-Pose (2008), Usai (2008), OECD (2009a), Ponds *et al.* (2010).

²⁴⁰ The empirical work in this project is highly abundant on EPO patent applications, because it is broadly accepted in empirical studies that applications seem to be stronger linked to the time of

($e_{i,t}$), which controls for unobserved determinants and random shocks.²⁴¹ The implementation of additional factors should grant higher efficiency and add some explanatory power to the production function.

Regional differences in R&D elasticities are interpreted as region-specific effects stemming from unique innovation infrastructure, which can also reflect private and public sector R&D characteristics (Freund, 2008; Usai, 2008). Therefore, R&D-activities can be disaggregated to their sectors of origin; i.e., the business sector ($BusinessRD_{i,t}$), governmental entities ($GovRD_{i,t}$), and the higher-education sector ($UnivRD_{i,t}$). Equation 2.2.3 represents such a production function.

$$INV_{i,t} = BusinessRD_{i,t}^{\alpha_1} GovRD_{i,t}^{\alpha_2} UnivRD_{i,t}^{\alpha_3} e_{i,t} \quad (2.2.3)$$

Regarding spatial interaction and spillovers, several studies have criticized the sole implementation of region-specific inputs. Therefore, the inclusion of external factors seems logical as external factors and spatial spillovers may represent significant determinants of regional innovative activity and regional development (Crescenzi *et al.*, 2007b; Usai, 2008).²⁴²

Although the knowledge production function approach is determined by some methodological issues, there is a wide consensus that the positive relationship between R&D input and patent output is significant and strong at the regional level, and that spatial interdependence represents an essential phenomenon with significant impact on patenting activity (Audretsch and Feldman, 1996; Usai, 2008).²⁴³ According to the aforementioned points, it can be argued that a non-normal distribution of R&D activity should explain the skewed distribution of patenting activity. Thus, the analysis of the geographic distribution of research and patenting activity seems to be crucial. In the following, selected studies on the US-American and European case are briefly summarized.

2.2.3.3. Knowledge Flows and R&D Spillovers in Europe and the US

Regional knowledge production is considered to exhibit significant inter-regional spillover effects. In this regard, studies applying the KPF approach combine the “industrial,” “technological” and “geographic” dimension of knowledge production (see sections 2.1.6.5 and 2.2.1). In the following, selected studies at the regional level are reported with special focus on distance decay effects of R&D spillovers (i.e., spatial dependence).²⁴⁴

invention than granted patents. Moreover, most studies see statistical evidence for a time lag between two and three years (Greunz, 2005; Frietsch and Schmoch, 2006; Fraunhofer, 2009).

²⁴¹ The latter variable is extensively challenged in early production function and convergence studies (e.g., the Solow residual in growth literature).

²⁴² Oerlemans *et al.* (2001, 347), among others, concluded that “[u]nder the condition of low problem levels, innovator firms utilise relatively more internal resources to innovate successfully. [...] In the case of highly complex innovation processes, this inwardness is no longer possible. The number and nature of innovation problems force innovators to utilise external resources.”

²⁴³ For additional conclusions refer to Funke and Niebuhr (2000a), Funke and Niebuhr (2000b), Niebuhr (2000), Paci and Pigliaru (2001), Greunz (2003a), Greunz (2004) and Freund (2008).

²⁴⁴ For a more detailed overview refer to table B.1 in the appendix. See also Keilbach (2000), Acs (2002), Usai (2008) and Freund (2008) for an overview.

Several studies have reported empirical evidence that the structure of knowledge production, the inter-regional transfer and diffusion of knowledge and the location of research activity may differ between Europe and the United States (Crescenzi *et al.*, 2007b; Usai, 2008; Kroll, 2009). In the following, selected knowledge production function studies on the United States and Europe are presented. An additional summary is reported in the appendix.²⁴⁵ For the European case, the scarcity (and heterogeneity) of data at the regional level and several statistical reforms have prevented the formation of a consensus and major stylized facts. The number of regional studies is still relatively small compared to studies at the national level.²⁴⁶

In a US study, Acs *et al.* (1997) analyzed the impact of university and private R&D activities on regional innovation output with a knowledge production function. The authors used data from high-technology US-firms. The analysis was executed by applying cross-sectional data for states and metropolitan statistical areas (MSA) in order to estimate a knowledge production function with industry and university R&D as covariates. They found a positive impact of industrial and university R&D on local innovative output. More precisely, they depicted a positive and significant impact of university R&D on innovative activity with rather limited spatial range (approximately 50 miles around the university). However, they could not report a significant positive result for private R&D activities. They did not find statistical evidence for a significant and positive contribution of private business R&D to university research.²⁴⁷

Acs *et al.* (2002) analyzed the US MSA level.²⁴⁸ Similar to Acs *et al.* (1997), they concluded that university research has a spillover range of approximately 50 miles around MSAs. Spillovers from private R&D, however, show tendencies to be contained within regional borders without inter-regional significant effects (negative but not significant), although elasticities for intra-regional business R&D are five times higher compared to university R&D (compared to state level regression). For addressing model misspecifications by means of spatial dependence, they additionally introduced spatial lags of the intra-regional covariates (business R&D, university R&D) by means of concentric rings (threshold distance of 50 and 75 miles), which may support the assumption of strong distance decay effects beyond MSA borders. The ML estimation (auto-regressive model) showed approximately the same results as the OLS method with distance decay of spatial lags (cross-regressive).²⁴⁹

²⁴⁵ For a summary, refer to table B.1 in the appendix. There exists an innumerable quantity of country-level studies. For further details see Verspagen (1997), Usai (2008), Freund (2008) and OECD (2009a). Verspagen (1993), among others, estimated a patent production function in a pooled cross-country time series data set. The sample consists of the 24 OECD countries and 13 newly industrialized countries (NIC). The elasticity of R&D activity is well above unity pointing to increasing returns to R&D intensity. Note, however, that the author only studies the country-level, meaning that inter-regional variation is not addressed.

²⁴⁶ The subsequent review places emphasis on selected European studies (published between 2000 and 2009). Nevertheless, the review is non-exhaustive.

²⁴⁷ These results support the hypothesis that different incentives may exist within the public and private sector, which may rather promote new knowledge to circulate in the public and university sector.

²⁴⁸ For similar results and a critical review refer to Keilbach (2000), Acs (2002) and Usai (2008).

²⁴⁹ The overall regression fit of their knowledge production function specification, which includes R&D indicators is above 0.5 ($0.599 \leq R^2 \leq 0.661$). Respectively, the regression fit of their extended knowledge production function model is above 0.7 ($0.718 \leq R^2 \leq 0.763$).

The authors reported no evidence that private R&D is endogenous to university R&D in the MSA.²⁵⁰

Varga (2000) contributed with a study at the level of US states and the MSA, showing that knowledge spillovers do not only exist within metropolitan areas. Varga reported evidence for significant positive spillovers from neighboring metropolitan areas up to 75 miles which has been similarly reported by Acs (2002).²⁵¹ Finally, a spatial range of 50-75 miles showed robust result for geographical externalities (knowledge spillovers) in the US MSA case.

Bottazzi and Peri (2000) studied European regions. In calculating the number of patents per square kilometer of all regions (large regional units) under analysis as the dependent variable (patent density), the authors tested the effect of regions' R&D expenditures (per square kilometer) and the overall influence of R&D expenditures within predefined distance bands (concentric rings), i.e., 0-300, 300-600, 600-900, 900-1,300 and 1,300-2,000 kilometers away from the regional center. For spatial spillovers resulting from R&D expenditures (cross-regressive) and patent applications (autoregressive), a significant positive impact on innovative activities in neighboring regions was reported. However, the spatial covariates only showed up with a significant positive sign for a distance band up to 300-600 kilometers, which represents a much larger distance, compared to the 50-75 miles distance bands reported in US studies.

Bottazzi and Peri (2003) similarly measured the extent of localized knowledge spillovers for 86 large European NUTS regions. Distance bands were identical to Bottazzi and Peri (2000). However, the analysis was complemented by controlling for technological distance. They defined a 30x1 vector (technology proximity indicator) for each region out of 625 IPC fields. Technological proximity was tested by generating the correlation coefficients of the technology vectors between the 86 regions.²⁵² Their spatial lag of regional R&D expenditures was significant for a 0-300 kilometer distance band. When disaggregating the 300 kilometer distance band, only R&D expenditures up to 100-200 kilometer showed a significant positive effect. The used patent data solely represent a 1/100 random extraction of EPO patent applications (6010 patents in total).

Greunz (2003a) estimated knowledge production functions for 153 European NUTS1/2 regions and reported a significant and positive effect of R&D expenditures, pursued in the first-, second- and third-order contiguity-based neighboring regions (median distances 91, 176, and 248 miles), on regional patenting activity. The spillover effects were not significant anymore beyond 250 kilometers. Technological distance was additionally included into the model by means of 118 IPC fields (technology sections), which turned out to show a significant impact of technologically lagged R&D controls.²⁵³ The efficiency of the model increased with additional technologically lagged controls. Moreover, she offered the interesting result that national borders matter significantly in European regions in terms of patenting and that spatial significant R&D spillovers are mostly mediated by the business sector.

²⁵⁰ In opposition, they argued that there is evidence that university research in an MSA is endogenous to private sector R&D activity.

²⁵¹ The model specification is performed in an OLS and IV set-up, which yields an overall regression fit above 0.599 ($0.599 \leq R^2 \leq 0.781$).

²⁵² The overall fit of the spatial model is above 0.70 ($0.70 \leq R^2 \leq 0.91$).

²⁵³ The overall fit of the spatial model is above 0.9 ($0.92 \leq R^2 \leq 0.93$).

Lim (2004) used the knowledge production function approach to estimate the effect of specialization, diversity and competition on patents per capita at US-MSA level, which covered 313 observations. The author applied different estimators (OLS, ML, 2SLS, robust OLS). Specialization (localization) and diversity (urbanization) were both positive and significant, whereas only the spatially lagged diversity control was significant and positive.²⁵⁴ However, the model set-up did not include R&D controls.

In a similar set-up, Moreno *et al.* (2005c) estimated a knowledge production function for 138 NUTS1/2 regions with spatial lags of 0-250, 250-500 and 500-750 kilometers distance. The authors reported significant positive effects from the first two spatial contiguity-based R&D expenditure lags.²⁵⁵ The regression was done in an OLS- and ML-environment. The test statistics for remaining spatial dependence, i.e., LM-ERR and LM-LAG, were not significant due to several included control variables. In most cases, regional GDP (gross domestic product per capita) and the manufacturing employment share showed significant and positive point estimates, although spatial lags of business sector R&D expenditures seemed to decrease the significance of manufacturing employment.²⁵⁶

Bilbao-Osorio and Rodríguez-Pose (2004) estimated a knowledge production function for 103 European NUTS1/2 regions in a cross-sectional set-up. They reported significant positive effects on patenting activity from regional GDP and business R&D expenditures.²⁵⁷ Opposed to peripheral regions, European regions were not affected by university R&D. Moreover, the regional stock of patents, the patent growth rate and the size of the high-tech sector exhibited significant and positive effects on GDP growth for the whole sample of European regions.

Moreno *et al.* (2005a) estimated a knowledge production function for European NUTS1/2 regions (similar to Greunz (2003a)). R&D activities of first-, second-, and third-order neighboring units had a significant and positive effect on the knowledge output of the spatial unit. Spatially lagged R&D activities showed strong distance decay effects, meaning that spillovers occur at a proximate distance. R&D expenditures at the first- and second-order distance contributed with elasticities around 0.22, whereas the effect from third-order neighbors was quite smaller (0.17). R&D expenditures at the 4th-order contiguity level were not significant. Moreover, Moreno *et al.* (2005b) estimated a knowledge production function for 175 NUTS1/2 regions with contiguity based spatial lagged controls, addressing

²⁵⁴ The model fit is around 0.4 ($0.448 \leq R^2 \leq 0.461$).

²⁵⁵ It is worth noting that several contributions to the European case operate at a very aggregated level, which offers a rather small sample of cross-sectional data; mostly at the NUTS1 level.

²⁵⁶ The overall model regression fit was above 0.9 ($0.908 \leq R^2 \leq 0.918$) for both cross-regressive alternatives. The fit of the auto-regressive model was above 0.899 ($0.899 \leq R^2 \leq 0.908$). Moreno *et al.* (2003) similarly estimated a knowledge production function for 138 regions (respectively 123) with spatial lags of patent applications per capita as dependent variable. Additionally, they estimated a version with spatial lags of R&D expenditures (contiguity based). The overall model performance was above 0.9 ($0.908 \leq R^2 \leq 0.915$) for the latter version, whereas the former version had an R^2 above 0.899 ($0.899 \leq R^2 \leq 0.908$). All equations of the basic knowledge production function were estimated in an OLS framework (spatial cross-regressive model); LM-ERR and LM-LAG were not significant due to spatially lagged control variables.

²⁵⁷ However, in most cases, GDP and R&D expenditures are highly correlated with patenting potentialities/patent applications. In this respect, GDP and R&D expenditures are highly correlated, which eventually introduces a bias. The overall model fit is similar to the above discussed contributions ($0.74 \leq R^2 \leq 0.85$), although their work does not contain spatially lagged variables.

auto-regressive interdependence.²⁵⁸ The knowledge production functions were estimated in an OLS- and ML-framework for different sectors/industries. Additionally, the knowledge production function was complemented with technological distance controls that showed up with significant coefficients.

Greunz (2005) reported no direct inter-regional effect from governmental R&D expenditures. However, it is worth noting, that the results showed that the business and university R&D sector were both positively affected by lagged governmental R&D expenditures. Opposed to Acs *et al.* (1997), who have not found evidence for spatial dependence of private business sector R&D but only for university R&D, the results of Greunz (2005) indicate that inter-regional knowledge spillovers mainly originate from business sector R&D activities.

OhUallachain and Leslie (2007) estimated a knowledge production function for 50 US states. They showed that commercial patenting is highly dependent on R&D expenditures, whereas business R&D is positive and highly significant; university R&D and governmental/federal R&D is insignificant or has a significant negative effect on commercial patenting.²⁵⁹

Crescenzi *et al.* (2007b) estimated knowledge production functions for US patent growth for the period 1990-2002.²⁶⁰ Their estimations for the US case covered 266 MSAs (145 MSAs/CMSAs respectively). They demonstrated that knowledge spillovers in the US do not cross a 80-110 km distance band, which supports the hypothesis of highly localized spillovers. The authors argued that the United States show significant research clustering and strong distance decay effects.²⁶¹ In comparing Europe and the US, Crescenzi *et al.* (2007a) reported a much higher population density in European regions compared to the US, indicating that major European metropolitan areas are located at a proximate distance. They argued that this could be one reason for a much stronger circulation of knowledge in Europe, which is reflected by stronger spatial autocorrelation of patenting activity. In this respect, the authors observed much stronger significant and positive effects on annual patent growth rates for 96 European NUTS1/2 regions compared to US MSAs. Spatially lagged R&D expenditures for the European case were significant although the authors introduced several additional controls (e.g., country dummy variables, agglomeration indicators, industry specialization, social filter). Interestingly, population density was not significant for Europe but significant and positive for the 266 US MSAs. The Krugman index, which measures specialization of regional employment, was significant and negative for European regions.²⁶²

Hauser *et al.* (2008) criticized existing (and recent) regional knowledge production function regressions by means of model misspecifications. The authors argued that the incorporation of social filters (e.g., political interest, friendship ties, trust, associational activity and technology and self improvement), generated by factor analysis, minimizes nuisance spatial

²⁵⁸ The overall model performance is represented in a regression fit above 0.43 ($0.43 \leq R^2 \leq 0.86$).

²⁵⁹ The regression fit is above 0.7 ($0.725 \leq R^2 \leq 0.870$).

²⁶⁰ Earlier knowledge production function contributions used the stock of patent applications (applications/grants per year).

²⁶¹ The regression fit of the models are above 0.12 ($0.12 \leq R^2 \leq 0.32$).

²⁶² The regression fit for European regions was around 0.3 ($0.21 \leq R^2 \leq 0.47$).

dependence.²⁶³ Their regressions are based upon 51 European NUTS1 regions. EPO patent applications per million inhabitants (log) were used as the dependent variable. R&D activity (aggregate of business, government, university, non-government) showed a significant and positive effect on patenting activity. This effect was six times larger compared to skilled employment in high technology sectors (HRST).²⁶⁴

Finally, in an OECD context, Usai (2008) estimated a knowledge (patent) production function by using PCT applications (Patent Corporation Treaty). The regressions covered 30 OECD countries and 61/271 spatial units (271 TL2 OECD regions, 61 North American regions, 201 European regions). The econometric results showed a significant and positive effect from intra-regional R&D activity and neighboring regions' R&D spillovers. Similarly, the spatially lagged dependent variable in an auto-regressive model was significant and positive.²⁶⁵ However, the applied spatial lags in the cross-regressive setup seemed to differ from earlier contributions as the first-order contiguity lag of R&D expenditures was not significant after implementing the second-order contiguity-based lagged R&D covariate. Moreover, population density was not significant. It can be concluded that the latter two results are endogenous to the aggregation level as the OECD TL2 classification solely consists of large (macro) areas. This issue also applies to all of the aforementioned studies that were conceptualized at the aggregated NUTS1/2 level.²⁶⁶

To conclude, almost all reviewed KPF studies have demonstrated that intra-regional R&D activity and patenting activity are strongly correlated, that R&D activity exhibits a significant and positive effect on regional patent output, i.e. patent applications or granted patents, that inter-regional R&D spillovers are significant and positive but undergo strong distance decay effects, and that the distribution of research and patenting activity, although measured in most studies at a very aggregated spatial level, is (highly) skewed. Nevertheless, the origins (and micro-foundations) of regional spillovers remained a "black box" in the presented studies and the interpretation of such spillovers as knowledge externalities is certainly misleading (Breschi and Lissoni, 2001a; Breschi *et al.*, 2005).²⁶⁷ Furthermore, regarding the quantity of existing KPF studies (at the NUTS1/2 level) and the remaining poor data availability, the estimations of regional KPFs seem to have hit fairly decreasing returns. Unfortunately, harmonized R&D statistics below the NUTS2 level do not exist, which represents another meaningful reason to approach the presented research questions with an alternative methodology.

²⁶³ Hauser *et al.* (2008, 869) concluded that "[t]he spatial concentration of social capital is as important as the concentration of R&D and human capital in explaining observed autocorrelation of innovation."

²⁶⁴ The overall regression fit of their setup was above 0.8 ($0.87 \leq R^2 \leq 0.90$).

²⁶⁵ The overall model efficiency of the European cross-regressive knowledge production function (spatial lag of R&D) is $R^2 = 0.908$, compared to $R^2 = 0.683$ for North America (United States) and $R^2 = 0.897$ for the whole OECD sample.

²⁶⁶ In opposition, the empirical analyses in this thesis focus on TL3 regions.

²⁶⁷ For additional national studies refer to, e.g., van der Panne (2004), Autant-Bernard and Massard (2007), Fritsch and Slavtchev (2007b), Richter and Freund (2008), Freund (2008), Arancegui *et al.* (2008), Andersson and Gräsjö (2009) and Patuelli *et al.* (2010). See also table B.1, appendix, for an overview.

2.2.4. Localization, Urbanization and Regional Development

As has been demonstrated in the last section, regional knowledge production is associated with strong regional spillovers at a proximate distance. Another prevalent debate in geographical economics and economic geography, i.e., the “industry dimension”, centers the effects of regional industrial structures on regional employment growth, productivity, innovative capacities and innovation output. With respect to the latter, the debate is also known as MAR-Jacobs externality debate as theoretically discussed in section 2.1.6.²⁶⁸ It can be argued that this debate primarily centers the “industrial” dimension (see also table B.1, appendix, for an overview).

Glaeser *et al.* (1992), among others, concluded, after having analyzed the top five industries and employment structures in US cities, that a higher diversity is associated with higher growth rates. Industry specialization, on the other hand, reduces urban employment growth.²⁶⁹ In comparison, Henderson *et al.* (1995) argued that specialization appears to matter more for mature industries and technology fields. Conversely, urban diversity is essential for establishing new industries, which links the debate to the life-cycle concept (of regions, industries and clusters). Moreover, according to the theoretical review of urbanization economies and innovation externalities, the generation of new knowledge and the production of new products and services shows tendencies to be more concentrated in metropolitan areas which show a diversified industry structure.

Recently, researchers also developed interest in analyzing the effects of spatial technology and industry structures on research and innovative activity. Duranton and Puga (1999, 8) concluded that

“[n]ot only is the creation of new plants biased towards larger and more diverse cities, but so is the location of innovative activities that lead to new products.”

Similarly, Audretsch and Feldman (1999) argued that cities are the places where innovation occurs, and focused on the effects of Jacobs externalities from local industry structure. In using data on US product innovations they concluded that more than 90% of innovations are generated in metropolitan areas but that these spatial units account for approximately 30% of the US population. Furthermore, they found that regional industry specialization has a negative effect on innovative output, whereas city size and diversity across industries with a common science base have a significant and positive effect. However, Audretsch and Feldman (1999) could not find any positive effect from localization (specialization) on employment growth and innovative activity. Their results give support to the idea that highly localized industries, profiting from static and dynamic localization economies, may represent mature industries or clusters that rely on large scale production and intra-industry knowledge transfer (see also Duranton and Puga, 1999; Feldman, 2000; Audretsch *et al.*, 2008).

²⁶⁸ The observed studies differ in their econometric methodologies and techniques and the dimension and specificity of the used database. The heterogeneity of the empirical results is mirrored to a certain degree in the heterogeneity of empirical approaches.

²⁶⁹ Glaeser *et al.* (1992) analyzed the growth of industries in 170 US cities (1956-1987) in order to find empirical evidence for specialization and/or diversity. The authors did not find statistical evidence for MAR, but positive significant coefficients for diversity on industry growth. It is also reported from other studies that doubling city size increases productivity by 3-8%.

Strongly related to the “industrial” dimension of agglomeration economies, the so-called “specialization-diversity” debate was enriched by contributions that focus on “technological relatedness” and “related variety” and the effects of industry structures on knowledge transfer, productivity and employment growth (Neffke *et al.*, 2009; Boschma and Frenken, 2009a).²⁷⁰ Jaffe *et al.* (1993), for example, found out that knowledge spillovers are not confined to closely related technologies (or industries); the authors argued that around 40% of patent citations did not come from the same patent class as the originating patent (refer to section 2.2.5). Accordingly, relatedness can be seen as an essential aspect of industry dynamics. Frenken *et al.* (2007) concluded that regions with a higher degree of variety among related industries will be determined by stronger local knowledge spillovers. Boschma and Frenken (2009a) also pointed to the importance of technological relatedness, arguing that new industries can connect to existing industries via various channels of knowledge transfer due to cross-fertilization. Similarly, Boschma and Iammarino (2009) brought forward the argument that regions may benefit from other regions via inter- and intra-industry knowledge flows as already theoretically discussed in section 2.1.7.5.

Although there exist many empirical studies on the “specialization-diversity” debate in an industry and city context, empirical evidence on the effects of the local industry structure (mostly employment) seems at best inconclusive (de Groot *et al.*, 2009; Beaudry and Schiffauerova, 2009). Feldman (2000) conceded that clear-cut answers remain elusive as long as empirical findings on urbanization and localization tend to vary.²⁷¹ de Groot *et al.* (2009) reviewed regression coefficients from more than 30 empirical studies in a meta-study. Both types of agglomeration economies, localization and urbanization, showed positive coefficients as often as they did the opposite.²⁷² After classifying and reviewing different sources of agglomeration economies Duranton and Puga (1999, 24) similarly concluded that

“[this] does not imply that one type of city is economically more desirable than the other. [...] Some cities specialise in churning new ideas and new products (which requires a diversified base [...]), whereas other cities specialise in more standardised production (which, in turn, is better carried out in a more specialised environment).”

According to their understanding, the different types of local economic environment may matter at different stages of a product’s (and industry) life-cycle (Duranton and Puga, 1999, 2001).

To conclude, almost all regional knowledge production function studies confirmed the existence of distance decay effects of knowledge (R&D) spillovers, irrespective of their origin

²⁷⁰ Refer to Boschma and Iammarino (2009) and Neffke *et al.* (2011) for an overview.

²⁷¹ Refer to Audretsch and Feldman (1996), Audretsch and Feldman (1999) or van der Panne (2004) for further discussions.

²⁷² Glaeser (2000, 92) concluded that “[...] for the moment, the role of concentration [i.e., of localization] and diversity does not seem to have been resolved by the literature. Different time periods and different samples give different results which suggests that there is no universal truth on this topic.” Similarly, Breschi and Lissoni (2001a, 5) have argued that “[...] all the best-known studies on localised knowledge spillovers (LKS) seem to be unanimous in concluding that knowledge spillovers, either intra-industry or inter-industry, are important and strongly bounded in space.” Beaudry and Schiffauerova (2009, 334) argue that “[the] analysis of the evidence presented in the paper strongly hints at measurement (level of aggregation of both industrial and geographical classifications) and to some extent at methodological (MAR and Jacobs indicators) issues as the main causes for the divergence observed in the literature and to the fact that the debate regarding MAR or Jacobs externalities remains unresolved.”

(R&D activity, patents).²⁷³ Nevertheless, central issues have to be mentioned: (i) the regional classification represents a problem as aggregation from small to large units induces an averaging process which induces and/or enforces spatial autocorrelation between observations (Arbia and Petrarca, 2010); (ii) fractionally counted patent data automatically induce some kind of spatial autocorrelation in empirical analysis if a significant fraction of patent application originates from research activities with co-assignees/ co-inventors from neighboring regions; (iii) evidence regarding inter- and intra-industry effects remains inconclusive. Accordingly, the issue of regional “diversity vs. specialization” will be challenged by an alternative methodology (see chapter 3, section 3.5).

2.2.5. Patent Citations, Paper Trails and Real Spillovers

An alternative strand of research, which is very popular in studies on research clustering, R&D spillovers and knowledge diffusion, is the patent citation approach. It can be argued that the citation approach is the answer to elementary critiques regarding the existence, importance and micro-foundations of knowledge spillovers (Krugman, 1992, 2011). The approach combines the “industrial,” “technological” and “geographic” dimension of knowledge production.

Adherents try to directly measure the extent of knowledge flows by using patent citation data. The analysis is characterized by the attempt to reconstruct paths of knowledge diffusion, i.e., paths of citations included in patent documents and their specific location and distance (Verspagen and Schoenmakers, 2000; Fischer *et al.*, 2005; Scherngell, 2007).²⁷⁴ The citation approach allows ex post statements about the spatial range of knowledge spillovers and flows. In applying this approach, the research methodology represents an attempt to follow a “paper trail” that is left by citations (Feldman, 2000). Jaffe *et al.* (1993, 578) challenged Krugman’s famous neglect regarding knowledge diffusion and argued that

“[knowledge spillovers] do sometimes leave a paper trail, in the form of citations in patents.”

An advantage of the citation analysis is that citation data can be applied in detail on specific technologies (IPC sections) and agents, which enables sector- and/or technology-specific conclusions. However, citations in patent documents are in most cases added by professional patent examiners at the patent offices (EPO, WIPO or USPTO) but not exclusively by the inventor and/or applicant (Alcacer and Gittelman, 2004; Scherngell, 2007; Criscuolo and Verspagen, 2008). Accordingly, included citations may not reflect the stock of knowledge of the person at that time when the patent was applied for; it may, in the other extreme, rather represent the detailed stock of knowledge of the patent examiner. Criscuolo and Verspagen (2008) showed that the share of patents with all citations included by the inventor has been constantly declining (from 10% in 1985 to 5% in 2000), while the fraction of patents with all citations added by the examiner has been rather constant. Additionally, they showed that the shares of all citations added by

²⁷³ For a final overview refer to table B.1 in the appendix.

²⁷⁴ See also Jaffe *et al.* (1993), Maurseth and Verspagen (1999), Keilbach (2000) and Maurseth and Verspagen (2002).

EPO examiners instead of inventors differ tremendously. In organic chemistry, e.g., almost 15% (65%) of all citations are added by the inventor (examiner), while in information technology only 2% of all citations are added by the inventor (93% by examiner). Their results also support the importance of spatial distance for EPO patent citations (Criscuolo and Verspagen, 2008).

The patent citation approach does neither capture knowledge flows via co-inventorship activity, i.e., co-patenting linkages, nor knowledge transmission via researcher mobility in networks, labor migration (brain drain, brain gain), knowledge flows between firms and between customers and firms (Scherngell, 2007; Fischer *et al.*, 2009; Paci and Usai, 2009).

The perhaps most prominent contribution in patent citation analysis is Jaffe *et al.* (1993) (and Jaffe and Trajtenberg (2002)), who used a “case-control-matching approach” in order to verify patent citations as a potential transfer channel of knowledge spillovers. The authors compared the location of cited patents with the location of citing patents by using the official inventor location.²⁷⁵ As Jaffe *et al.* (1993, 579) have argued:

“[W]hy should innovations tend to cluster spatially more in some industries than in other industries [...]? The most difficult problem confronted by the effort to test for spillover localization is the difficulty of separating spillovers from correlations that may be due to a preexisting pattern of geographic concentration of technology related activities. That is, if a large fraction of citations to Stanford patents comes from the Silicon Valley, we would like to attribute this to localization of spillovers. A slightly different interpretation is that a lot of Stanford patents relate to semiconductors, and a disproportionate fraction of the people interested in semiconductors happen to be in the Silicon Valley, suggesting that we would observe localization of citations even if proximity offers no advantage in receiving spillovers. Of course, the ability to receive spillovers is probably one reason for this pre-existing concentration of activity.”

In their study, Jaffe *et al.* (1993) calculated two probabilities: (i) a patent cites another patent registered by a nearby agent (e.g., university, firm), with both patents referring to the same technology and having originated from a similar point in time; (ii) two patents are similarly geographically linked, without existence of formal links through such patent citations. The overall result of their analysis was that intra-national and intra-regional citations happen more often than one would expect from the distribution of patenting activity. Additionally, they observed that citations happen more frequently when the citing and cited patent belong to the same spatial unit (see also Keilbach, 2000; Scherngell, 2007). They found that knowledge spillovers are not confined to closely related industries or technologies. In this respect, they suggested that around 40% of patent citations do not come from the same patent class as the originating patent (Jaffe *et al.*, 1993; Keilbach, 2000). This result can be interpreted as an indication in the direction of Jacobs externalities and recent contributions to related variety and technological relatedness (section 2.1.6.3) (Boschma and Frenken, 2009b; Neffke *et al.*, 2009). Other studies, e.g., Malerba *et al.* (2003, 3) came to the conclusion that

“[patent citations] can be regarded as a noisy signal for spillovers.”

²⁷⁵ See Fischer *et al.* (2005) and Scherngell (2007) for an overview.

Similarly, Alcacer and Gittelman (2004, 14) discussed the citation approach and concluded that

“[o]verall, our results do not change the presumption that patents trace out knowledge flows: inventors face strong legal pressures to reveal all they know, and our results do show that inventor citations follow a pattern we would associate with inventor knowledge. [...] the bimodal pattern does not contradict that knowledge spillovers are localized.”

Another study is the one of Maurseth and Verspagen (2002). They analyzed the impact of language and national borders on the knowledge diffusion across 112 spatial units in 14 countries. They concluded that there exists a negative correlation between flows of knowledge and spatial distance. They showed that knowledge diffuses more easily across countries when they have the same language.

Thompson and Fox-Kean (2005), in opposition, who built on the work of Jaffe *et al.* (1993), suggested that the localization of spillovers measured by patent citations was generally overestimated. Additionally, the authors critically discussed earlier studies. Similar criticism has been presented by Agrawal *et al.* (2003), who argued that a careful extraction of control patents (control samples) is a necessity for patent citation analysis as citations will automatically be co-located even in the case of absence of knowledge spillovers as soon as technology fields are geographically clustered (see chapter 3, section 3). It has also been questioned whether the results of citation analysis pertain to a perhaps too high aggregation level. Otherwise, it may be possible that earlier patent co-operations explain most of these spillovers (Thompson and Fox-Kean, 2005).

In a recent study, Scherngell (2007) analyzed patent citations of high-technology EPO patent applications between large European regions (NUTS1). He showed that geographic distance had the smallest negative effect in the electronic industry, whereas the pharmaceutical industry and aviation industry showed strong decay effects. Moreover, language and national borders had the expected negative impact on patent citations. Summarized, Scherngell showed that high-tech patent citations suffer tremendously from spatial distance and that the citation structure shows strong concentration and core-periphery structures. Additionally, he observed inter-regional patent citation linkages between leading European core regions. Peripheral regions, in opposition, are generally characterized by small numbers of received and made citations in almost all analyzed technology fields (see also Fischer *et al.*, 2009). Although Scherngell did not explicitly examine the regional typology of the regions under observation, urban regions tend to receive the largest fraction of European patent citations in the sample (e.g., Ile-de-France, Oberbayern, Stuttgart, Noord-Brabant, Darmstadt, Düsseldorf, Lombardia, Köln, Stockholm, Rhone-Alpes). This result is in line with the findings on research clustering and patent densities as will be presented and discussed in chapter 3 (section 3.5). Moreover, his results on citation linkages are similar to the results on co-patenting linkages between regions in this study (see chapter 4).

In a similar set-up, Paci and Usai (2009) offered an EPO patent citation analysis for a group of 175 NUTS0, 1 and 2 regions for 17 countries. Although the authors made use of an IPC-technology field concordance table for descriptives, they did not offer additional (relational network) results with respect to different technology fields. They concluded from their analysis that (i) citation links decrease with spatial distance, (ii) citation flows are

higher between contiguous regions (that are sharing a common border), and (iii) citations happen more frequently between regions that have a similar technology base. Interestingly, the authors additionally argued that spatial distance has generally lost influence on patent citation intensity, which means that patent citations became less sensitive with respect to physical distance of researchers.²⁷⁶ Paci and Usai (2009, 675) argued that

“[t]his picture seems to indicate an increase in the spatial scope of knowledge diffusion which goes in the direction proposed in the literature under the label of “death of distance” [Cairncross, 1997].”

A similar development for scientific European co-publications was reported by Hoekman *et al.* (2010) from their gravity model estimation at the NUTS1/2 level (see section 2.2.7). Their study, although different with respect to methodology and aggregation level, points into the same direction as the results reported in this thesis, i.e., the inter-regional co-patenting network analysis (see chapter 4, sections 4.3.4 and 4.3.5).

Sonn and Storper (2008) argued that the localization of patent citations (i.e., the proportion of local citations) has increased within the last two decades, which can be interpreted as a significant increase in localization and concentration of knowledge spillovers. Their findings are in line with those of Paci and Usai (2009), although the latter argued that national borders became less important in the course of time.

Finally, Bergman and Usai (2009) reported that knowledge flows within the EU, measured via patent citations, are strongly localized in European core member states and that these flows emerge from a small number of strongly agglomerated places.²⁷⁷

The following conclusions can be drawn from the reviewed studies. Patents and their cited-citing ratio are highly concentrated in space. Spatial distance is said to hamper research collaboration intensity but negative effects from national borders seem to have vanished. For more details, the interested reader is referred to the above mentioned literature for further information.²⁷⁸ However, although based upon relational data, the studies of Scherngell (2007) and Paci and Usai (2009) are problematic by technical reason. Most citation studies applied the standard NUTS classification, which may lead to a severe bias in network data (data on citation, co-patenting, co-publishing, among others). This is a crucial concern as the underlying spatial classification system shows a bias in the absolute number and size of regions included in the analysis, e.g., Denmark as a single region vs. 40 German regions (Paci and Usai, 2009).²⁷⁹ For this reason, another spatial classification system is applied in the own empirical analyses in chapters 3, 4 and 5. Thus, potential risks that might originate from a problematic spatial classification system are prevented. Furthermore, the

²⁷⁶ Paci and Usai (2009) also make use of an IPC-technology field concordance table; they apply the “Yale-concordance” and the one proposed by Schmoch *et al.* (2003). Due to the fact that the results have not changed, their basic scenario is based on the Yale-technology concordance. This is interpreted as another sign that the Schmoch *et al.* concordance is generally considered an established concordance table.

²⁷⁷ For similar conclusions see Fischer *et al.* (2005), Scherngell (2007) and Fischer *et al.* (2009).

²⁷⁸ Additionally, Feldman (1999), Audretsch and Feldman (1999), Feldman (2000), Breschi and Lissoni (2003), and Döring and Schnellenbach (2006) contributed with seminal overviews and discussions of the related literature.

²⁷⁹ Other studies in this respect are Scherngell (2007), Hoekman *et al.* (2009), Maggioni and Uberti (2009), Hoekman *et al.* (2010).

citation approach is problematic, because it is not sure that knowledge spillovers, by means of documented patent citations, have really been realized. Almost 90% of all citations are traced by patent examiners, which raises severe doubts regarding the citation approach (Criscuolo and Verspagen, 2008). Moreover, the citation approach completely ignores the major fraction of knowledge that is frequently transmitted via the market process and within intra- and inter-regional network linkages, i.e., co-inventor networks (Ejeremo and Karlsson, 2004; Maggioni and Uberti, 2009; Hoekman *et al.*, 2010). Accordingly, patent citations cannot be interpreted as a valid measure of (direct) interaction between individuals or regions.

Due to the presented methodological drawbacks and the ongoing dispute with respect to the patent citation approach, it will not be applied in the following empirical analyses. Regarding the mentioned deficits, it is also important to acknowledge that a parallel line of analysis exists, measuring knowledge flows by application of data on co-inventor networks. The co-inventor approach is reviewed in section 2.2.7. A detailed European co-inventor network analysis is favored, i.e., an EPO co-patenting network analysis at the regional level (see chapter 4).²⁸⁰

2.2.6. Researcher Mobility, Social Networks and Diaspora

Regarding the micro-foundation of knowledge transmission, another interesting working channel represents the interaction between persons in social networks that allows the non-codified transmission of “tacit knowledge” (see chapter 2, section 2.1.7.2). This approach is intertwined with studies on knowledge diffusion via labor markets, spatially mobile networks of researchers and diaspora networks (see chapter 2, section 2.1.7.5).²⁸¹ Moreover, the approach is partially intertwined with patent citation analysis. Accordingly, the social network-mobility approach combines the “industrial,” “technological,” “geographic” and “social” dimension of knowledge production, whereas the main focus is on the latter.²⁸²

Researchers are regarded as carriers of highly specialized, implicit knowledge. Related to this approach, a good starting point are the concerns of Breschi and Lissoni (2001a, 976), who argued that

“[t]he role of geographical distance in the economics of knowledge transmission [...] is still rather controversial.”

Therefore, it is of great necessity to analyze the spatial context and channels of knowledge transmission in more detail.

Almeida and Kogut (1999) and Zucker *et al.* (1998), among others, assumed that the spatial concentration of knowledge flows is related to the features of labor markets for highly skilled workers. There exist several studies that have examined how labor mobility of

²⁸⁰ A detailed European co-patenting network study at the national and regional level follows in chapter 4.

²⁸¹ A discussion is offered in Burger *et al.* (2009), Bergman (2009), Ter Wal and Boschma (2009) and Franz (2010).

²⁸² See also Almeida and Kogut (1999) and Tripl (2009).

inventors, and researchers and their networks act as a key mechanism for knowledge transmission (diffusion), which gave rise to research on social networks and diaspora (Almeida, 1996; Almeida and Kogut, 1999; Saxenian, 2006, 2007). Although localized knowledge spillovers rely on local networks and thus on geographical space, the local nature of knowledge transfer is explicitly based on the tacit nature of knowledge due to technology-specific determinants of inventorship (see section 2.1.7.5) but not primarily due to pure distance decay effects (see section 2.1.6.7). The network approach is related to the idea that informal knowledge exchange happens within social networks of inventors and their research collaborations (Gordon and McCann, 2000; Breschi and Lissoni, 2003). Breschi and Lissoni (2006) analyzed the structure of Italian inventor networks with special focus on the mobility of scientists. Breschi and Lissoni (2006, 9) concluded that

“[i]t remains true, however, that many social networks dedicated to the production of knowledge as a club good are geographically bounded, since spatial proximity may help the network members to communicate more effectively and patrol each other’s behaviour.”

With respect to co-patenting activity of researchers, Breschi and Lissoni (2009, 439) recently argued that

“[t]he most fundamental reason why geography matters in constraining the diffusion of knowledge is that mobile researchers are not likely to relocate in space, so that their co-invention network is also localized.”

Breschi and Lissoni (2006, 8) furthermore center club good characteristics of such networks and the features of epistemic communities that determine the knowledge transmission process within (and between) communities:

“[S]pillovers from an active club member will reach distant fellow members with some delay or imprecision, and will possibly never reach outsiders. [...] To the extent that many [social] networks are concentrated in space, co-localisation would appear as a significant determinant of access to spillovers.”

Moreover, with respect to patent citations, Breschi and Lissoni (2004, 14) argued that the spatial dimension (see section 2.2.5) is strongly related to the structure and dynamics of social networks. They concluded that

“[t]he population of inventors is more than a tiny and unchecked sample of all individuals who can influence inventors themselves. Rather, it may possibly represent the most immediate and influential social environment from which inventors draw ideas and information, at least from technical contents of their patents.”

Thus, these processes of localized labor mobility and informal knowledge exchange seem to be very sensitive to the underlying network structures (Burger *et al.*, 2009; Bergman, 2009).²⁸³ When scientists and researchers co-locate, there is a high probability that most informal contacts between researchers also take place at a proximate distance. It is argued that face-to-face interactions offer the possibility of complex and intense forms of communication and interaction (von Hippel, 1994; Lissoni, 2001; Hoekman *et al.*, 2010). Inventor

²⁸³ See also Almeida and Kogut (1999), Breschi and Lissoni (2001a), Breschi and Lissoni (2003), Breschi and Lissoni (2006), Agrawal *et al.* (2006), Breschi and Lissoni (2009) and TerWal and Boschma (2009).

networks generally rely on face-to-face contacts, which automatically gives a tacit nature to it (see section 2.1.7.2). The same argument was picked up by Breschi and Lissoni (2006, 8) who argued that

“[knowledge spillovers] would be localized if and only if a significant proportion of social networks are also localized in space. [...] If those people move away from where they originally learnt, researched, and delivered their inventions, knowledge will diffuse in space. [...] That is, knowledge flows (where pure spillovers or traded services) are localised to the extent that labour mobility also is.”

Concerning network developments, a first approach toward this hypothesis is to measure the effects of job-hopping in a spatial context. Therefore, local labor markets may represent superior levels of analysis opposed to larger administrative areas. In observing inter-regional labor flows, one may find a powerful explanation for spatial dependence in R&D and patent application activity; especially for explaining the geographical scope of research networks by technology class. Accordingly, some fraction of the investment in any innovation project will create technological externalities that positively affect other innovation projects as soon as researchers change their jobs or scientists exchange knowledge informally (Almeida and Kogut, 1999; Breschi and Lissoni, 2001a; Greunz, 2003a). Since labor mobility is considered being a regional phenomenon, knowledge spillovers and flows based on labor mobility are mostly localized (Balconi *et al.*, 2004; Breschi and Lissoni, 2009).²⁸⁴

In a US-study, Zucker *et al.* (1998) have analyzed the mobility of “star scientists” and their spatial range and underlying research networks.²⁸⁵ They focused on the relevance of human capital for knowledge spillovers in a study of the geographical location of biotechnology firms. Their main research interest was restricted to the very early stages of innovations in this sector, where results of scientific research in universities or research institutions are transformed into commercial products. Their empirical study is based on the assumption that specialized knowledge is generally embodied in individuals. Zucker *et al.* showed that the geographical location of firms is closely related to the location of star researchers in the field. They also showed that the company, with which the scientist was in contact, used the new pieces of knowledge. Accordingly, the results of the authors can be interpreted as evidence that there are no (pure) knowledge spillovers, as the external knowledge of the researcher is implicit knowledge (i.e., embodied/tacit knowledge) (see also Döring and Schnellenbach, 2006; Breschi and Lissoni, 2009).

In another US study, Almeida (1996) focused on the relationship between spatial mobility of engineers in the US semiconductor industry and the localization of patent citations in this technology field. According to their reported results, there exists a considerable relationship between researchers’ mobility and the spatial distributional structure of US patent citations. In a similar work, Almeida and Kogut (1999) have focused on the mobility patterns of patent holders (engineers) in different localized US industries. The authors

²⁸⁴ See also Almeida and Kogut (1999), Breschi and Lissoni (2001a), Breschi and Lissoni (2003) and Breschi and Lissoni (2004).

²⁸⁵ So-called “star scientists” are considered to represent the fraction of researchers, who are highly creative and productive and who discover “breakthrough technologies” (Feldman, 2000).

reported that the local transfer of knowledge across companies is endogenous to the inter-firm mobility of patent holders and that labor mobility is high but localized. They argued that Silicon Valley is one of the few clusters where mobility positively affects the innovative output of firms. The high mobility of researchers between firms in Silicon Valley is generally attributed to region-specific social institutions.

Singh (2005) referred to the network and citation approach in a US-study and found strong empirical evidence that social ties increase the probability of knowledge flows between individuals (measured by patent citations). In this respect, Singh combined the patent citation and social network approach. Identically to Breschi and Lissoni (2003), the author concluded that geography matters because interpersonal networks tend to be localized in a few places.

Oettl and Agrawal (2008) similarly argued that network linkages between researchers generally remain, although researchers frequently relocate in space (i.e., job hopping). They suggested that these linkages are reflected by patent citations by former colleagues. As the market does not (fully) price these flows, Oettl and Agrawal argued that flows of knowledge via labor mobility represent a kind of externality. Nevertheless, it can be argued that firms are generally aware of this external source of knowledge. Thus, experts and star scientists are in particular recruited because of their accumulated implicit knowledge (see also Bergman and Usai, 2009).

Breschi and Lissoni (2009) suggested that networking activity across agents and locations is responsible for a large fraction of localized knowledge flows between individuals (and regions). They concluded that the effect of non-market externalities (i.e., the spatial lag in knowledge production function models) was generally overestimated in past KPF studies due to methodological issues.

In a European context, Miguelez *et al.* (2009) recently used regionalized PCT patent data (EURO PCT) for studying the mobility of highly-skilled individuals as a possible mechanism of inter-regional knowledge transfer. Building on Breschi and Lissoni (2009), the authors hypothesized that knowledge flows are localized to the extent that inventors' mobility is also localized, which would explain the existence of local spatial dependence in explanatory spatial data analysis. Similarly to Miguelez *et al.* (2009), Miguelez and Moreno (2010) found strong support for the positive relationship between regional labor market mobility and regional patent densities for a sub-sample of European macro regions. They concluded that there exists a positive correlation between intra-regional labor mobility and regional patent applications.

To summarize, social network-mobility studies have, depending on the analyzed epistemic community, generally reported a highly localized mobility of researchers, which indicates that (implicit) knowledge transmission is localized to the extent that networks are localized. Furthermore, migratory movements of researchers seem to affect the "paper trail" of patent citations (see previous section) due to emerging and disappearing informal network linkages (i.e., social ties) and diaspora. This aspect has already been brought forward in the theoretical review (see section 2.1.7.5). Nevertheless, the statistical identification of researchers' mobility represents a meaningful issue in studies that intend to cover dozens of countries, hundreds of regions and many industries. With respect to this problem, a

promising line of research is dedicated to the analysis of regional co-inventor networks, i.e., co-patenting networks, which will be discussed in the following.

2.2.7. Research Collaborations and Co-Patenting Networks

The internationalization of technology and R&D shows large cross-country differences (Guellec and van Pottelsberghe de la Potterie, 2001; Belitz *et al.*, 2006). Therefore, an alternative strand of research increasingly examines co-patenting structures in order to analyze the structures and dynamics of R&D collaboration activities in an international, regional and firm-level context (Maggioni *et al.*, 2007; TerWal and Boschma, 2009; Boschma and Frenken, 2010).²⁸⁶

Inventor/ co-patenting network analysis is said to have potentialities to contribute to the understanding of regional innovation systems and core-periphery patterns in knowledge intensive industries (Maggioni *et al.*, 2007; Burger *et al.*, 2009; Powell and Giannella, 2010). Besides the structural composition of linkages and networks (Kroll, 2009), recent empirical research places special emphasis on the changing structure of research networks (TerWal and Boschma, 2009; Burger *et al.*, 2009).²⁸⁷ This approach combines the “industrial,” “technological,” “geographic” and “social” dimension of knowledge production, agglomeration economies and networks. In light of the previous theoretical discussion in chapter 2 (see sections 2.1.7.3, 2.1.7.4 and 2.1.7.5), inter-regional research networks are considered to represent pivotal factors that affect the geography of innovation.

It is also argued that co-patenting studies offer a way to directly measure international and inter-regional knowledge flows, i.e., an assessment of the globalization of applied R&D (Frietsch and Schmoch, 2006). Moreover, the analysis avoids several shortcomings and technical issues of the aforementioned approaches. Accordingly, the analysis of regional co-patenting networks can be regarded as a fruitful alternative (Johansson and Quigley, 2003; Ejermo and Karlsson, 2004; Iammarino and McCann, 2006).

The co-patenting approach is considered the only methodology that explicitly addresses the theoretical issues of inter-regional and extra-cluster research linkages in an appropriate way (see also sections 2.1.7.4 and 2.1.7.5). Moreover, unlike patent citations, co-patents detect the localization of researchers working on the same inventions. Therefore, co-inventorship can be regarded as a good approximation of intended technological and scientific collaboration (Maggioni *et al.*, 2007; Maggioni and Uberti, 2009). This has also been argued by Ejermo and Karlsson (2004, 2), who concluded that

“[k]nowledge transfers should be qualitatively and quantitatively more substantial than citations as indicators of the overall flows of knowledge within an innovation system. After all, even if citations do reflect knowledge spillovers, deliberate co-operation must be of much larger magnitude than casual and random “spillovers.” Co-authorship structures therefore seem more adequate for assessing the relative merits to the extent that knowledge travels across space.”

²⁸⁶ Burger *et al.* (2009) and Bergman (2009) represent comprehensive reviews of patent citation and network studies. See also Singh (2005), Lam (2007) and Lobo and Strumsky (2008).

²⁸⁷ See also Orsenigo *et al.* (1997), Iammarino and McCann (2006) and Glückler (2007).

Co-inventor studies examine the structure and determinants of these collaborative patterns which are considered meaningful mechanisms of inter-regional R&D knowledge flows and spillovers (Ejermo and Karlsson, 2004; Bergman and Maier, 2009; TerWal and Boschma, 2009). Several co-inventor studies have been conceptualized at the national level (Ejermo and Karlsson, 2004; Ponds *et al.*, 2010). However, only a few contributions challenged the network structures beyond national borders (Kroll, 2009; Maggioni and Uberti, 2009; Hoekman *et al.*, 2010). Moreover, a detailed analysis of the distribution of these networks across geographic space is still missing in a pan-European context.

For the purpose of analyzing inter-regional networks of inventors the information on applicants and inventors in patent data is in particular valuable (Maggioni *et al.*, 2007; Paci and Usai, 2009; TerWal and Boschma, 2009). Accordingly, patent data are used as relational data.²⁸⁸ Identical to Balconi *et al.* (2004), Ejermo and Karlsson (2006) and Maggioni *et al.* (2007), among others, the co-patenting analysis in this study (see chapter 4) implicitly assumes that researchers, who are listed within the patent application, know each other (personally) and share explicit and implicit knowledge in order to generate new technologies. Therefore, co-patenting activity is considered to be a meaningful proxy for the analysis of innovative collaboration activity between individuals and spatial units.²⁸⁹

Linkages between agents and regions can be ex post analyzed in order to identify co-patenting activity and co-inventor networks.²⁹⁰ The major reason for taking the address of the inventor as the central selection criterion for localizing patents is that MNEs generally assign their patents to companies' headquarter locations. Accordingly, patents which are realized in firms' R&D subsidiaries will in most cases exhibit the address of the headquarter when using the applicant's address for analysis, although most of the inventors will be located as residents in the subsidiaries' regions (Verspagen and Duysters, 2004; TerWal and Boschma, 2009). Consequently, co-patenting studies allow researchers to distinguish between relatively open and integrated places (cities, regions, countries) and places that follow implicitly or explicitly a more closed (isolated) path of research activity.²⁹¹

There exist several possible cases of co-patenting activity in a regional context: (i) research collaboration and co-patenting between local and neighboring units, (ii) co-patenting between local and foreign units, (iii) co-patenting between several local and foreign units.²⁹² In several technology fields international co-patenting, or at least regional border-crossing research activity, is driven by multinational corporations that vary considerably in their organizational structures. As R&D teams of a single company can be located across a number

²⁸⁸ In addition, co-patenting studies are extremely powerful when combined with covariates, which supports the interpretation of econometric results from co-patenting studies.

²⁸⁹ Refer to Wilhelmsson (2009).

²⁹⁰ This methodology, however, can only be applied in sectors and industries, in which intellectual property rights (i.e., patents) are generally used. Furthermore, this methodology is said to be biased towards (successful) inter-firm knowledge exchange and protection via patenting (TerWal and Boschma, 2009). For an analysis of co-patenting data the information on the inventor location can be applied to identify knowledge flows between agents, cities, regions and countries.

²⁹¹ Furthermore, the data on R&D linkages can be enriched by data, if available, on foreign R&D labs in the country, foreign R&D expenditures or the number of foreign-owned inventions. However, studies also have to consider different sectors and technology fields because patenting intensities and co-patenting propensities vary considerably.

²⁹² e.g., the agent-level, city-level, regional level, country-level.

of cities, regions or countries, it can be assumed that multinationals are responsible for a meaningful fraction of inter-regional R&D collaboration linkages (Belitz *et al.*, 2006; Lam, 2007; Fraunhofer, 2009), although large corporate R&D labs have fallen in prominence (Powell and Giannella, 2010). To conclude, it can generally be differentiated between two forms of inter-regional co-operation in R&D: (i) within-organization inter-regional collaboration due to joint research of inventors in different locations but affiliated within a single multinational company (cross-border knowledge flows without spillovers outside the company); (ii) between-organization inter-regional collaboration and joint research of inventors with different organizational and national affiliation who collaborate for an invention. The latter case is considered to induce knowledge spillovers beyond companies' borders.

A serious issue, however, is the judgement about the direction of inter-regional knowledge flows on the basis of co-patenting activity. It seems to be overly simplistic to assume that foreign research labs merely absorb knowledge from their host countries. It is argued that such laboratories are engaged in processes that involve knowledge exchange between domestic and foreign researchers (Fraunhofer, 2009). Moreover, co-patenting information only allows researchers to identify the residence (work place) of inventors, but not their nationality or path of migration.²⁹³ As a consequence, statistical judgements can only be made about research collaboration intensities from co-patenting data, especially at the regional level. In this regard, Bergman and Usai (2009, 10) recently proposed that

“[c]o-patenting is a good indicator of the localisation of inventors that have worked at the same invention and can be a good proxy for scientific and technological collaboration across space. [...] The starting point for a network analysis of the innovation process is the micro-level of individual agents. [...] by aggregating data at a given geographical level (i.e NUTS2 or NUTS3), one may build a geography-based innovator network.”

With respect to the current state of research on co-patenting networks, TerWal and Boschma (2009, 742, 753) recently suggested that

“[v]irtually no studies on the dynamics of the structure of networks in space exist [...]. [F]urther research is needed on how the structure of networks evolves over time and space and, particularly, how the evolution of networks is related to the evolution of clusters. [...] treating patent data as relational data provides us with considerable opportunities to study the dynamics of regional innovation networks, which is, till today, a rather unexplored though promising field of study.”

Taking the aforementioned statements seriously, the empirical analysis in this study (see chapter 4) follows the methodological arguments and propositions of Bergman and Usai (2009) and TerWal and Boschma (2009) and places the emphasis on the structure of European research collaboration activities and co-patenting networks (see chapter 4, section 4.3.5).

In the following, results of selected co-patenting studies are briefly reviewed. The list of European studies remains however quite small (as the approach is relatively novel in literature) which again clarifies the need for additional empirical studies.

²⁹³ Accordingly, it would be definitely misleading to develop opinions about brain-gain or brain-drain between regions or countries based upon co-patenting data.

Research collaboration and knowledge co-production in co-inventor networks have been studied at the regional and national level. Andersson and Ejeremo (2002) and Ejeremo and Karlsson (2004) analyzed co-inventorship activity for Swedish regions based on patent data. Van Looy *et al.* (2003) analyzed co-patenting activity of knowledge generating organizations (e.g., institutes). In this respect, co-patenting between universities and public research institutes and industrial companies are becoming an increasingly important topic.²⁹⁴ Moreover, institutional set-ups and practices vary tremendously (Martin *et al.*, 2008). The establishment of legal frameworks for university patenting also has an impact on co-patenting activity (Fraunhofer, 2009). Owen-Smith and Powell (2004) made use of a “pipeline concept” and discussed the transmission channels used in distant knowledge intensive interactions between agents. They concluded that physical distance is not the only important factor, even though knowledge flows (and spillovers) may be more effective within a regional network than across national borders. The authors showed that agents in the Boston biotechnology industry accessed knowledge via local interaction and strategic partnerships at an inter-regional and international distance. They argued that firms construct network linkages in order to benefit from research excellence abroad (see also Bathelt *et al.*, 2004; Powell and Giannella, 2010). However, regions need significant absorptive capacity in order to communicate and absorb forefront knowledge (Owen-Smith and Powell, 2004; Ejeremo and Karlsson, 2006; Freund, 2008).²⁹⁵

In a Dutch study, Ponds *et al.* (2010) performed a network analysis for Dutch regions based on scientific publications. They came to the conclusion that physical distance essentially matters for scientific co-operation.

In a recent US study, Powell and Giannella (2010) analyzed the average spatial co-inventor distance (miles) by using USPTO patent data. They observed an increasing dispersion of co-patenting activity between the years 1975 (101-161 miles) and 2005 (215-185 miles) in the technology fields aerospace, biotechnology, optics, pharma/chemicals and semiconductors. Similarly, Johnson *et al.* (2006) reported that the distance between co-inventors has on average increased from 117 miles (1975) to approximately 200 miles (1999). They argued that emerging technology fields, e.g., computers, semiconductors and biotechnology, exhibit much stronger clustering than mature industries (and technology fields). They also argued that these technology fields have started to spatially spread within the last years. These findings are very similar to the computations for the European case reported in this thesis (see chapters 3 and 4).

In a European context, Maggioni *et al.* (2007) used co-patent data as one indicator in their analysis of the importance of traditional spatial spillovers vis-à-vis relational spillovers. They analyzed a sample of 109 European regions at the NUTS2 level within a gravity equation model. The authors combined data on the participation in the same research networks (EU Fifth Framework Programme) and EPO co-patent applications. In this way, they examined the factors that support patenting activity. The authors made the

²⁹⁴ Researchers in the public sector are increasingly managing their intellectual property. However, this issue is still pronounced differently in European member countries.

²⁹⁵ Related to these results and interpretations, Malecki concluded that “[s]ome places are able to create, attract, and keep economic activity [...] because people in those places make connections with other places” (Malecki, 2002, cited in Bathelt *et al.*, 2002, 17). See also Cohen and Levinthal (1990) and Bathelt *et al.* (2004).

distinction between geographical and relational spillovers and structural features. They empirically tested if relationships, which are based on inter-regional networks between excellence centers, generally predominate research relationships at a proximate distance (contiguity). However, it is important to note that Maggioni *et al.* (2007) only analyzed a few European countries (France, Germany, Italy, Spain and the United Kingdom) and that they applied the very aggregated NUTS1/2 classification, which might implement several issues (e.g., spatial autocorrelation due to aggregation/averaging process).

In a later work, Maggioni and Uberti (2009) focused on international network linkages. Their analysis completely ignored intra-national linkages. The gravity model regressions covered data on internet hyperlinks, EPO co-patent applications, European networks of researchers and data on Erasmus student mobility. The authors concluded that knowledge linkages seem to concentrate in a few European NUTS2 “super-regions,” which means that European structures are rather resembling “scale-free networks” but not “small worlds.” Again, it has to be noted that the sample of regions included in their analysis, although at the well-known NUTS2 level, is heterogenous. This generally implies distorted network structures as the number of unique and overall linkages (edges) is endogenous to the regional classification system.²⁹⁶

Kroll and Mallig (2009) offered a comparison of US and European co-inventor network structures. Their main objective was to examine differences with respect to the spatial scope of network linkages. Their analysis is static as it does not offer a dynamic network comparison. Nevertheless, they clearly demonstrated that US networks are by and large more localized than European networks, although the applied European spatial classification system is rough (NUTS1 level).

Hoekman *et al.* (2009) discussed results of their European co-inventorship analysis with special focus on scientific (journal) co-publications (Web of Science) combined with EPO co-patenting data. They analyzed 1316 European NUTS3 regions and argued that the majority of co-publications seem to happen at a proximate distance between several central network nodes. Their study gives additional indication that European research excellence is by and large dominated by a small number of European NUTS regions. However, the applied spatial classification system in their study is considered to be highly problematic as German regions account for 439 of all 1316 EU-27 regions (33.15%), which obviously implements a central bias into the generation and analysis of relational data.²⁹⁷

Similarly, in a recent study, Hoekman *et al.* (2010) analyzed the effects of geographical distance and borders on the intensity of research collaboration at a higher spatial level, now across 313 European regions in 33 EU countries. Based upon co-publication data for the years 2000-2007, the authors found that the tendency towards collaborations with partners at a proximate distance did not decrease, while the bias towards collaboration within countries did decrease.²⁹⁸ Hoekman *et al.* concluded that the observed decreasing effect of national borders may be an indication towards an ongoing integration process of regions into the ERA. However, innovative collaborations are still sensitive to physical

²⁹⁶ This issue is also challenged in the empirical analysis in this thesis in chapter 4.

²⁹⁷ This issue is picked up as another spatial classification system is used in the empirical analyses of this study (refer to chapters 3, 4 and 5).

²⁹⁸ Their results are quite similar to the conclusions of Paci and Usai (2009).

distance. Finally, it should be noted that the high level of spatial aggregation in their study, i.e., NUTS1-2 regions, tends to eliminate variation in regional co-patenting activity and to enforce spatial autocorrelation.²⁹⁹ In view of this, the NUTS 1/2 level has been heavily criticized, e.g., in a recent study of Paci and Usai (2009, 672), who argued that

“[t]he NUTS2level, or higher, is commonly used in the regional analyses based on European data even though the phenomenon under examination [co-patenting] would deserve some attention at a more disaggregated territorial level.”

To take this critique seriously, research clustering and co-patenting activity will be analyzed at a more disaggregated level in the following empirical analyses in this study (see chapters 3 and 4).

Having reviewed studies in the co-inventor/co-patenting network tradition, it can finally be concluded that there exists a relatively small body of contributions to inter-regional co-patenting and core-periphery structures of research collaboration in a European context. An in-depth analysis of the structural dynamics of technology-specific inter-regional co-patenting networks is still missing. It is generally argued that Europe is determined by a meaningful dispersion of patenting activity and a significant dispersion and expansion of co-patenting activity, although the empirical evidence is rather weak. Regarding this meaningful deficit, the empirical analysis in this study will emphasize the structures and dynamics of inter-regional co-inventor networks and research collaborations between European regions in chapter 4. Besides a detailed analysis of foreign co-inventor activity (number, shares) at the national level (section 4.3.4), the empirical analysis places emphasis on inter-regional co-inventor networks at the TL3, TL2 and TL1 levels and on 43 technology fields (section 4.3.5).

²⁹⁹ Studies that make use of detailed co-patenting data are Maggioni *et al.* (2007), Kroll (2009), Maggioni and Uberti (2009), Christ (2009), Ponds *et al.* (2010) and Miguelez and Moreno (2010).

3. Innovative Places, Research Clustering and Co-Agglomeration in Europe

3.1. Analyzing Research Clustering in Europe

A first step towards a better understanding of research clustering is to measure the spatial distribution of researchers and patenting activity and to identify research clusters by means of a harmonized descriptive approach. Researchers in the regional economics and economic geography tradition have long since established the necessity to identify, analyze and explain regional disparities and spatial concentration; in this respect, they considered the identification and analysis of “core–periphery structures” as the central issue within the research agenda. However, Martin and Sunley (2003, 24) argued that

“[t]here is no agreed method for identifying and mapping clusters, either in terms of the key variables that should be measured or the procedures by which the geographical boundaries of clusters should be determined.”

Harris (1954), among others, proposed the so-called “market potential approach” (see also Schürmann and Talaat, 2002; Head and Mayer, 2004). This spatial concept aims at calculating an indicator of market potential at the regional level, taking into account the size of economic markets in the vicinity of the county corrected for the spatial distance to the market. Similarly, Keeble *et al.* (1982) constructed a “peripherality index” based on the European NUTS1 level. Copus (1999) calculated a similar index for 1,105 European regions at the NUTS3 level, which aims to explore core-periphery structures. Although industrial organization and production theories have already found their place in geographical economics, theories on research clustering, inventorship and innovation were missing a spatial dimension for a long time, as is the case with data-driven, quantitative empirical studies (Audretsch and Feldman, 1996, 1999; Acs *et al.*, 2002). Ratanawaraha and Polenske (2007), among others, gave a comprehensive overview of studies that center on regional disparities and the spatial concentration of innovation and disparities of research activities, which in a European context is a rather small listing. Further to this, Malecki (2010, 493) has recently pointed to the issue that,

“[a] paper on the geography of knowledge presupposes that knowledge is not uniformly but, rather, unevenly distributed across the landscape.”

Unfortunately, empirical studies that include the full population of European regions can be counted on the fingers of one hand. To conclude, the majority of empirical findings on European research clustering and inventorship location structures are based upon either (i) anecdotal evidence, (ii) qualitative (case studies) but not quantitative studies that are hard to generalize, (iii) a small sample size due to meaningful data constraints, (iv) a-spatial concepts that fail to incorporate geography, (v) growth regressions and convergence studies

that ignore country size and regional heterogeneity or (vi) biased samples of regions and/or countries that are not representative (Arbia, 2001; Brakman and van Marrewijk, 2008).

In the European context, the member states and their commission set the ambitious goal at the Lisbon 2000 European Council of becoming “*the most competitive and dynamic knowledge-based economy in the world, capable of sustainable economic growth with more and better jobs and greater social cohesion*” (European Commission, 2000).³⁰⁰ However, there is only weak empirical evidence from a small number of studies with respect to the distributional dynamics of research activity across European regions (Ciccone, 2002; Breschi and Lissoni, 2004). A few studies have pointed to core-periphery patterns of patenting activity and a much stronger clustering of patenting compared to high-tech manufacturing production (Breschi, 2000; Paci and Usai, 2000b; Caniëls, 2000). However, most studies have been organized at the national level. Breschi (2008), e.g., analyzed the structural set-up of Italian firms and their EPO patent applications by industry for the period 1990-1998.

With regard to the European case, and especially focusing on the regions that form the European Research Area, several studies highlight that European nation states converge in terms of GDP per capita, whereas European regions at the level of member states by and large do the opposite (Frenken and Hoekman, 2006; Paas and Schlitte, 2007)(see also section 5.3). This stylized fact seems to support the argument that regional-level processes are much more complex and heterogenous and may be better reflected by evolutionary economics and economic geography approaches and theories (Arbia, 2001; Paci and Usai, 2009). Although several studies have analyzed the spatial dynamics of GDP per capita and gross value added (GVA), the spatial structure of inventorship and research activity in Europe, and especially its structural change within the last 30 years, represents crucial unanswered research questions and offers room for many hypotheses.

The following analysis uses regional data on patent applications at the European Patent Office (EPO) and compares the structures and trends of research clustering and patenting activities across 819 European regions and 27 countries. Furthermore, differently from previous studies on the European case (see chapter 2, section 2.2), the whole population of European regions and a comprehensive range of different technology field aggregates occupy center stage. In comparison with other studies, the following cluster analysis does not solely explore selected high-technology fields or single industries (see also Scherngell, 2007; LeSage *et al.*, 2007; Paci and Usai, 2009).

With regard to the current empirical state of research, the quantitative analysis in section 3.4 tries to find empirical evidence for the following research questions: (i) Is European research activity in terms of EPO patenting activity highly concentrated and thus unequally distributed across the European landscape of regions (and in the European Research Area)? (ii) Do high-technology fields show an equal distribution between European regions or can different patterns of spatial concentration and inventorship agglomeration be observed by technology field? (iii) Is Europe characterized by an increasing or decreasing share of specialized regions by means of revealed technological advantage measures? (iv) Finally,

³⁰⁰ See European Commission (2011c). The targets were renewed in the communication from the Commission Europe “*2020 A strategy for smart, sustainable and inclusive growth*”(COM(2010) 2020 final) from March 2010.

can significant dispersion and thus a decreasing skewness of EPO patenting be observed within the last two decades? The analysis is related to the different theories on core-periphery structures reviewed in chapter 2, section 2.1, and contributes to the empirical approach presented in section 2.2.2.

Another serious issue in empirical cluster research concerns the identification of research clustering and the measure of relative cluster strength (section 3.5) by technology field aggregate. As is frequently argued, a main challenge in the cluster literature represents the statistical identification of technology field-specific clustering of research activity, within and across the group of regions that represents the European research landscape. Moreover, the computation of a comparable cluster index is essential as the population covers more than 800 TL3 regions (OECD, 2003, 2006).

As theory and empirical research bring forward different arguments as to why the agglomeration of technology and industries is fruitful for economic development, as discussed in chapter 2 (sections 2.1 and 2.2), section 3.5 foregrounds the empirical analysis of research clustering at the regional level in the enlarged European Union (i.e., the European Research Area). Thus, recent debates (specialization-diversity, local-global knowledge transfer) are considered as a chance to analyze technology-specific research clustering in Europe. An established literature on specialized/diversified cities and regions and several case studies on existing innovation clusters already exist. However, a harmonized research clustering study, covering all the regions of the enlarged European Union and the ERA at the OECD TL3 level, using a composite index based on EPO patent data and analyzing 50 (established) technology fields, does not exist. Therefore, the study gives priority to the development and application of a comparable measure that covers a large fraction of technology fields and the full population of European regions. Although case studies provide detailed relational data and region- and cluster-specific information, they are said to suffer from a serious disadvantage. As has been argued by Griliches (1979, 91),

“[c]ase studies are [...] very data- and time-expensive and are always subject to attacks as not being representative, since they tend to concentrate on prominent and successful innovations and fields.”

Identifying and measuring clustering strength is an especially serious issue when the spatial sample contains a large number of observations: in this study, all 819 TL3 regions of the EU-25 countries, Switzerland and Norway. Additionally, the modifiable area unit problem (MAUP), based upon zonation and aggregation, is a frequently arising issue that might influence the results (see chapter 4, section 4.2.1.2).³⁰¹

Furthermore, a comparable and generalized descriptive approach is needed. Following Litzenberger and Sternberg (2006) and Litzenberger (2007), a low hierarchical concept of clustering - and thus a rather general approach - represents the so-called industrial

³⁰¹ Ecological bias is documented as two separate effects of MAUP that occur during the analysis of regional data (Openshaw, 1984; Anselin, 1988a). First, the “scale effect” by MAUP represents variation in statistical results regarding different levels of aggregation. That being the case, statistical association between variables essentially depends on the size of regions. In general, correlations between observations increase with regions’ size. Second, the “zonation effect” describes variation in correlation statistics caused by the (re-)grouping of data into different regions at the same scale, i.e., spatial boundaries (Anselin, 1988a; ESRI, 2010).

or regional cluster, where economic activities coincide in close proximity, i.e., the agents are close to each other (Litzenberger and Sternberg, 2006; Litzenberger, 2007). However, this concept does not contain formal and informal linkages as a necessary condition. The following analysis is restricted to the very basic definition, as it permits (i) a standardized measure and (ii) a consistent comparison across the entire population of European regions.

A further advancement of such a cluster definition towards a higher hierarchical level would be possible through the incorporation of formal and informal relationships and linkages (Breschi and Lissoni, 2009), the consideration of formal and informal institutions (i.e., norms, conventions) (Dobler, 2009), and organized co-operation between agents, which can improve innovative potentialities and support activities of individuals. Consequently, the region would be considered a regional innovation network, and, in view of this, the empirical analysis should use relational data (TerWal and Boschma, 2009; Hoekman *et al.*, 2009, 2010; Christ, 2009).

In comparison with the aforementioned concepts, the highest hierarchical level of regional development represents the regional innovation system approach, which places emphasis on innovation capabilities and absorptive capacity. In this approach, the competitiveness of a region is dependent on several factors, e.g., institutions, the entrepreneurial population, the inter- and intra-regional network structure, technology and industry paths and STI policy, among others.³⁰² However, as Doloreux and Parto (2005, 145) have argued,

“[t]he diversity of the units of analysis employed in studies of regional innovation systems presents a major problem in developing a unified conceptual framework towards a construct of “the region” as a theoretical object of study. As a result, this prompts renewed confusion vis-à-vis not only the application and assessment of innovation system at the regional level (whatever defined), but also its territorial boundaries.”

The quantitative analysis in this chapter is restricted to a “top-down” approach as has been similarly proposed by Litzenberger and Sternberg (2006) and Litzenberger (2007). Consequently, EPO patent applications are the central indicator for the subsequent empirical analysis.

The aim of the research clustering study is to challenge several research questions related to the spatial clustering of European research activity: (i) Exploring in which European regions significant research clustering occurs; therefore, the analysis covers different technology fields for the periods 1990-1994 and 2000-2004; (ii) identifying the numbers and structures of research clusters in the ERA, by country and technology field, and their dynamics in the course of time; (iii) answering the question of whether urban and metropolitan regions are much more diversified in research clustering than rural regions; i.e., analyzing the number of strong research clusters for the entire population of 819 European regions.³⁰³ The cluster study is related to the different theoretical concepts on core-periphery structures reviewed in chapter 2, section 2.1, and contributes to the empirical approaches presented in sections 2.2.2 and 2.2.4.

³⁰² Refer to Cooke *et al.* (1997), Cooke (2001), Doloreux and Parto (2005) and Cooke (2008).

³⁰³ This is what we would expect from the literature review. In order to challenge this research question, the identified structure of region-specific research clustering will be related to the settlement type.

The following Box 3.1 summarizes the main characteristics of patent applications, especially those at the EPO.³⁰⁴

Box 3.1: Patent Applications

Patent offices perform several important tasks and official activities. They administer patent applications, examine claims and grant a temporary monopoly. However, if a patent protection is only reached in, e.g., Austria and Italy, the technology can still be used freely by competitors in the UK, in Portugal, Spain, France, among others. If an international coverage is intended by the applicant(s) more than one national patent office has to be approached (Frietsch and Schmoch, 2006; Fraunhofer, 2009; European Patent Office, 2011e).

For the statistical analysis of patent data, researchers have to be aware of the so-called “home advantage” or “home bias.” There usually exists a higher probability that a national applicant files a patent at her (his) national patent office compared to foreign applicants. US applicants, e.g., have this home advantage at the United States Patent and Trademark Office (USPTO) whereas Japanese applicants show this home bias at the Japanese Patent Office (JPO); similarly, German applicants show a strong tendency to file patents at the German Patent and Trademark Office (DPMA). In opposition, applicants from small countries usually try to file in larger foreign countries or at international patent offices as they suffer from small home markets (Frietsch and Schmoch, 2006; Legler and Krawczyk, 2006).

Compared to national patent applications, an application at the EPO shows remarkable advantages. First of all, the application can be made in any of the three official languages of the EPO (i.e., English, French, German). There exists only one central examination process and granting decision, although protection in several countries is intended. Nevertheless, at the end of the process, national (translated) patent documents are required. In the case of entering the national phase, translations of the documents are necessary and the annual (national) fees have to be paid. In view of this, usually not all countries are selected for the realization of patent protection (Scherngell, 2007; Fraunhofer, 2009).

To conclude, it is difficult to compare patent applications of the same invention at different patent offices (e.g., USPTO, EPO, JPO, DPMA). There are also several considerable differences regarding reliability and validity of the collected data (i.e., data on applicant, inventor). Varying emphasis is placed on the correctness of collecting data. Information has differing relevance to patent offices. The USPTO, e.g., is an inventor-oriented system; the EPO, in comparison, is an applicant-oriented system. In the case of the EPO, the collected inventor (or applicant) information is considered to represent a reliable source of information (1977 - today) (Scherngell, 2007; Fraunhofer, 2009).

The remainder of this chapter is as follows. Section 3.2 discusses the advantages and drawbacks of patent statistics, especially related to EPO patent data. Section 3.3 then describes the underlying database structure and the data extraction process from a regional and technological point of view. Section 3.4 analyzes the global distribution of research activity, i.e., patenting activity, in the European Research Area (ERA). Section 3.4.1 reports the empirical research methodology of the study and section 3.4.2 highlights the empirical findings with respect to the distribution/concentration of EPO patenting activity across the European regions. Afterwards, section 3.5 places special emphasis on

³⁰⁴ A detailed overview of the patent application process is presented in Scherngell (2007) and European Patent Office (2011c).

the identification of research clusters and innovative places in Europe for predefined technology field aggregates. Section 3.5.1 introduces the cluster measurement literature and the “specialization-diversity debate,” which has already been addressed in section 3.4 and theoretically discussed in chapter 2. Section 3.5.2 presents the research methodology of the study. Section 3.5.3 briefly summarizes the used regional typology, spatial classification and IPC-TF concordance. Afterwards, section 3.5.4 highlights the empirical results and gives a detailed overview of research clustering across European regions. Section 3.5.5 places emphasis on the analysis of co-agglomeration and technological relatedness of research clusters in Europe. Finally, section 3.5.6 centers research clustering in urban areas and capital regions of Europe.

3.2. Patent Data as Indicators in Empirical Analysis

3.2.1. Advantages of Patent Data as Indicators

As is frequently discussed in the literature, the concept of measuring R&D activity (input approach) is closely related to research and innovation activities in the manufacturing industry, which leads to a general bias towards the manufacturing sector (Legler *et al.*, 2006). Measuring R&D distribution across companies, regions and sectors, and the analysis of the internationalization of R&D is extremely difficult; in particular if the analysis is aimed at a very detailed technological and regional level at the same time. With regard to international studies at the level of firms and regions, severe issues and challenges are obviously existent, i.e., data unavailability and biased samples. Therefore, data on R&D expenditures can be substituted by output oriented indicators such as patent statistics and data on scientific publications (Frietsch and Schmoch, 2006; Legler *et al.*, 2006; Belitz *et al.*, 2006).³⁰⁵ The subsequent Box 3.2 offers a short summary of the European Patent Convention (EPC) and the European Patent Office (EPO).³⁰⁶

The exploration and detailed analysis of information included in patent documents is considered to be one of the most established, appropriate, directly available and historically reliable instruments for exploring innovative activity (Griliches, 1990; Patel and Pavitt, 1997; Malecki, 2010, among others). No other STI-indicator can be traced back over such a comparatively long time period as patent applications and the information included in granted patents (Griliches, 1981, 1992; Jaffe, 1989; Jaffe *et al.*, 1993). According to Griliches (1990, 1661), patent data are an essential source in economic research, as

“[i]n this desert of data, patent statistics loom up as a mirage of wonderful plenitude and objectivity.”

From a legal perspective, patent applications at the EPO have to satisfy at least three essential criteria, (i) inventive step, (ii) novelty and (iii) industrial applicability (Griliches,

³⁰⁵ See also Guellec and van Pottelsberghe de la Potterie (2001), Greif (2001), Scherngell (2007), Hoekman *et al.* (2010) and Ponds *et al.* (2010).

³⁰⁶ For further details on EPC contracting states and their date of accession see European Patent Office (2011a), European Patent Office (2011d) and European Patent Office (2011e). Refer also to DPMA (2011) for a general overview and comparison of trade marks, patents, designs, topographies and utility models.

1990; Maurseth and Verspagen, 2002; Frietsch and Schmoch, 2006). Patents offer, from a legal perspective, an exclusive right of commercial application of special pieces and recombination of economically useful knowledge to the applicant for securing a quasi monopolistic revenue; however, the quasi monopolistic position is of a temporary nature.³⁰⁷ It is argued that the majority of technological inventions will enter national or international markets as an economically useful product or process. According to this thinking, patents can be interpreted as an input (or throughput) indicator; they represent potential market activities of companies (firm level), sectors (industry level) and countries (national level). In this respect, patents can be seen as a proxy for potential future competitiveness (Frietsch and Schmoch, 2006; Belitz *et al.*, 2006; Frietsch and Jung, 2009). Especially in high-technology fields, patent data can be used as an indicator of present and future competitiveness of companies, sectors, or even nation states (Acs, 2002; Frietsch and Schmoch, 2006; Scherngell, 2007).³⁰⁸ Belitz *et al.* (2006, 52) argued that patent applications indicate the output of corporate research with a “demonstrated market potential.” The information in patent documents can be disaggregated to low spatial levels, e.g., cities, counties, districts, provinces, regions, and the information on inventorship can be allocated to individual economic units (individuals, firms) and larger aggregates. The information is also precise and accurate by means of an identification of the timing of the invention (priority date, date of publication, date of granting) (Griliches, 1990; Maurseth and Verspagen, 2002; Belitz *et al.*, 2006). Griliches justified the application of patent data in the empirical analysis due to their high correlation with business R&D activities. Thus, Griliches (1990, 1702) concluded that

“[i]n the absence of detailed R&D data, the much more plentiful patent data can be used instead as an indicator of both, inventive input and output.[...] Nothing else even comes close in the quantity of available data, accessibility, and the potential industrial, organizational, and technological detail.”

Patent applications are strongly correlated with business sector R&D activities. Keller *et al.* (2004), among others, have shown that German R&D intensities are highly correlated with DPMA patent densities ($R^2 = 0.51$) with a lag of one year. Moreover, they calculated a much higher correlation coefficient between the share of R&D intensive industries and patent densities ($R^2 = 0.81$). In view of this, it can be plausibly assumed that any patent application (at the EPO) follows substantial investments in research and development (Frietsch and Schmoch, 2006; Belitz *et al.*, 2006; Fraunhofer, 2009).³⁰⁹ With respect to analyses of international co-operation in R&D, co-patenting data represent an extremely superior database, as they allow the analysis of codified (and tacit) knowledge flows between agents, companies, regions, countries and sectors in the course of time. Frietsch and Schmoch (2006, 101) labeled this “*an assessment of the globalisation of applied research and development.*” Further to this, patent data allow a detailed analysis of inter-regional co-operation (co-patenting) if researchers from different research sites (of one or more companies) are jointly involved. Quite the contrary, data on R&D expenditures do in

³⁰⁷ For details regarding the European Patent Convention (EPC1973) see European Patent Office (2011d). For revision see European Patent Office (2011e).

³⁰⁸ See also Patuelli *et al.* (2010) and Malecki (2010).

³⁰⁹ For additional contributions refer to Grupp (1998), Feldman (2000), Greif (2001) and Scherngell (2007).

most cases not allow spatial disaggregation; it is especially not possible to find data for the entire population of the 819 European regions. Moreover, the analysis of patent applications and granted patents on the basis of inventors' location instead of applicants' location is superior because international co-operations generally suffer from the fact that not all participants and team members are necessarily listed as applicants in the patent application. In opposition, all inventors have to be named according to strict legal requirements (Frietsch and Schmoch, 2006).³¹⁰ This is a crucial aspect with respect to co-patenting analyses (see chapter 4).

Box 3.2: The European Patent Convention and the EPO

The European Patent Convention (EPC) was signed in the year 1973 and entered into force in the year 1977. The EPC provides the official and legal framework for the granting process of European patents, via a single, harmonized procedure within all EPC member countries. Based upon the EPC, the European Patent Office (EPO) was implemented as a “regional” office, which examines patent applications on behalf of EPC member countries. The EPC is a multilateral treaty instituting the European Patent Organization. It provides an independent legal system according to which European patents are granted. By filing an EPO patent application by means of a single procedure in one of the official languages (English, French, German), it is possible for agents to secure patent rights in all countries that have signed the EPC. Thus, the EPO grants patents, which are valid in all its member states in which the applicant has validated his rights. Within three months of the granting process of a European patent application, the agent has to complete and submit various formalities. Validation of the application requires the full translations of all documents into the respective national languages and the payment of national fees. Granted EPO patents then have the same legal rights as granted national patents. However, on the national stage, European patents are subject to national laws (Scherngell, 2007; Fraunhofer, 2009; European Patent Office, 2011a,d,e).

As of January 2008 there are 34 EPC member countries and extension agreements exist with five additional countries which offers agents the possibility to extend their rights to those countries upon request. EPC member countries are: Austria, Albania, Belgium, Bulgaria, Croatia, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Liechtenstein, Lithuania, Luxembourg, the Former Yugoslav Republic of Macedonia, Malta, Monaco, the Netherlands, Norway, Poland, Portugal, Romania, San Marino, Serbia, the Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey and the United Kingdom (Scherngell, 2007; Fraunhofer, 2009; European Patent Office, 2011a,d,e).

More generally, EPO patent applications can originate from (i) direct EPO filings without a priority claim (i.e., first filing), (ii) extensions of an earlier national patent application (within 12 months of first national filing), or (iii) from international patent applications using the WIPO-PCT procedure. The first two categories are known as the “Euro-direct” approach, while the third one is known as the so-called “Euro-PCT” approach. In addition, the Patent Co-operation Treaty (PCT) allows inventors to file “pre-applications” to offices world-wide at relatively low costs. The PCT is organized by the World Intellectual Property Organization (WIPO) (Scherngell, 2007; Fraunhofer, 2009; European Patent Office, 2011e).

³¹⁰ Therefore, the analysis in the following chapters is restricted to the inventor location.

Finally, patent data can be used to empirically challenge research clustering, knowledge stocks and technological specialization profiles at the level of researchers, companies, regions, sectors and countries. This transforms patent data to a superior indicator for technological competence and research excellence (Griliches, 1990; Romer, 1990b; Porter and Stern, 2000). According to the above presented meaningful advantages and rational arguments, patent data are considered to represent a well-established indicator for research and development activity (Belitz et al., 2006; Scherngell, 2007; Maggioni et al., 2007).³¹¹

3.2.2. Drawbacks and Technical Issues of Patent Data

However, it is worth noting that researchers have to take into account many issues and drawbacks intrinsic to patent statistics, patent raw data and the specific patenting system (e.g., the European Patent Office, USPTO, JPO). There is accepted criticism in the literature that patent data only represent a very imperfect measure of innovative activity; the measures suffer from several limitations, shortcomings and issues related to patent data peculiarities (Griliches, 1990, 1992b,a).³¹²

First, patentable inventions represent only a subset of all possible R&D outcomes (Fischer *et al.*, 2005; Scherngell, 2007). Patents only give an indication of patented and patentable results from research activity (Griliches, 1990; Feldman, 2000; Belitz *et al.*, 2006). Accordingly, patent data do not represent the full range of the innovation output, whereas R&D expenditures (i.e., input indicator) normally include all activities from basic research onwards. However, R&D data and patent statistics do not cover process innovations, creative imitation and reverse engineering (Capello, 2007, 196). Furthermore, a crucial disadvantage is that patent data generally suffer from a time lag between the R&D activity, the patent application and the publication in databases. Additionally, from a legal perspective, various reasons exist for not applying for patent protection besides the reasons related to the costs. Patenting is in most cases a strategic decision of agents; thus, not all generated inventions are patented by agents even though the inventions would satisfy the official requirement for patentability (Fischer *et al.*, 2005). Therefore, patent protection is indeed not the only way to reap market success from economically useful pieces of knowledge. That being the case, agents and firms may apply protection strategies like secrecy, rapid product launching or design and product complexity, which can supplement or replace patent protection (Griliches, 1992c; Bessen and Hunt, 2007; Hoekman *et al.*, 2009).³¹³ Moreover, many scientific results devoid of immediate applicability and little incremental technological improvements might not be patentable (Fischer *et al.*, 2005). Concerning this matter, researchers generally take for granted that the incentives for the decision to apply for a patent are highly correlated with expectations about market potentialities

³¹¹ See also Fischer *et al.* (2005), Scherngell (2007), Fraunhofer (2009), Patuelli *et al.* (2010) and Malecki (2010).

³¹² Refer also to Griliches (1981), Archibugi and Pianta (1992), Guellec and van Pottelsberghe de la Potterie (2001), Blind *et al.* (2006), Scherngell (2007), Hoekman *et al.* (2009), Patuelli *et al.* (2010), Malecki (2010).

³¹³ Refer also to Belitz *et al.* (2006), Frietsch and Schmoch (2006), Scherngell (2007) and Fraunhofer (2009).

of new ideas and technological knowledge.³¹⁴ In addition, the distribution of the patent value is highly skewed (Guellec and van Pottelsberghe de la Potterie, 2000; Brusoni *et al.*, 2006; van Zeebroeck, 2007).³¹⁵ Furthermore, technology fields and sectors exhibit different patenting propensities (Harhoff *et al.*, 2003; Foray, 2004; Frietsch and Schmoch, 2006).³¹⁶ Moreover, these propensities are assumed to be dynamic and thus change in the course of time (Belitz *et al.*, 2006; Frietsch and Schmoch, 2006). Additionally, patent documents are considered to contain mainly codified knowledge (Malecki, 2010).³¹⁷ Accordingly, tacit knowledge diffusion cannot be addressed in a meaningful way. Finally, the construction of a patent database (i.e., the identification and consolidation of researchers, companies, regions, countries and technology fields) represents a time-consuming process that requires complex methods and computing power (Maraut *et al.*, 2008).

Despite the presented drawbacks and disadvantages of patent data, their usage represents, however, a unique and excellent resource for analyzing innovative performance, research activity and regional technological potentialities (Griliches, 1990; Maurseth and Verspagen, 2002; Henderson *et al.*, 2005).³¹⁸ No other STI-indicator has such a closeness to encompass innovation-related tasks and detailed spatial information (Griliches, 1990; Keller *et al.*, 2004; OECD, 2008). In this respect, patent data can be used in different research fields, e.g., studies on economic growth, on the internationalization of R&D, on technological change and industrial performance, and studies on the dynamics at the level of firms and regions. In conclusion, Griliches (1990, 1702) has argued that

“[i]n spite of all the difficulties, patents statistics remain a unique resource for the analysis of the process of technical change. Nothing else comes close in the quantity of available data, accessibility, and the potential industrial, organizational, and technological detail.”

The approaches and empirical analyses in this study follow this way of reasoning and make use of data on European patent applications between 1977 and 2007 as a proxy variable for R&D activity/output as has been proposed in other studies (Maggioni *et al.*, 2007; Paci and Usai, 2009; Maggioni and Uberti, 2009).

3.3. The Database: Patent Data, Regions and Research Activity

3.3.1. Overview and General Information

In order to challenge the presented hypotheses and research questions, a purely quantitative approach is applied that makes use of EPO patent applications at the level of OECD

³¹⁴ Mansfield (1986), e.g., could show that 66-87% of all patentable inventions indeed were protected by patents. See also Greif (2001).

³¹⁵ For an overview refer to Harhoff *et al.* (2003), Brusoni *et al.* (2006), Scherngell (2007), TerWal and Boschma (2009), van Zeebroeck *et al.* (2009) and Degner and Streb (2010).

³¹⁶ See also OECD (2007c), OECD (2008), OECD (2009c) and Malecki (2010).

³¹⁷ Tacit vs. codified knowledge is a distinction of major importance that goes back to Nonaka and Takeuchi (1995) (see also chapter 2, section 2.1.7.2).

³¹⁸ See also Mansfield (1986) and Archibugi and Pianta (1992).

TL3 regions (OECD, 2003, 2006). Additional descriptions and information regarding the constructed spatial patent database are presented in detail in the appendix (see tables B.2, B.3 and B.4, appendix). The empirical analyses in this chapter are based upon OECD RegPAT data (January 2009) (Maraut *et al.*, 2008; OECD, 2009e).

The OECD raw data have been implemented into a MySQL database as presented in the appendix, table B.2. Inventor locations are assigned to European regions (TL3, TL2, TL1) by identification of the registered inventor address. In this respect, the study follows the methodological propositions and suggestions of, e.g., Maurseth and Verspagen (2002), Balconi *et al.* (2004) and Paci and Usai (2009), meaning that the inventor location is preferred. Section 3.4 approaches the distribution of research activity, i.e., patent applications at the EPO, for the period 1977-2004 by explicitly measuring the structural dynamics of patenting across 819 European regions for 43 technology fields and 6 high-technology fields (laser, aviation, computer and automated business equipment, micro-organism and genetic engineering, communication technology and semiconductors).³¹⁹ Thus, patent applications are linked to regions according to the OECD TL3 classification at a yearly base between 1977 and 2007 (full coverage).³²⁰

The analysis is focusing on the distribution and structural dynamics of European inventorship activity, i.e., patenting activity, across European regions, which consequentially prefers EPO to PCT (triadic) patent applications, due to an explicitly defined macro level (the European continent and the ERA). Thus, the population of the 819 European regions should minimize potential spatial bias.³²¹ Furthermore, this study uses patent applications, not granted patents. Patent applications are published earlier than grants and reflect technological competitiveness in a more appropriate way; moreover, availability of these data is better (Fraunhofer, 2009).³²²

The analysis is restricted to the years 1977-2004 for patent density measures and 1988-2004 for population corrected disparity measures.³²³ Patent shares, absolute patent numbers, patent densities (patents per million population and per square kilometer) are calculated. Population data have been collected according to the established NUTS2003 classification for the period 1988 until 2005 at the NUTS3 level (European Commission, 2007c; OECD,

³¹⁹ The study uses full time series instead of random years because the latter might not be representative for the overall evolution of inequality in EPO patenting.

³²⁰ However, the subsequent analyses center the period 1980-2004.

³²¹ European regions have a higher propensity to protect new knowledge in terms of EPO patent applications. EPO patent filings are used and analyzed in this study as the EPO is a trans-national authority; it is expected that the home advantage is somehow balanced due to this choice (Fraunhofer, 2009).

³²² According to Fraunhofer (2009), only those EPO applications are covered by publicly available databases, which are maintained until the publication, 18 months after priority filing. Applications that are withdrawn or rejected are excluded from public patent databases (e.g., RegPAT). The share of withdrawn or rejected EPO patent filings may amount to nearly 50% of the published filings at the EPO.

³²³ In RegPAT (January 2009), EPO filings are completely published only for the priority years up to 2006/2007 due to a publication phase of 18 months. As more than 60% of the applications enter the EPO via the PCT-route (see Box 3.2) and the fact that entering the regional phase at the EPO might be postponed up to 30 months, the priority years 2005 and 2006 are incomplete.

2007b).³²⁴ In a second step, these data have been transformed to more “functional” and statistically more appropriate regions according to the OECD TL3 classification (OECD, 2003, 2006). Table B.3 in the appendix summarizes the regional structure and typology of the database in detail.

The agents are in general inventors, whose postal address, which is their work place location (e.g., R&D subsidiaries), can be used to determine their major location in geographic space (Verspagen and Duysters, 2004; Criscuolo and Verspagen, 2008; Fornahl and Brenner, 2009).³²⁵ Based on inventor address information, every patent application is assigned to European TL3 regions by fractional counting. Fractional counting means that each inventor, who is located in a certain region, gets an identical fraction of the patent application. Accordingly, if a patent has, e.g., three inventors from three different spatial units, each spatial unit gets a share of one third (regional inventor share).³²⁶

3.3.2. The Spatial Classification System

However, a serious problem in geographical economics and the geography of innovation literature is the definition and usage of spatial units. At least, two entities are needed that are in general called a place or a region. However, the difficulty with this concept is rather unnoticed. It seems that people have to suffer from the same theoretical vagueness with the “concept of the region” as is the case with the “concept of the industry,” which essentially depends on statistical classifications and conventions. Both concepts resemble some intermediate and flexible levels of aggregation and are thus not easy to define. The aggregation of places to a region depends essentially and ultimately on the underlying research question and empirical application. The definition of borders mainly depends on the existence of spatial dependence, which could be an indication for functional regions (see appendix, tables B.2 and B.3). Accordingly, the aggregation issue is highly fuzzy and crucial in applied research. The TL3 classification could be roughly interpreted as more homogenous labor market regions. Admittedly, the usage of TL3 units simplifies the issue of functional spatial boundaries of regional systems.³²⁷

³²⁴ The Nomenclature of Statistical Territorial Units (NUTS) is a hierarchical system for dividing up the economic territory of the EU; see European Commission (2011k).

³²⁵ As inventors tend to be spatially dispersed with some distance to the applicant’s location, the inventor location is focused. Taking the applicant as the focal point would lead to a substantial bias, as large firms maintain several R&D units, while all patents are applied for from the firm’s headquarter (TerWal and Boschma, 2009; Miguelez and Moreno, 2010; Patuelli *et al.*, 2010).

³²⁶ In this respect, the 819 European regions add up to 904.917,129 EPO patent applications (fractional counting by priority date) and 1.616.257 inventor IDs (full counting by priority date and year) within the period 1977-2004.

³²⁷ The extracted patent data from OECD RegPAT database (January 2009) are regionalized according to the NUTS2003 classification (Maraut *et al.*, 2008) to 1259 NUTS3 regions; afterwards, they are aggregated, according to the OECD TL3 classification, to larger functional areas, e.g., 97 German spatial planning regions (OECD, 2003; Greif and Schmiedl, 2006; Freund, 2008). TL3 units are interpreted being counties or districts with kind of functional boundaries, although the regional size of the units vary to some extent. Therefore, TL3 units are taken as the general geographical classification concept, which also simplifies comparison with other studies and is much more related to functional units. Other studies aggregate German counties to 112 local labor marker regions (LLR), e.g., Eckey *et al.* (2007) and Dauth (2010). Similarly, Italian regions are aggregated to 686 local labor systems

The TL3 level is the most detailed, harmonized and statistically useful regionalization level available for the OECD and Europe (OECD, 2003, 2006). In this respect, the underlying database extraction in this chapter (and the relational data extractions in the following chapters) focuses on 819 (EU-25+CH+NO) TL3 units as highlighted in table B.3 (appendix).³²⁸ The full population of observations is formed by 774 TL3 regions of the EU-25 member states and Norway (19 TL3) and Switzerland (26 TL3). 651 units belong to the EU-15 and 123 belong to the NMS. Switzerland and Norway are included in the analysis in order to avoid black holes in the spatial structures; especially in the regional co-patenting network analysis in chapter 4.³²⁹

3.3.3. The IPC-Technology Field Concordance

From a technology field point of view, aggregation and matching of the International Patent Classification (IPC), which is included in every patent application, and larger technology field aggregates is accomplished in this thesis by utilization of the EC DG Research and FhG ISI-OST-SPRU IPC-technology field concordance of Schmoch *et al.* (2003). Although there exist alternative concordance tables for aggregating and matching patent classes with industries (Verspagen *et al.*, 1994), the ISI-SPRU-OST concordance represents one of the most recent approaches to this issue (Schmoch *et al.*, 2003). This concordance has been similarly implemented by, e.g., Paci and Usai (2009), Fornahl and Brenner (2009) and D'Agostino *et al.* (2010).³³⁰ Additionally, 6 established high-technology fields are analyzed for the period 1977-2004 according to a high-technology concordance table (EUROSTAT, 2009).

Box 3.3 offers a short overview of the IPC classification system that has been used to match IPC codes and technology field aggregates. A detailed TF-IPC concordance table is available in the appendix (see table B.4, appendix).

In the following analyses, EPO patent applications are linked to technology fields (see table B.4) in terms of full counting in order to compute the spatial distribution of research activities and to calculate the geographic concentration and disparities of patenting activity. If the patent document contains several IPC codes the unique counting method is applied. If a patent application contains five different IPC codes, which are included in

(LLS); however, 103 Italian regions are used, which include most commuting activities (de Dominicis *et al.*, 2007).

³²⁸ The 439 “Stadt-/Landkreise” in Germany (NUTS3) are aggregated to 97 so called “Raumordnungsregionen” (BBR, 2011), Dutch and Belgian NUTS3 units to the NUTS2 level (which is OECD TL3). Similarly, Greek islands and small units are aggregated to Greek NUTS2 units and solve several issues: (i) Several NUTS3 units are relatively small and numerous in comparison with other EU NUTS3 units. The application of, e.g., 439 German NUTS3 regions would increase the influence of German regions in the analysis significantly. (ii) Additionally, when using NUTS3 patent data, the existence of relatively small regional units may induce the issue of commuting of inventors between their place of residence and place of work and would thus induce a location bias.

³²⁹ However, new or potential member states are excluded, e.g., Croatia, Romania, Bulgaria and Liechtenstein, due to data constraints.

³³⁰ The ISI-SPRU-OST concordance is a joint project of the Fraunhofer ISI, Karlsruhe, Germany, the Observatoire des Sciences et des Techniques (OST), Paris, France and the SPRU, University of Sussex, Brighton, UK (Schmoch *et al.*, 2003).

five different technology fields at the same time, the patent is fully added to each of these five fields.³³¹ Accordingly, if a patent application contains several IPC codes of only one single technology field, then the patent is uniquely linked to the technology field by the first corresponding IPC code (unique but full counting). If a patent document corresponds to several technology field aggregates in terms of included IPC codes, the patent is uniquely linked to each technology field by factor one, multiplied with the fractional share of the local inventor. Thus, patents with many IPC codes have a higher propensity to be linked to more than one technology field. As a consequence, multiple counting is possible as a single IPC code can be included in several technology field aggregates (Schmoch *et al.*, 2003; Frietsch and Schmoch, 2006; Belitz *et al.*, 2006).³³²

Box 3.3: The International Patent Classification - IPC

The IPC is an international non-overlapping hierarchical classification system for patents that consists of eight sections (first level), 118 classes (second level), 628 subclasses (third level), 6.871 main groups (fourth level) and 57.324 subgroups (fifth level) to classify inventions claimed in the patent documents (IPC 8). The IPC divides technologies into eight general areas (sections) (European Patent Office, 2011b):

A: Human Necessities; B: Performing Operations, Transporting; C: Chemistry, Metallurgy; D: Textiles, Paper; E: Fixed Constructions; F: Mechanical Engineering, Lighting, Heating, Weapons; G: Physics; H: Electricity. Within these areas technology is divided and subdivided into a detailed level, which allows the subject matter of a patent specification to be very thoroughly classified.

Although there exist alternative concordance tables for aggregating and matching patent classes with industries (see, e.g., Verspagen *et al.*, 1994), the EC DG Research and FhG ISI-OST-SPRU IPC concordance of Schmoch *et al.* (2003) represents one of the most popular approaches.

3.4. Geographic Concentration and Regional Disparities of Research Activities

3.4.1. Measuring Geographic Concentration and Regional Disparities

3.4.1.1. Aggregate Distribution, Specialization and Disparity

As has been demonstrated within the empirical review, the statistical analysis of the entire population of 819 European regions with regard to technology fields and the TL3 level still represents a rather unexplored field of research. Therefore, the first and foremost objective of this study is to provide a pure quantitative approach and systematic analysis of the

³³¹ See Scherngell (2007), Paci and Usai (2009) and Fornahl and Brenner (2009) for similar methods.

³³² However, as the data for each technology field have been extracted and linked separately, patents are uniquely counted and technology fields cannot be simply aggregated. For larger technology fields, modified mySQL extraction queries have been executed to produce larger aggregates and to avoid biases from multiple-counting. It is essential to note that there exists no single and dominant patent counting method or matching mechanism. Further details on the constructed database are available the appendix.

spatial distribution of inventorship and research activity over time and space at the level of European regions. The analysis in this section challenges the hypotheses and research questions which have been proposed in section 3.1 (and in the introductory chapter, section 1.2). Therefore, the study introduces and discusses the descriptive methodology in the following.

The most common way to analyze and assess the applicability of inequality/disparity coefficients is by comparing the behavior of such indices with respect to several axioms. The axioms are theoretically derived as preferable properties of disparity measures (Cowell, 1995; Combes and Overman, 2004; Gallagher, 2008). Box 3.4 summarizes these generalized preferable axioms that disparity/inequality measures should fulfill (Cowell, 1995; Combes *et al.*, 2008; Jenkins and Kerm, 2009).³³³ An objection against the Gini is the difficulty of subgroup decomposition and subgroup consistency.³³⁴ Additionally, the Gini index measures the same inequality of economic activity, irrespective of the true spatial location of observations (clustering or not), meaning that spatial dependence and thus spatial autocorrelation (chapter 4, section 4.2) cannot be identified (Arbia, 2001; Anselin, 2007; Christ, 2009). However, given the wide popularity and the otherwise favorable properties of the Gini index, it will be applied in the following as the central measure for European patenting concentration. Accordingly, different Gini alternatives are computed at the aggregated European level (European TL3 regions).³³⁵

Box 3.4: Preferable Axioms of Inequality Measures

It is argued that the common way of analyzing and judging the applicability of inequality coefficients is by comparing the behavior of such indices with respect to several axioms that are theoretically derived as preferable properties of such measures: (i) scale independence, i.e., income homogeneity: multiplying incomes with an identical positive scalar will not change disparity, (ii) population homogeneity, i.e., population independence: replicating income several times will not change disparity, (iii) anonymity: personal characteristics, other than the income, will not determine the ordering principle, (iv) the transfer principle, i.e., the Pigou-Dalton condition: transfers from a richer to a poorer agent will reduce disparity (Kim, 1995; Maggioni, 2002; Combes *et al.*, 2008).

Just a few measures can satisfy the four axioms: the coefficient of variation, the Gini coefficient, the Atkinson class of measures, and the generalized entropy family of measures, with the Theil index being the prominent example (Cowell, 1995; Ratanawaraha and Polenske, 2007; Combes *et al.*, 2008).

Brakman *et al.* (2005) differentiate between regional specialization and concentration. Thus, concentration is generally issued in a similar manner compared to specialization. The main difference to specialization measures is that instead of a comparison of industrial

³³³ See also Amiti (1999), Paci and Usai (2000b), Keilbach (2000), Henderson (2003a), Aiginger and Pfaffermayr (2004), Midelfart-Knarvik *et al.* (2004) and Combes and Overman (2004).

³³⁴ This is an essential problem for EU-wide studies at the regional level that try to depict within- and between country differences in geographical distribution and inequality. Global inequality can result from nation-specific distribution characteristics, but also from significant differences between countries (Duro, 2004; Brühlhart and Traeger, 2005; Paas and Schlitte, 2007).

³³⁵ The issue of spatial interdependence and autocorrelation is addressed in chapter 4.

structures within a single region, concentration measures apply a comparison of regions' industrial structures across all regions involved (Amiti, 1999; Arbia, 2001; Jenkins and Kerm, 2009).³³⁶ Accordingly, industrial specialization of regions goes hand in hand with spatial concentration of industries as the two concepts reflect different approaches to the same statistical phenomenon (Combes and Overman, 2004; Ratanawaraha and Polenske, 2007).

Absolute specialization means that a small share of industries account for a large share of economic activity of a region under analysis. In contrast, absolute concentration is about whether a few regions tend to account for a large share of economic activity of an industry (Ratanawaraha and Polenske, 2007; Combes *et al.*, 2008). However, a much more complex analysis is the distributional measure with respect to all industries, technology fields and regions. The corresponding types of concentration and specialization are then expressed in relative terms (related to a reference region or industry). Relative concentration is about whether regions tend to account for a large share of economic activity of a certain industry or technology field relative to their average share in all other industries compared to a larger aggregate. Relative specialization is about whether industries tend to account for a large share of the economic activity of a region relative to the average share in the larger spatial aggregate (Krugman, 1991; Brakman *et al.*, 2005; Farhauer and Kröll, 2009).

From an empirical point of view, some cross-country studies (at the national level) tend to measure an increasing concentration and specialization of economic activity. In contrast, some regional studies at the level of the US MSA or European NUTS/TL3 units tend to measure the opposite development.³³⁷ According to Brakman *et al.* (2005, 29), specialization and concentration seem to diverge,

“[e]ven though they conceptually are each other's mirror image.”

It should be noted that the studies by and large differ with respect to aggregation levels and spatial classification systems that essentially determine the results. This represents the modifiable area unit problem. In view of these issues, spatial concentration measures are more difficult than expected. Combes *et al.* (2008, 255) argued that

“[g]eographers and economists alike have sought to develop indices that capture inequality across industries, time, and space. It will become readily apparent that the issue is more complex than it seems at first glance. Although some indices have become standard, the ideal index remains to be discovered.”

3.4.1.2. Skewness and Kurtosis

To get a first detailed picture, the features of the distributions of EPO patent applications and EPO inventors by technology field are computed and compared. In view of this, kurtosis and skewness are two statistical instruments for analyzing the distributional characteristics. Skewness and kurtosis show how the distribution of a variable deviates from

³³⁶ Central contributions are also Hoover (1936), Krugman (1992), Ellison and Glaeser (1997) and Combes *et al.* (2008).

³³⁷ See, e.g., Kim (1995), Midelfart-Knarvik and Steen (1999), Keilbach (2000), Combes and Overman (2004), Brakman *et al.* (2005), Scherngell (2007) and Fornahl and Brenner (2009).

a normal distribution. Skewness is the third central moment that measures the degree of symmetry of a probability distribution as presented in equation 3.4.1:

$$\nu = \frac{m^3(\mu)}{\sigma^3} = \frac{n}{(n-1)(n-2)} \sum \left(\frac{x_i - \bar{x}}{s} \right)^3 \quad (3.4.1)$$

If skewness is greater than zero, the distribution is skewed to the right, having more observations on the left. $m^3(\mu)$ is the third central moment and σ is the standard deviation. Kurtosis, on the other hand, is based on the fourth central moment, measuring the thinness of tails or peakedness of a probability distribution as presented in equation 3.4.2:

$$\xi = \frac{m^4(\mu)}{\sigma^4} - 3 = \left[\frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{x_i - \bar{x}}{s} \right)^4 \right] - \frac{3(n-1)^2}{(n-2)(n-3)} \quad (3.4.2)$$

with $m^4(\mu)$ being the fourth central moment. If the kurtosis parameter value of a random variable is less than three (or negative), the distribution has thicker tails and a lower peak compared to a normal distribution. By contrast, a kurtosis parameter value larger than three indicates a higher peak and thin tails. A normally distributed random variable should have skewness and kurtosis near zero (between zero and three respectively). Note that biased distributions at the regional level towards a few locations can also result from population differences (and thus spatially varying population densities) (Arbia, 2001; Maggioni, 2002).

3.4.1.3. The Herfindahl-Hirschman Index

Another well-known measure is the Herfindahl-Hirschman-Index (HHI). In this study, HHI centers the spatial concentration of inventorship activity across the 819 European regions (Caniëls, 1996; Fingleton *et al.*, 2007; Combes *et al.*, 2008).³³⁸ The HHI places the number of EPO patent applications x_{ij} of a region j in a technology field i in relation to the EPO patent application numbers of the spatial aggregate $\sum_j x_{ij}$, which represents the regional share $x_{ij}/\sum_j x_{ij}$. Summing up $x_{ij}/\sum_j x_{ij}$ and taking the root (α) then forms the HHI for each technology field i (equation 3.4.3) (Fornahl and Brenner, 2009).³³⁹

$$HHI_i = \left[\alpha^{-1} \sqrt{\sum_{j=1}^n \left(x_{ij} / \sum_{j=1}^n x_{ij} \right)^\alpha} \right] \quad (3.4.3)$$

³³⁸ For further information regarding inequality and concentration measures refer to Krugman (1991), Ellison and Glaeser (1997), Laursen (1998), Amiti (1999), Midelfart-Knarvik *et al.* (2002), Maggioni (2002), Aiginger and Pfaffermayr (2004), Combes and Overman (2004), Scherngell (2007), Ratanawaraha and Polenske (2007) and Farhauer and Kröll (2009).

³³⁹ It must be noted that HHI is sensitive to α with $\alpha = 2$ being the standard HHI parameter value. Thus, the sensitivity of the HHI measure increases with α . The HHI reports total inequality, if one single region holds all patent applications; in contrast, the HHI shows equal distribution, if all regions hold 1/819.

3.4.1.4. The Location Quotient and Relative Technological Advantage

The location quotient (LQ) is another influential measure of spatial specialization and is illustrated in equation 3.4.4 (Litzenberger, 2007; Gallagher, 2008; Jenkins and Kerm, 2009). LQ_{ij} expresses the importance of an industry or technology field i in region j under analysis, based on its relative share in the local or national economy (Maggioni, 2002).³⁴⁰ Innovation studies use the same descriptive approach for patent data analysis. This coefficient is labeled revealed technological advantage (RTA).

$$LQ_{ij} = \left[x_{ij} / \sum_{j=1}^n x_{ij} \right] / \left[\sum_{i=1}^m x_{ij} / \sum_{i=1}^m \sum_{j=1}^n x_{ij} \right] \quad (3.4.4)$$

x_{ij} is the activity in industry or technology field i in region j ; $\sum_j x_{ij}$ is the activity in industry or technology field i in the spatial aggregate of regions j ; $\sum_i \sum_j x_{ij}$ is total economic activity in the aggregate of regions and $\sum_i x_{ij}$ is total regional economic activity (all technology fields) in region j . Rearranging equation 3.4.4 leads to the classical relative specialization index, which is normally applied in employment studies (Overman et al., 2001; Henderson, 2003). Thus, a location quotient $LQ_{ij} < 1$ means that the economic activity in the industry or technology field is less present in the region under observation compared to the reference region (higher spatial aggregate). In contrast, $LQ_{ij} > 1$ illustrates a relative higher share of industry or technology field activity compared to the aggregate of regions (reference region). Alternatively, LQ_{ij} is alternatively labeled “Balassa index” or “Hoover-Balassa index” in studies of international trade, whereas the label “location quotient” is traditionally widely used in regional science and geographical economics (Krugman, 1992; Maggioni, 2002; Litzenberger, 2007).³⁴¹ The measure is one of relative specialization as it measures the spatial fraction of an industry or technology field in one region in comparison to the fraction of the aggregate of regions in the sample. Maggioni *et al.* (2007, 482) labeled this relation in an innovation context a “*traditional location quotient for high-tech patents.*” However, most studies apply this ratio under the term revealed technological advantage (RTA) (Frietsch and Schmoch, 2006; Polenske, 2007; Ratanawaraha and Polenske, 2007). Further to this, the indicator neither says anything about the absolute size of an industry or area nor about spatial concentration what Fingleton et al. (2007, 69) termed an “*omission of mass effects [by LQ].*” Thus, it is possible to obtain a high value of LQ (RTA) for small spatial units in the sample.³⁴²

³⁴⁰ Appropriate and commonly applied variables for this measure are industry employment, production and plant level data. It is essential to note that the coefficient can also be used for alternative STI data analyses, such as R&D employment and product innovations. In the end, however, the only trustable and direct measure for inventorship location patterns are patent applications. See also Hoover (1936), Caniels (1997), Amiti (1999) and Holmes and Stevens (2004).

³⁴¹ See also Maggioni *et al.* (2007), Dewhurst and McCann (2007), Fingleton *et al.* (2007) and Gallagher (2008).

³⁴² An easy way to make use of the Balassa index as an agglomeration index and indicator of spatial distribution is to calculate the standard deviation of LQ for each technology field or industry under analysis across cities, counties, districts or regions.

3.4.1.5. The Relative Technology Density

As the analysis is explicitly related to EPO patent data equation 3.4.4 is transformed into 3.4.5 in order to account for spatial population characteristics:

$$RTD_{ij} = \left[x_{ij} / \sum_{j=1}^n x_{ij} \right] / \left[pop_j / \sum_{j=1}^n pop_j \right] = s_{ij} / y_j \quad (3.4.5)$$

Accordingly, the study applies a comparison of the shares of EPO patent applications s_{ij} of regions j by technology field i and the regional shares of population y_j , which differs from the conventional Krugman approach (Krugman, 1991), which will be discussed in the next paragraph. In this respect, the regional shares of EPO patent applications s_{ij} of each of the 819 TL3 regions for a predefined sample of 51 technology field aggregates have to be calculated (Schmoch *et al.*, 2003). These shares have to be compared with the population shares y_j of the observations between 1980 and 2005; afterwards, yearly relative technology density indices (RTD) have to be computed for all 819 European TL3 regions. The RTD then represents the sort criterion with $RTD_{i1} < RTD_{i2} < \dots < RTD_{in}$ for additional technology field-specific Gini computations.³⁴³

3.4.1.6. The Locational Gini Coefficient

The obtained relative technology density (RTD) indices are used for calculating locational and spatial Gini coefficients. The traditional methodology commonly uses the Gini coefficient as a measure of inequality/disparity of income or wealth (Maggioni, 2002; Litzenger, 2007; Combes *et al.*, 2008).³⁴⁴ The Gini coefficient normally compares income distributions with population distributions at the micro level (households, workers, other individuals). The concept uses pairwise comparison of all observations. The standard Gini, G_{ST} , is then a normalization (division by 2) of the relative mean difference from the arithmetic mean of all observation pairs (interval $[0, 1]$). The Gini coefficient is defined mathematically based on the Lorenz curve concept (see figure 3.1). It represents the ratio of the area that lies between the line of equality and the Lorenz curve over the total area under the line of equality. Low Gini coefficients indicate more equal distributions, with $G_{ST} = 0$ corresponding to complete equality; the bisecting line in the graph then corresponds to the Lorenz curve. However, higher Gini coefficients represent a more unequal distribution, with $G_{ST} = 1$ corresponding to complete inequality (maximum concentration surface, δ). To be computed validly, no negative (regional) income can be distributed. If the Gini coefficient is being used to describe household income inequality (which is the

³⁴³ This calculation is identical to calculations that make use of calculated patent intensities (LQ with the absolute number of patents in the numerator and the absolute number of population in the denominator).

³⁴⁴ Generally, the Gini coefficient is a measure of statistical dispersion, developed by the Italian statistician Corrado Gini (Gini, 1921). For an overview and application to German subgroup income inequality see, e.g., Rukwid (2007) and Hagemann and Rukwid (2007). For further aspects refer to Gallagher (2008) and Jenkins and Kerm (2009).

common empirical case), then no observation can have a negative income (Combes *et al.*, 2008).³⁴⁵

Regarding regional disparities, economic activity of regions is unequally distributed when the largest share of activity is located in only a few regions (assumption of homogeneous observations with $1/n$ weight). One can also think of technology fields or industries being spatially concentrated if the majority of specific activities takes place in only a few regions, compared to the reference distribution (still the case of unweighted observations), which means that both distributions can vary tremendously as shown by the deviation of the Lorenz curve from the bisecting line (45-degree line) in figure 3.1. More generally, the Gini coefficient relates the distribution of a selected economic activity, ξ , to an average or superior distribution of another variable, ζ , that represents the reference distribution (which is in most cases an interval of identical size with $1/n$). The conventional Gini coefficient is calculated according to equation 3.4.6, with n being the number of regions in the sample, x being the parameter value of the economic activity of regions i and j , and μ being the mean of the parameter value x as presented in subgraph (a) of figure 3.1. The Gini is then an “absolute” Gini index, because it uses the uniform distribution as a benchmark with $1/n$ (Combes *et al.*, 2008, 260).

$$G_{ST} = \frac{C}{1/2} = \left[\frac{1}{2\mu n^2} \sum_{i=1}^n \sum_{j=1}^n |x_i - x_j| \right] \quad (3.4.6)$$

In case of a discrete feature distribution as presented in the right subgraph of figure 3.1, the maximum concentration surface is not $1/2$ but $1/2 - 1/2 \times 1/n$. Thus, the normalization of G_{ST} into G_{ST}^* allows the comparison of differing sample size; in this study different technology fields and numbers of regions, as presented in equation 3.4.7.³⁴⁶

$$G_{ST}^* = \left[\frac{1}{2\mu n(n-1)} \sum_{i=1}^n \sum_{j=1}^n |x_i - x_j| \right] \quad (3.4.7)$$

For large sample size, the G_{ST} reaches 1 only asymptotically with $0 \leq G_{ST} \leq 1 - 1/n$. Normalization of G_{ST} into G_{ST}^* for $[0, 1]$ is then accomplished by division of G_{ST} with $1/2 \times (1 - 1/n)$ which guarantees $0 \leq G^* \leq 1$ (Litzenberger, 2007; Gallagher, 2008). However, note that $(1 - 1/n)$ only normalizes for observations that have identical weights.³⁴⁷

With respect to the homogeneity issue, G_{ST}^* has to be modified in order to account for heterogeneity of observations. The modified Gini index is then often called a “relative” Gini (Combes *et al.*, 2008, 261). From a methodological point of view, in the case of spatial dispersion of industry or inventorship activity, one can think of several modifications of G_{ST}^* . In a spatial context the conventional G_{ST}^* measure would take regions or locations as n identically weighted (uniformly distributed) observations (with $1/n$) and the number of firms, employees or patent applications of these spatial units as relevant parameter values.

³⁴⁵ In case of patent applications, some observations can have zero values as patenting is highly concentrated; thus, a modified Gini calculation is applied.

³⁴⁶ Additionally, when the number of regions j is potentially smaller than the number of technology fields i , the Gini calculation can be corrected with $(1 - j)/i$.

³⁴⁷ G_{ST}^* computation assumes that n observations are homogeneous.

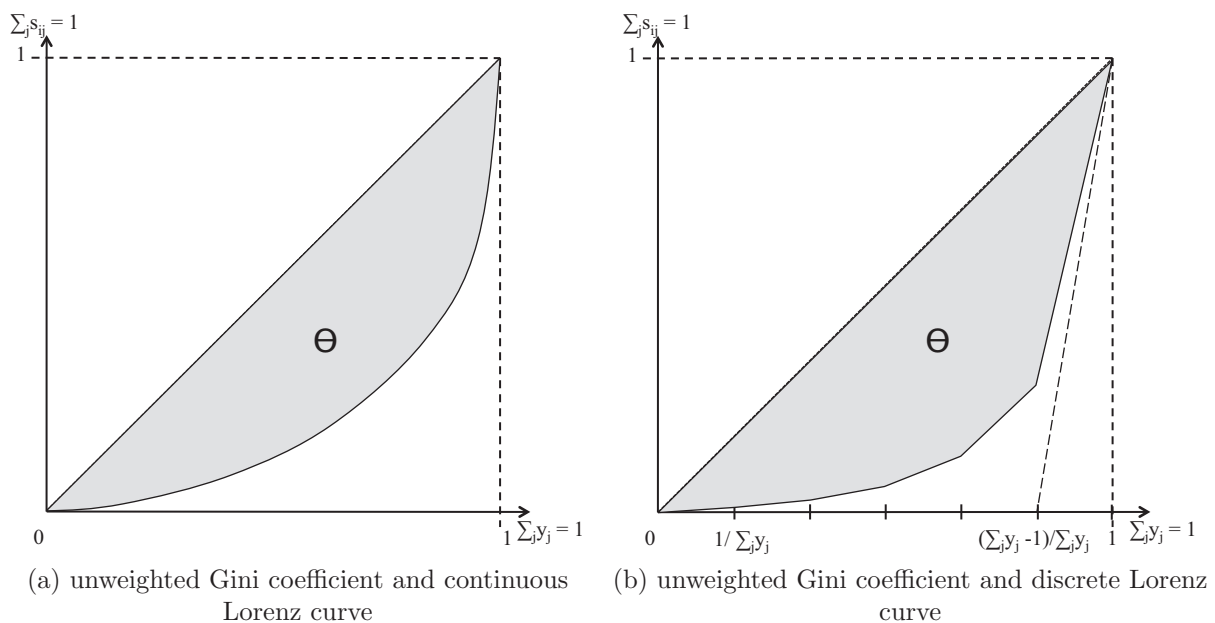


Fig. 3.1. Lorenz curve of an unweighted Gini coefficient

Source: own illustration.

The obtained G_{ST}^* coefficient would then measure inequality of economic activity across spatial units without explicitly weighting subspaces, meaning that each observation (here a region) holds an identical fraction of the reference distribution (e.g., identical in GVA, employment, population). This approach is generally unbiased when analyzing household income distributions (see figure 3.1, subgraph (b)). However, this approach is considered to be highly misleading and to distort the inequality measure in a regional context when regions vary in size and population (Combes *et al.*, 2008). In this respect, G_{ST}^* is only an adequate index in measuring the industry specific concentration with respect to the number of observations, but not heterogeneity by means of areal size/ surface or population characteristics (Litzenberger, 2007; Gallagher, 2008; Fornahl and Brenner, 2009).³⁴⁸ As a result, Gini computations in a regional context have to include explicit weights for the treatment of spatial heterogeneity, which supports the application of modified Gini coefficients. Figures 3.2 and 3.3 highlight this idea.

However, in a conventional NEG context, Krugman (1992) has utilized a locational Gini coefficient which does not take the absolute number of employees in an industry or sector into account but the regional share of employment of the subspace in the industry i . Therefore, Krugman has computed the location quotient, which represents a workhorse sort criterion for Gini calculations (Audretsch and Feldman, 1996; Litzenberger, 2007; Dewhurst and McCann, 2007). Relating this methodology to the case of European regions, the regional shares of economic activity in each technology field i for every subspace or region j have to be calculated, but also the shares of total economic activity of the spatial units, which is $\sum_i x_{ij} / \sum_i \sum_j x_{ij}$. The ratio of both shares is the well known location quotient LQ_{ij} . In case of technology field specialization, LQ_{ij} represents the well known revealed technological advantage index RTA_{ij} , which measures relative technology field occupancy of subspace j (Litzenberger, 2007; Maggioni *et al.*, 2007; Gallagher, 2008). $RTA_{ij} > 1$

³⁴⁸ See also Amiti (1998) and Arbia (2001).

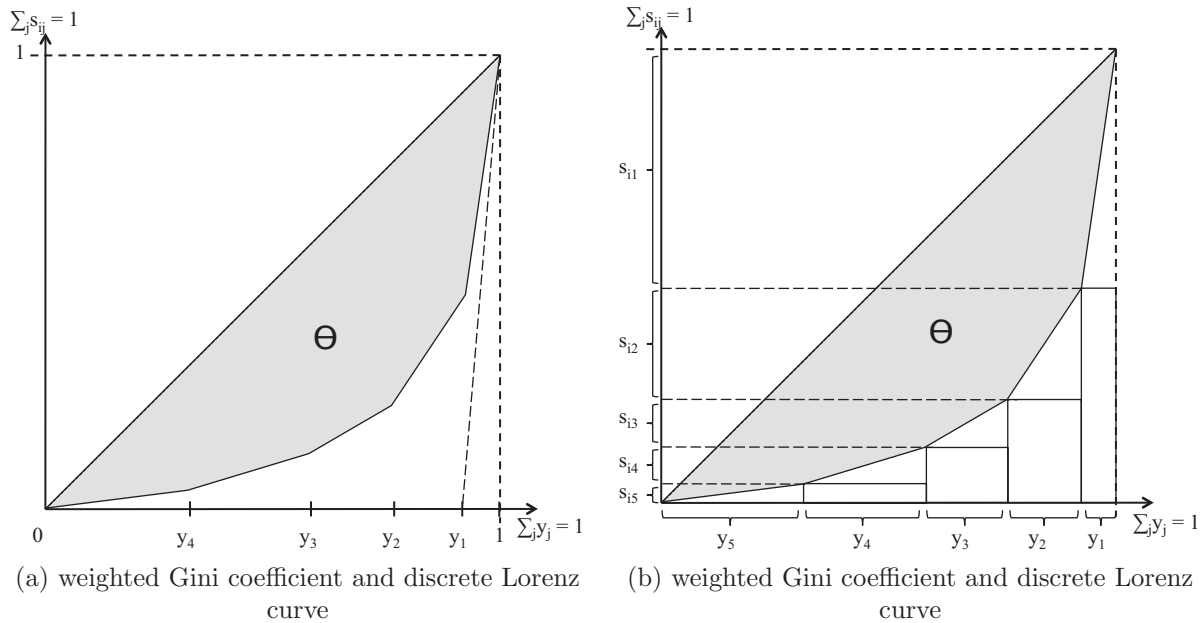


Fig. 3.2. Lorenz curve of a weighted Gini coefficient
 Source: own illustration.

means that the region j has a technological advantage in technology field i . Further to this, the locational Gini approach of Krugman measures employment specialization of a subspace j in relation to a higher spatial aggregate. Thus, Krugman and colleagues are comparing the distribution of industry specific employment with the distribution of total employment, which rather corresponds to an index of specialization or geographical disparity but not concentration (Combes and Overman, 2004; Ratanawaraha and Polenske, 2007). The same is true for the RTA_{ij} index. In this respect, it is preferred to modify the RTA -approach and to compute a relative technology field density measure as has been presented in equation 3.4.5.³⁴⁹ First, relative technology field densities (occupancy) (RTD) are computed for all subspaces with $RTD_{ij} = [s_{ij}/y_j]$; with s_{ij} being the EPO patent application share in technology field i of region j and y_j being the population share of the region. RTD is also the sort criterion for the modified and weighted Gini coefficient.

Figure 3.3 presents the modified Lorenz Curve approach and the resulting concentration surface.³⁵⁰ Equation 3.4.8 represents the “weighted” locational Gini.

$$G_{LOC} = 2 \left[\frac{1}{2} - \frac{1}{2} \sum_{j=1}^n y_j \left(s_{ij} + 2 \sum_{k=j+1}^n s_{ik} \right) \right] \tag{3.4.8}$$

³⁴⁹ Refer to Amiti (1998), Litzenger and Sternberg (2005), Litzenger (2007) and Gallagher (2008) for similar conclusions regarding employment data.

³⁵⁰ It should be noted that the computation results from RTD_{ij} are identical to the application of patent intensity of region j divided by the patent intensity of the aggregate of regions \sum_j . Relative technology field occupancy (RTD) and LQ_{ij} are then formally the same.

Equation 3.4.8 can be rearranged into 3.4.9:

$$G_{LOC} = 2 \left[\frac{1}{2} - \left[\sum_{j=1}^n \left(\frac{1}{2} y_j s_{ij} \right) + \sum_{j=1}^n \left(y_j \sum_{k=j+1}^n s_{ik} \right) \right] \right] \quad (3.4.9)$$

The G_{LOC} coefficient is a population weighted Gini index in terms of y_j , which also needs a modification according to the formerly described normalization procedure. Normalization of G_{LOC} into G_{LOC}^* is accomplished by correcting for the minimum populated region with $\min(y_j)$, which guarantees a maximum concentration surface as presented in equation 3.4.10.

$$G_{LOC}^* = \left[2 \left[\frac{1}{2} - \left[\sum_{j=1}^n \left(\frac{1}{2} y_j s_{ij} \right) + \sum_{j=1}^n \left(y_j \sum_{k=j+1}^n s_{ik} \right) \right] \right] \right] \left[\frac{1}{1 - \min(y_j)} \right] \quad (3.4.10)$$

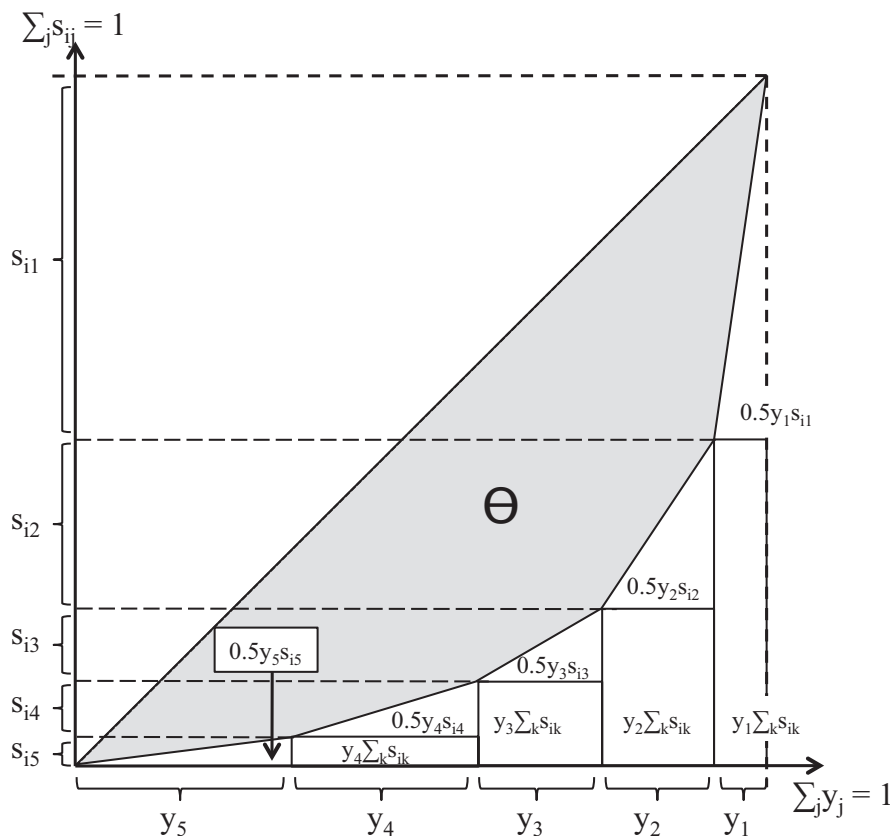


Fig. 3.3. The Lorenz curve of a locational (and spatial) Gini coefficient
 Source: own illustration.

In case that the share of economic activity of a technology field s_{ij} across subspaces j is identical to the reference distribution y_j , a relative technology field density with $RTD_{ij} = 1$ could be computed for every regional unit, and thus a locational Gini coefficient with $G_{LOC}^* = 0$. In this case, the Lorenz Curve is identical to the bisecting line. However, the

more the distribution of the industry or technology field (s_{ij}) differs from the reference distribution (y_j), the more RTD (LQ) differs from 1 and the larger is G_{LOC}^* . In this respect, G_{LOC}^* takes s_{ij} and y_j for each region and represents the cumulated sum of patent application shares of all subspaces, ordered by the regional technology density (RTD) of technology field i with $RTD_{i1} < RTD_{i2} < \dots < RTD_{in}$. Hence, the modified Gini-coefficient, G_{LOC}^* , which is applied in a different context by Kim (1995), Litzenberger (2007) and Gallagher (2008), resembles a concentration index that explicitly measures relative concentration of technology fields with respect to regional population.

3.4.1.7. The Spatial Gini Coefficient

Another possible spatial weight represents the size of the regional unit. For comparison purposes and completeness, an alternative Gini coefficient has also been computed, that is labeled G_{SPACE} , and which controls for spatial unit size by means of areal size/ surface (and represents again an index of geographical disparity). Consequently, the spatial density of economic activity under analysis comes directly to the fore (Roos, 2002b; Litzenberger, 2007; Gallagher, 2008).

Areal size/ surface is interpreted as being another possible geography control variable that introduces GIS data into the study, controlling for spatial density and thus for concentration of economic activity across European regions. G_{SPACE} (see 3.4.11) is identically calculated as G_{LOC} ; the only difference is that population shares y_j are replaced by the shares of areal size z_j . Accordingly, the normalized spatial Gini coefficient G_{SPACE}^* compares the distribution of inventorship (EPO patenting) activity shares s_{ij} in a technology field i with the distribution of areal size z_j (square kilometers) and is identical to equation 3.4.10, except z_j .

$$G_{SPACE}^* = \left[2 \left[\frac{1}{2} - \left[\sum_{j=1}^n \left(\frac{1}{2} z_j s_{ij} \right) + \sum_{j=1}^n \left(z_j \sum_{k=j+1}^n s_{ik} \right) \right] \right] \right] \left[\frac{1}{1 - \min(z_j)} \right] \quad (3.4.11)$$

In the concentration analysis of EPO patenting activity in Europe, the regional shares of EPO patent applications of subspaces s_{ij} in a predefined set of 51 technology fields are compared with the shares in areal size/surface z_j , which represents again the sort criterion for the Lorenz curve construction, as shown in figure 3.3 (y_j now replaced by z_j). $RTD_{ij} > 1$ means that region j 's patent share differs positively from its areal surface share z_j . In opposition, $RTD_{ij} < 1$ means that the region under analysis has a much smaller spatial patent density (per square kilometer) compared to the spatial aggregate. In this respect, RTD_{ij} is the sort sequence parameter value for the G_{SPACE}^* computation with $RTD_{i1} < RTD_{i2} < \dots < RTD_{in}$.³⁵¹ Groups of regions that are defined by huge differences in areal surface, although population shares being more or less equally distributed, can potentially produce differing G_{SPACE}^* parameter values compared to G_{LOC}^* .

Moreover, it is essential to note at this point that aggregation to higher regional levels could induce the so called modifiable areal unit problem (MAUP), which means that the

³⁵¹ Normalization into G_{SPACE}^* is identical as for G_{LOC}^* by correcting for the smallest spatial unit (now in terms of square kilometers), which maximizes the potential concentration surface θ in figure 3.3.

Gini coefficients (and other indices) can vary due to aggregation of surface or population (Arbia *et al.*, 2005; Dewhurst and McCann, 2007; Puga, 2010).³⁵² Small areal units tend to show large variation due to strong core-periphery issues of, e.g., population, employment, firm location. Thus, shares and intensities are endogenous to the aggregation level. In opposition, larger spatial units tend to produce much more stable numerical results (i.e., averaging process). However, meaningful geographic variation in EPO patenting - and that is what will be explored in this study - could be lost due to aggregation to a higher spatial level. For this reason, it seems reasonable to sacrifice fine technology field classifications in favor of a very detailed spatial system of regions.

3.4.2. Three Decades of EPO Patenting in Europe

3.4.2.1. Skewed Distributions and Core-Periphery Structures

3.4.2.1.1. Whisker Box-Plot

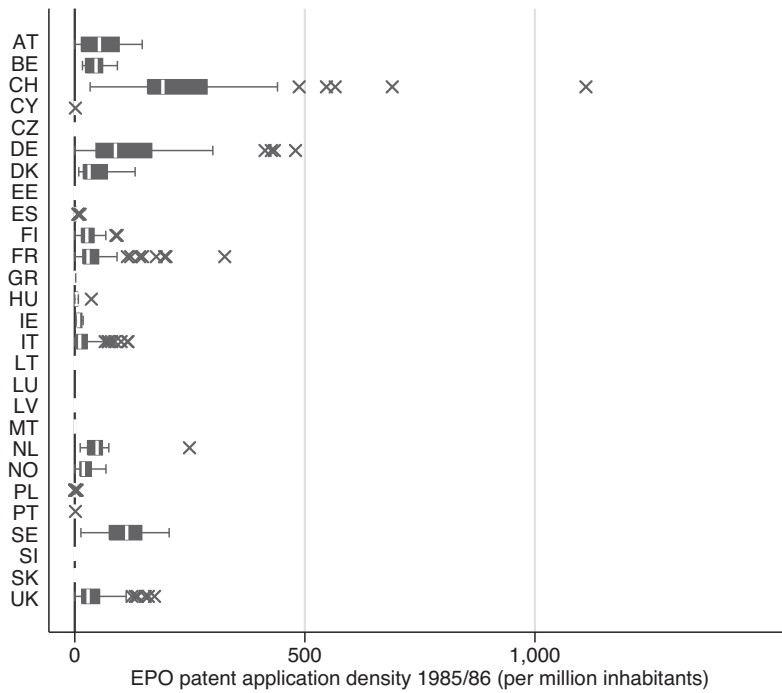
At the beginning, some distributional key facts of research activity (i.e., patenting activity) across the regions in the ERA should be summarized. Therefore, the analysis starts highlighting some descriptives. An important statistical tool for distribution analysis is the box-plot or whisker graph. Such graphs are produced for several time periods (average values). Figures 3.4, 3.5 and 3.6 highlight the distribution of EPO patent applications from European member states, i.e., patent densities at the regional level. For the purpose of a more detailed analysis, several subperiods are classified: 1985-1996, 1990-1991, 1995-1996, 2000-2001 and 2003-2004. The following box-plot figures include 25 European countries, Switzerland and Norway (819 TL3 regions), for which regionalized EPO patent data and population data are available, so that regional population corrected values can be constructed (see section 3.3 for details).³⁵³

Figure 3.6 summarizes the whisker plot for the period 2003-2004. It can clearly be depicted from the figures, that German regions are leading in overall EPO patenting activity, followed by Dutch, French and UK regions. Moreover, as can be seen from the graphs, several outliers are located in Germany, the Netherlands, France, the United Kingdom, Denmark and Belgium.³⁵⁴ Additionally, it can be observed that most countries in general show an increase in average patenting activity since the 1980s (lower quantile values are increasing).

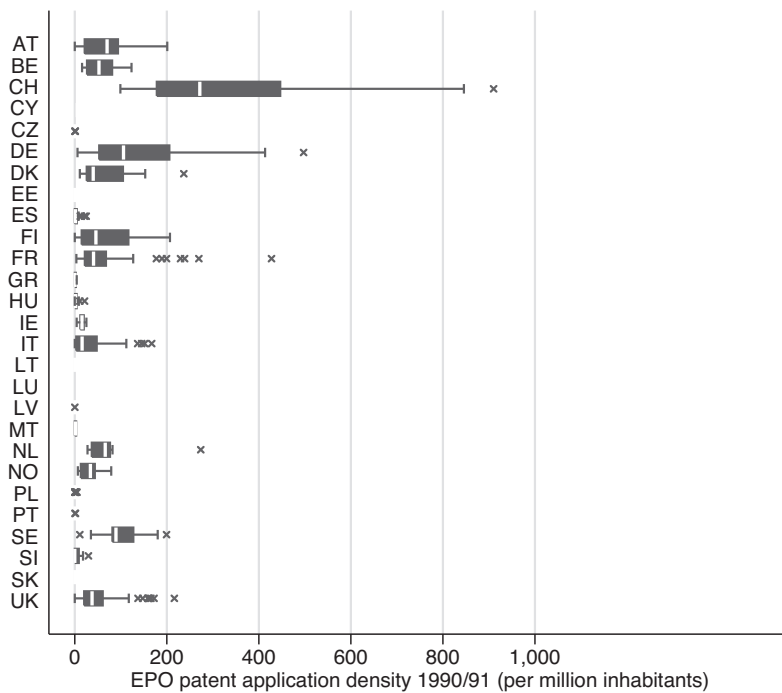
³⁵² The problem is that geographical phenomena cannot be measured at a single point but only within a pre-defined spatial area. The MAUP is intrinsic to the measure; it is a phenomenon that has a geographical dimension. It can be decomposed into two interrelated effects: (i) a zonation effect and (ii) a scale effect. The scale effect is the variation in numerical results with regard to the number of (spatial) zones; the zonation effect is the variation of statistical results due to aggregation of spatial units to districts, regions or countries (Arbia and Petrarca, 2010).

³⁵³ The following descriptives have been calculated with STATA 11 and ArcGIS 9.3.1.

³⁵⁴ Frietsch and Schmoch (2006), among others, point to similar results in their international study at the level of countries.

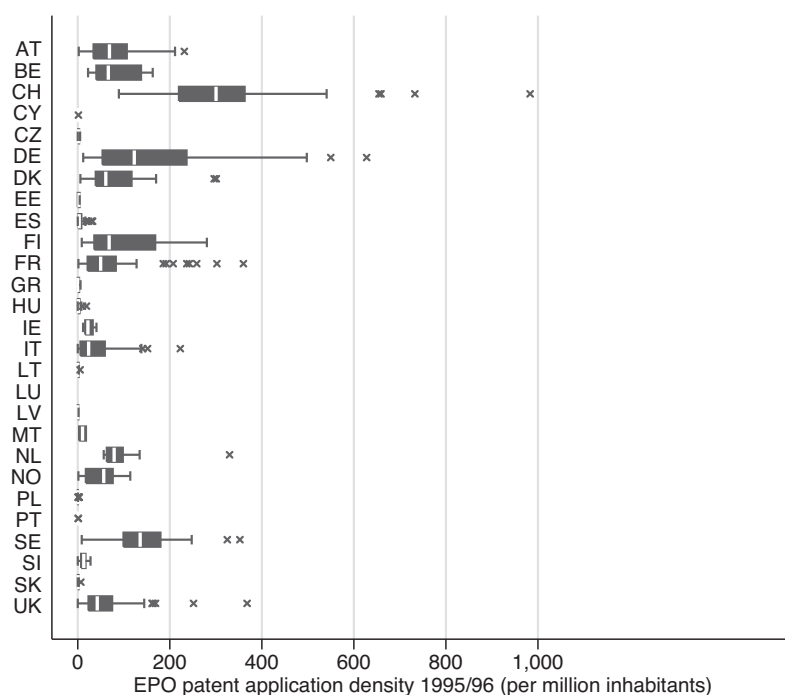


(a) Box plot overall EPO patent applications (mio.pop.), TL3 level, 1985-1986

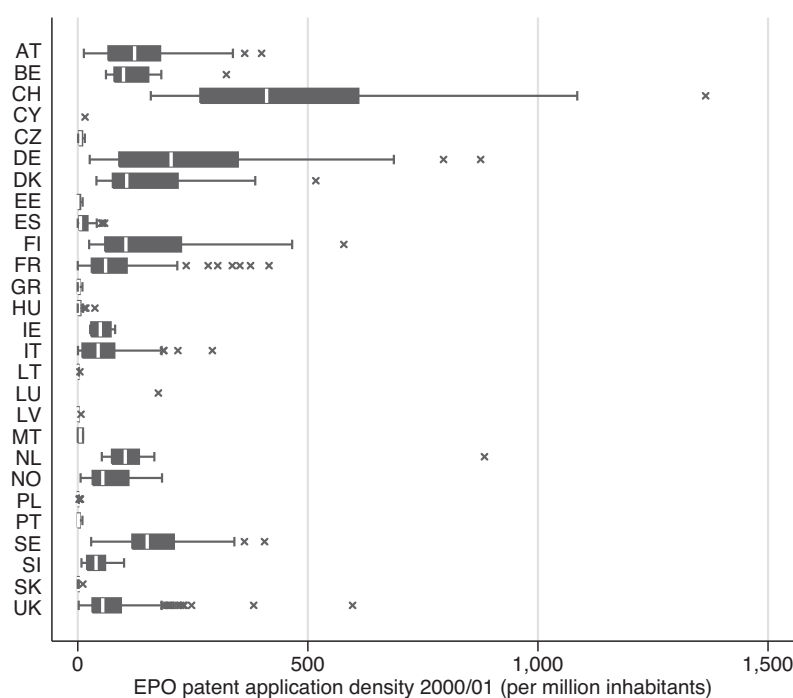


(b) Box plot overall EPO patent applications (mio.pop.), TL3 level, 1990-1991

Fig. 3.4. Spatial distribution: patent application density of European regions by country
Source: own calculations and illustration. *Notes:* Sample covers 819 European TL3 regions. Patent data generated by mySQL RegPAT (2009) database extractions and application of ISI-SPRU-OST concordance. TL3 population data for the period 1988-2004 constructed from EUROSTAT, OECD, ESPON and BBR data (OECD, 2003).



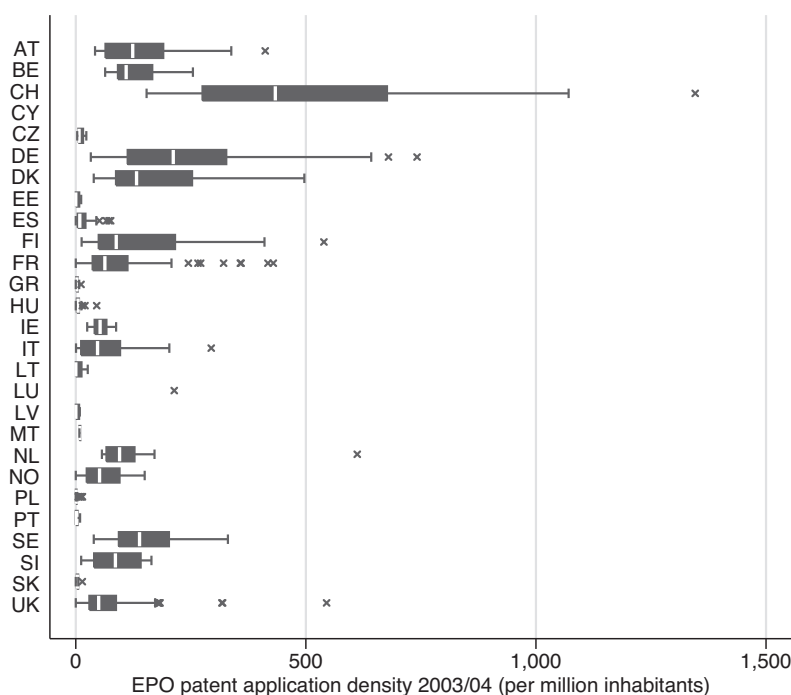
(a) Box plot overall EPO patent applications (mio.pop.), TL3 level, 1995-1996



(b) Box plot overall EPO patent applications (mio.pop.), TL3 level, 2000-2001

Fig. 3.5. Spatial distribution: patent application density of European regions by country

Source: own calculations and illustration. *Notes:* Sample covers 819 European TL3 regions. Patent data generated by mySQL RegPAT (2009) database extractions and application of ISI-SPRU-OST concordance. TL3 population data for the period 1988-2004 constructed from EUROSTAT, OECD, ESPON and BBR data (OECD, 2003).



(a) Box plot overall EPO patent applications (mio.pop.), TL3 level, 2003-2004

Fig. 3.6. Spatial distribution: patent application density of European regions by country

Source: own calculations and illustration. *Notes:* Sample covers 819 European TL3 regions. Patent data generated by mySQL RegPAT (2009) database extractions and application of ISI-SPRU-OST concordance. TL3 population data for the period 1988-2004 constructed from EUROSTAT, OECD, ESPON and BBR data (OECD, 2003).

3.4.2.1.2. Core-Periphery Structures and Patent Densities

For a more dynamic view, the regional shares of EPO patenting activity and patent densities are additionally visualized for the periods 1985-1986, 1990-1991, 1995-1996 and 2003-2004 in the European Research Area at the TL3 level. This preliminary (and simple) presentation should allow for additional hypotheses and indications with respect to the spatial distribution of research activity. The section is restricted to the presentation of research activity in selected high-technology aggregates, according to the IPC-technology field concordance table.³⁵⁵

Figures 3.7, 3.8, 3.9 and 3.10 show patent densities for the two mentioned aggregates and time periods. Figures 3.7 and 3.8 summarize overall EPO patenting activity (all IPC), whereas figures 3.9 and 3.10 highlight high-technology EPO patent applications. It can be concluded from the figures that the regions in the EU-25, Switzerland and Norway have, on average, increased their regional shares of EPO patenting within the last two decades. Additionally, figures A.3, A.4, A.5, A.6, A.7 and A.8 (appendix) show the regional distributions of 6 large high-technology aggregates, i.e., (1) *HT1 Aviation technology*, (2)

³⁵⁵ For a complete overview and list of abbreviations of all 51 technology field aggregates used in the following graphs and tables see table B.4 (appendix).

HT3 Computer & office machines technology, (3) *HT2 Communication technology*, (4) *HT5 Microorgan. & genetics*, (5) *HT4 Laser technology* and (6) *HT6 Semiconductors* for the periods 1990-1991 and 2003-2004. It is obvious that research activity, i.e., EPO patent applications, are highly concentrated and mostly clustered in European core areas. Especially high-tech patenting activity is highly clustered within the ERA, especially in the core regions and “growth poles.” The distribution is also well-known under the label “the blue banana” due to the visual effect in maps; it means that high-performing regions are mostly located in the European core regions, ranging from Southern UK regions over the North of France, Belgium, the Netherlands, Denmark, Southern Germany and Switzerland to the northern part of Italy (see also Heidenreich, 1998; Brakman *et al.*, 2005). The research clustering analysis in section 3.5 will give more attention to specific regions and their technological profile (section 3.5.4.2), whereas the following calculations center on global disparity.

However, the aforementioned figures (and maps) neither tell anything about relative spatial distribution or concentration of EPO patent applications by technology fields, nor about the intensity of research clustering. These issues will be addressed in the next sections. Nevertheless, the reported figures and descriptive measures give preliminary insights into the distribution of knowledge-intensive tasks across the regions of the European Union.

3.4.2.1.3. Kurtosis, Skewness and Herfindahl-Hirschman Index

Tables 3.1, 3.2 and 3.3 summarize the descriptive statistics for EPO patent applications and EPO inventors by technology field.³⁵⁶ The statistics aim to offer a first overview.

Table 3.1 shows the descriptive statistics (percentiles, HHI, maximum regional share and numbers per technology field) for EPO patent applications and table 3.2 summarizes the descriptives for EPO inventors. The tables include the average values for the periods 1990-1994 and 2000-2004. Table 3.3 summarizes the dynamics (change %) of the descriptive statistics for all 51 technology field aggregates between the 1990s and 2000s.

Besides the standard descriptives, a Herfindahl-Hirschman index (HHI) is reported, which measures spatial concentration by technology field; moreover, the change (%) of HHI and the other indices and variables is computed, from 1990-1992 to 2002-2004 (refer to table 3.3). It is definitely visible that most technology fields are characterized by decreasing HHI values (negative sign) for EPO patent applications and EPO inventors, which can be interpreted as a decreasing geographic concentration across the population of 819 TL3 observations (regions).³⁵⁷ This first picture of decreasing disparities is supported by the analysis of the number and share of regions in Europe with $n > 0$ EPO patent applications

³⁵⁶ The descriptives contain several calculations, e.g., minimum (min nb), maximum (max nb), mean (mean nb) and total numbers (tot nb), regional maximum share (max reg share), kurtosis (kurt), skewness (skew), 30% and 70% percentiles (P30, P70). Note that the results concerning HHI, kurtosis and skewness can depart from the following Gini calculations as spatial heterogeneity in terms of population and area size is not taken into account. For weighted measures refer to section 3.4.2.3.

³⁵⁷ The calculated HHI does not control for varying area size, meaning that all 819 TL3 regions have the same weight in the analysis. Thus, some differences are expected to occur when HHI is directly compared with, e.g., population-weighted Gini indices.

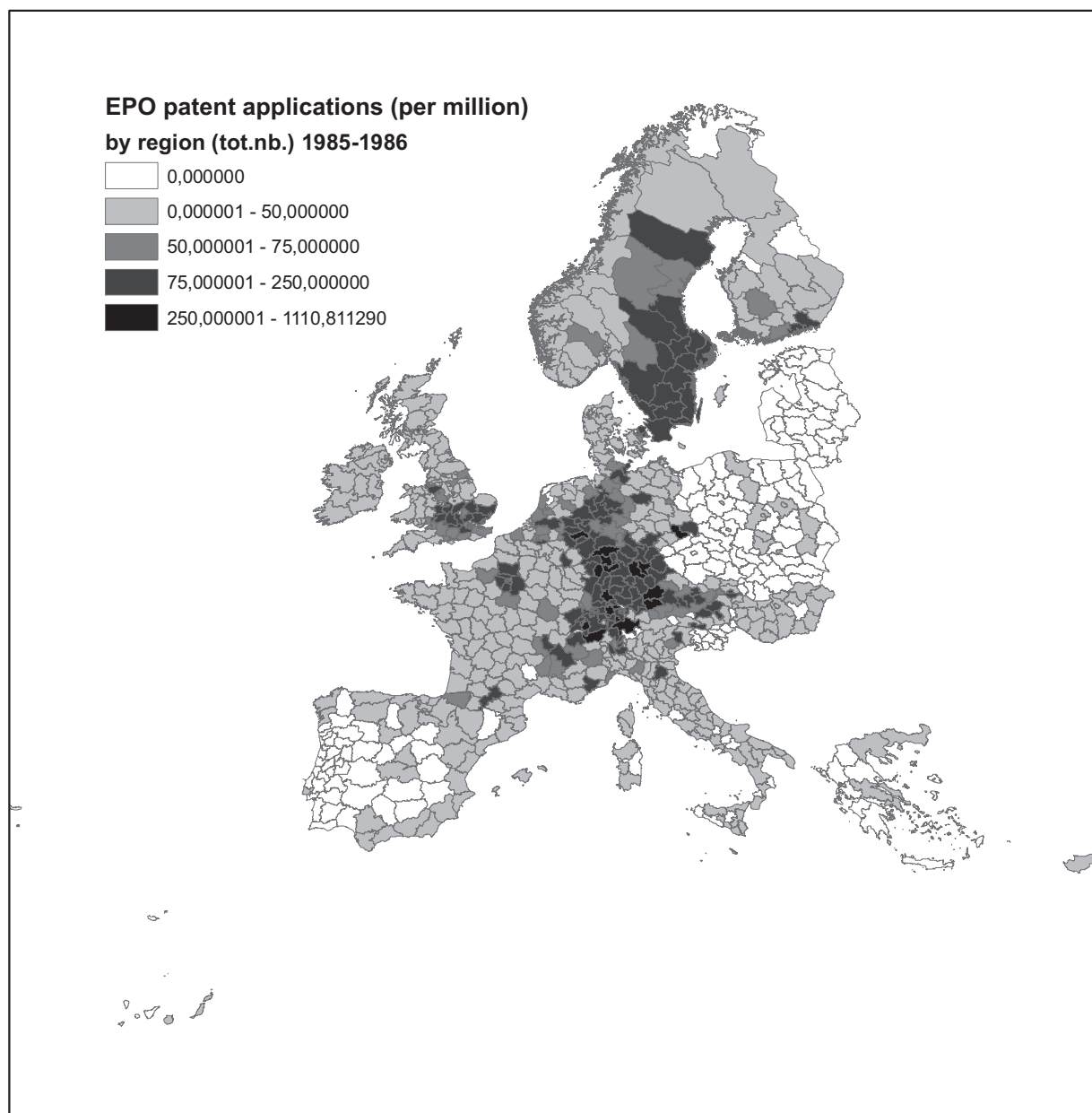


Fig. 3.7. Patent density (per million inhabitants) by region 1985-1986

Source: own calculations and illustration. *Notes:* Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.

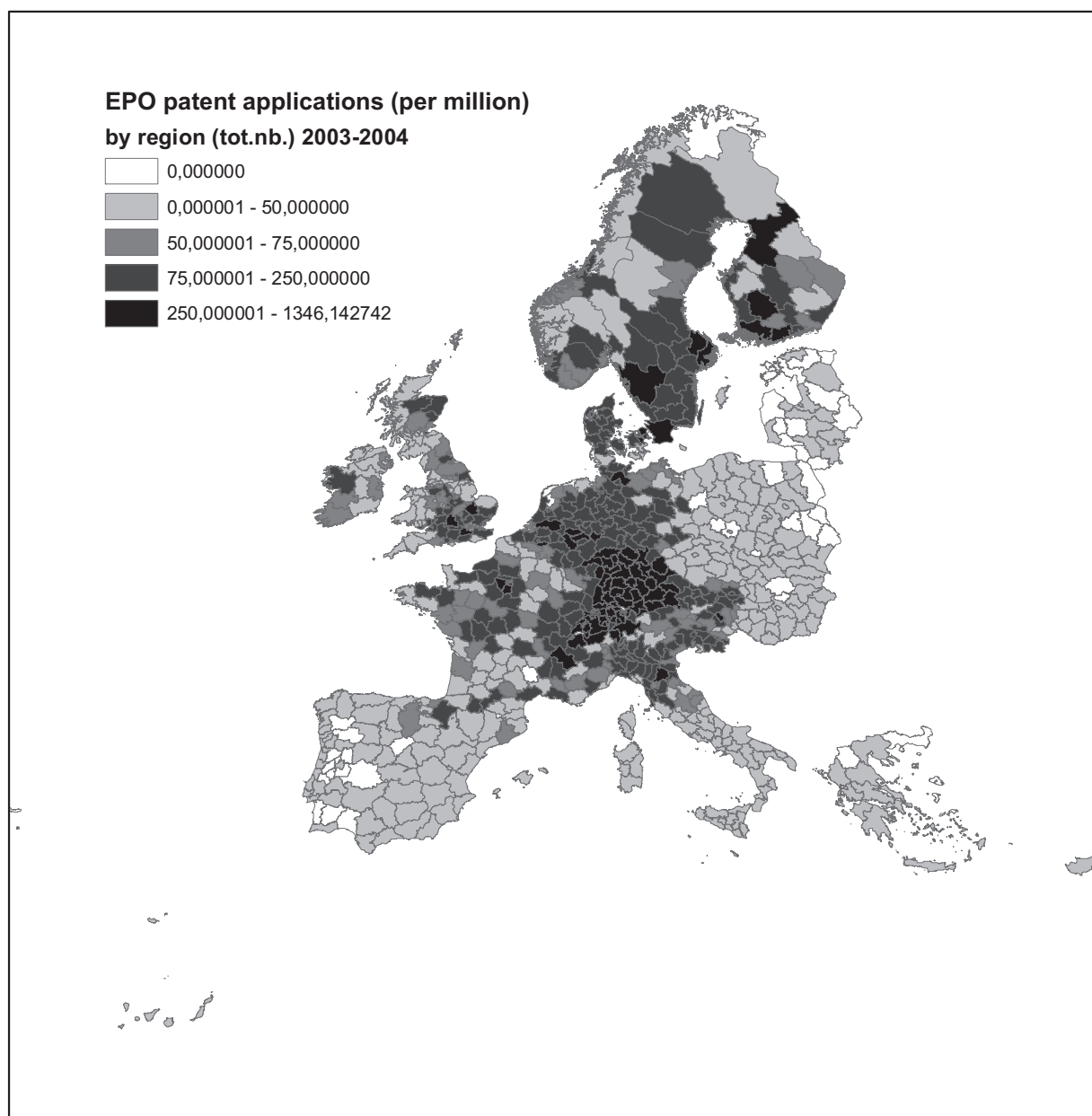


Fig. 3.8. Patent density (per million inhabitants) by region 2003-2004

Source: own calculations and illustration. *Notes:* Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.

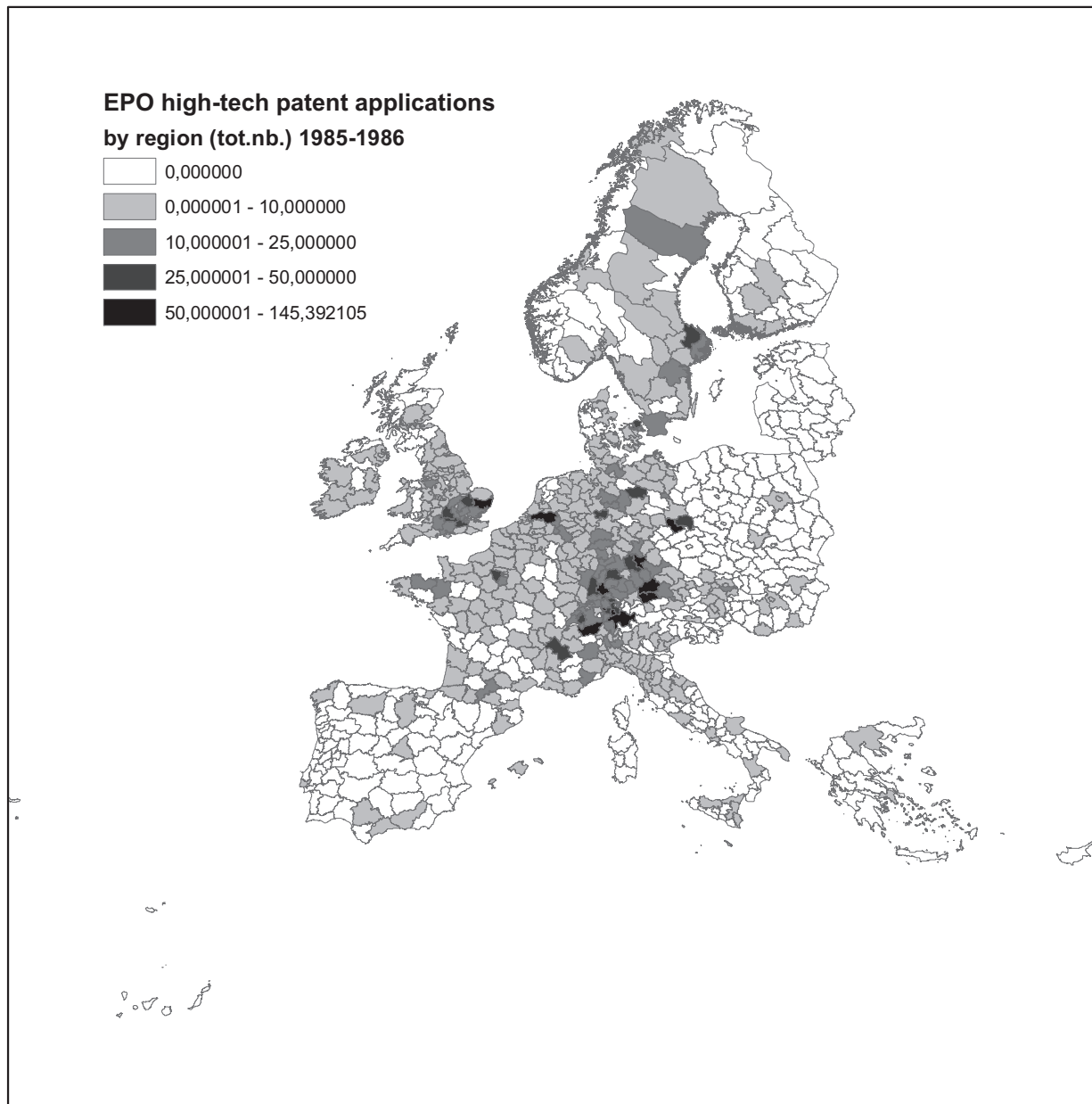


Fig. 3.9. High-tech EPO patent density (per million inhabitants) by region 1985-1986

Source: own calculations and illustration. *Notes:* Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.

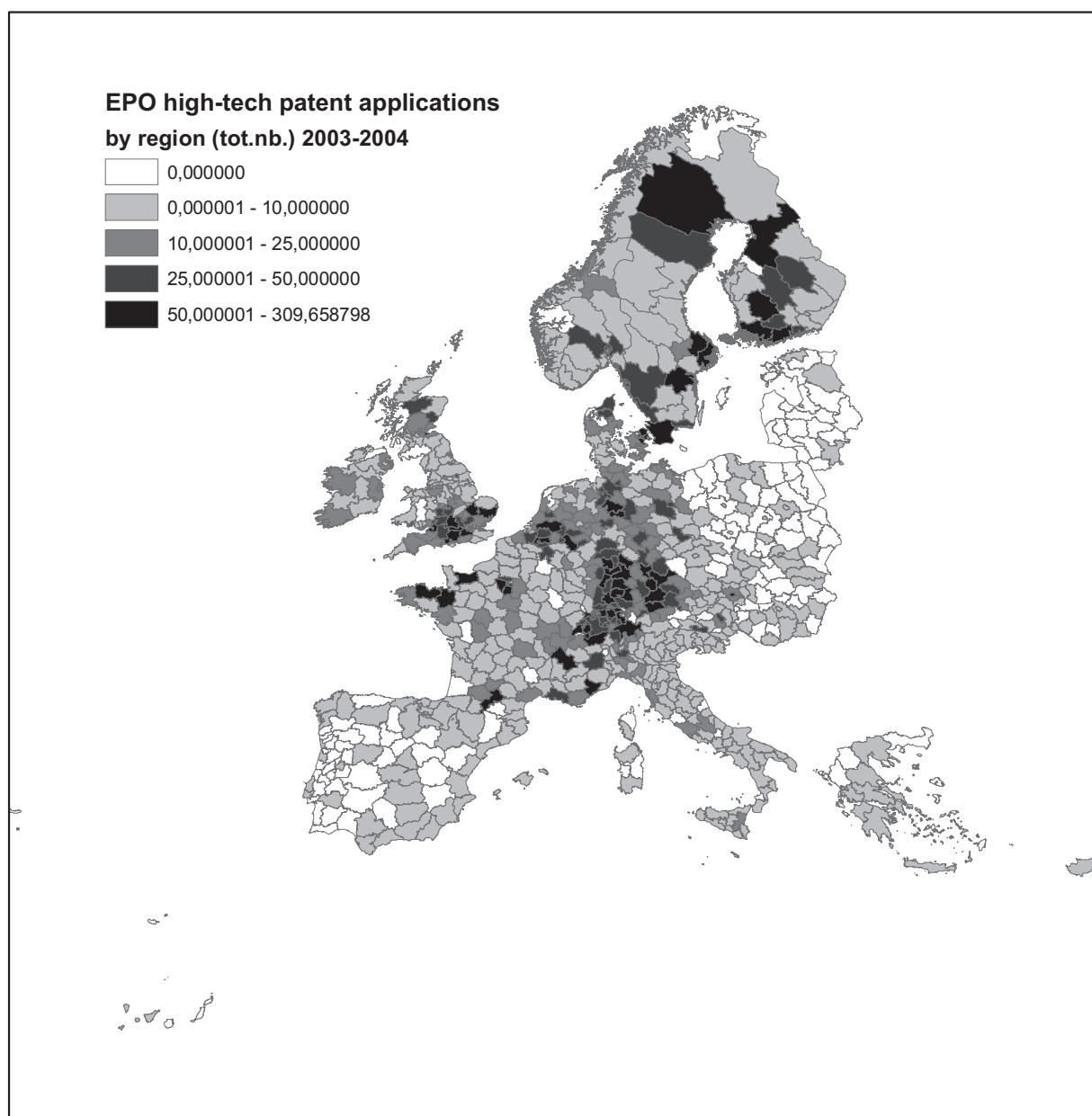


Fig. 3.10. High-tech EPO patent density (per million inhabitants) by region 2003-2004

Source: own calculations and illustration. *Notes:* Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.

and $n > 1$ EPO inventors (see figures 3.11 and 3.12).³⁵⁸ Europe is indeed characterized by an increasing number of regions that became active in research/ patenting activity. The lower percentiles (P30) have experienced an absolute increase of patent applications in nearly all technology field aggregates since the 1990s (see tables 3.1, 3.2 and 3.3). The percentile difference (P70-P30) has increased at the same time, which can only mean that the absolute numbers of patent applications have essentially increased around P70 as presented in table 3.3. However, the overall development is denoted by an overall increase in research activity in Europe; and especially in formerly non-innovative and backward regions below P50. This is highlighted in decreasing kurtosis and skewness indices, in increasing shares of regions with $n > 1$ inventors and $n > 0$ EPO patent applications in several technology fields (see table 3.3 and figures 3.11 and 3.12). Nevertheless, the main objective of the analysis is to account for spatial heterogeneity, which favors population- and area-weighted disparity indices (see section 3.4.2.3).

³⁵⁸ 294.980 EPO inventors (18,25% of all registered inventors) are linked to high-technology patent applications for the period 1977-2004.

Table 3.1. Descriptives: EPO patent applications by technology field

Technology Field	1990-1992 (mean value)											2002-2004 (mean value)														
	(1a) min nb	(2a) max nb	(3a) max reg share	(4a) mean nb	(5a) P30	(6a) P70	(7a) total nb	(8a) kurt nb	(9a) skew nb	(10a) HHI	(11a) regions n>0 patent	(12a) regions n>0 patent (%)	(13a) high distrib.	(1b) min nb	(2b) max nb	(3b) max reg share	(4b) mean nb	(5b) P30	(6b) P70	(7b) total nb	(8b) kurt nb	(9b) skew nb	(10b) HHI	(11b) regions n>0 patent	(12b) regions n>0 patent (%)	(13b) high distrib.
	SUM_44_TF	0.0	928.0	3.1%	37.0	1.8	23.9	30319.6	40.8	5.6	0.008	648	79%	Y	0.0	204.7	3.6%	67.1	5.2	43.2	54877.8	61.4	6.5	0.008	748	39%
TF1 Food_beverages	0.0	29.7	6.1%	0.6	0.0	0.3	491.2	118.5	8.6	0.011	237	4%	N	0.0	35.7	4.7%	1.0	0.0	0.6	794.6	56.4	6.2	0.010	318	39%	N
TF2 Tobacco_prod	0.0	3.4	11.5%	0.0	0.0	0.0	29.6	173.7	10.8	0.031	30	4%	N	0.0	11.8	20.1%	0.1	0.0	0.0	322.1	328.8	17.4	0.088	39	5%	N
TF3 Textiles	0.0	25.6	7.4%	0.4	0.0	0.1	347.2	102.2	9.3	0.023	163	20%	N	0.0	13.9	4.0%	0.4	0.0	0.2	322.1	46.3	6.0	0.012	184	23%	N
TF4 Wearing_apparel	0.0	2.2	5.6%	0.0	0.0	0.0	38.5	62.8	6.8	0.018	37	4%	N	0.0	4.3	3.6%	0.1	0.0	0.0	121.5	32.9	5.1	0.011	95	12%	N
TF5 Leather_articles	0.0	19.4	23.4%	0.1	0.0	0.0	83.0	455.0	20.0	0.076	50	6%	N	0.0	22.0	16.5%	0.2	0.0	0.0	133.1	439.8	18.9	0.038	89	11%	N
TF6 Wood_prod	0.0	6.4	4.6%	0.2	0.0	0.0	140.0	54.0	5.9	0.011	104	13%	N	0.0	7.0	3.8%	0.2	0.0	0.2	184.0	43.7	5.4	0.008	136	17%	N
TF7 Paper	0.0	20.3	4.9%	0.5	0.0	0.3	413.8	59.0	6.7	0.013	201	25%	N	0.0	22.2	4.0%	0.7	0.0	0.3	554.9	40.6	5.4	0.010	231	28%	N
TF9 Petrol_prod_nucl_fuel	0.0	15.3	7.0%	0.3	0.0	0.0	219.8	98.7	8.8	0.020	132	16%	N	0.0	15.4	5.0%	0.4	0.0	0.1	4618.4	65.6	7.1	0.011	177	22%	N
TF10 Basic_chemical	0.0	267.5	5.8%	5.6	0.1	2.5	4592.4	105.6	9.4	0.017	473	58%	Y	0.0	197.2	4.2%	5.6	0.3	3.1	4818.4	65.6	7.1	0.011	552	67%	Y
TF11 Pesticide_agrochem_prod	0.0	46.1	11.6%	0.5	0.0	0.1	396.7	153.7	11.7	0.046	162	20%	N	0.0	52.4	13.2%	0.5	0.0	0.1	397.1	178.3	12.2	0.043	167	20%	N
TF12 Paints_varnishes	0.0	6.2	20.5%	0.0	0.0	0.0	30.4	397.1	17.7	0.081	29	4%	N	0.0	1.3	6.1%	0.0	0.0	0.0	22.0	57.4	6.8	0.026	27	3%	N
TF13 Pharmaceuticals	0.0	128.9	4.1%	3.8	0.0	1.3	3137.2	45.4	6.0	0.013	406	50%	Y	0.0	166.4	2.8%	7.3	0.2	3.0	5961.6	24.5	4.5	0.010	551	67%	Y
TF14 Soaps_detergents	0.0	65.9	19.8%	0.4	0.0	0.0	332.2	408.0	18.3	0.057	131	16%	N	0.0	42.3	12.5%	0.4	0.0	0.0	337.8	196.8	12.6	0.036	148	18%	N
TF15 Other_detergents	0.0	41.1	5.7%	0.9	0.0	0.3	723.0	89.7	8.3	0.015	253	31%	N	0.0	32.8	5.5%	0.7	0.0	0.3	593.6	81.8	7.7	0.013	249	30%	N
TF16 Man_made_fibre	0.0	6.3	8.8%	0.1	0.0	0.0	71.3	101.5	9.0	0.032	55	7%	N	0.0	5.3	7.8%	0.1	0.0	0.0	68.6	94.3	8.1	0.020	71	9%	N
TF17 Rubber_plastic_prod	0.0	52.8	2.3%	2.8	0.0	2.2	2326.1	20.2	4.0	0.006	429	52%	Y	0.0	66.5	2.1%	3.9	0.3	3.2	3234.5	22.9	4.0	0.006	450	53%	Y
TF18 Non-metal_mineral_prod	0.0	51.2	3.6%	1.7	0.0	1.3	1417.6	43.3	5.3	0.007	375	46%	Y	0.0	45.5	2.4%	2.3	0.1	1.7	1869.4	22.2	4.0	0.006	450	53%	Y
TF19 Basic_metals	0.0	36.9	3.9%	1.1	0.0	0.8	937.9	59.2	6.4	0.009	321	39%	N	0.0	41.1	3.8%	1.3	0.0	1.0	1071.0	55.9	6.2	0.008	369	45%	Y
TF20 Fabric_metal_prod	0.0	73.9	4.3%	2.1	0.0	1.7	1730.0	75.8	7.1	0.009	390	48%	Y	0.0	119.3	4.4%	3.3	0.2	2.5	2740.4	80.9	7.3	0.008	483	59%	Y
TF21 Energy_machinery	0.0	82.4	5.1%	2.0	0.0	1.9	2899.4	80.3	7.2	0.010	343	42%	Y	0.0	173.6	5.7%	3.7	0.1	2.1	3071.1	98.5	8.1	0.011	451	55%	Y
TF22 Nonspec_machinery	0.0	72.9	3.2%	2.8	0.0	1.2	2269.4	37.5	5.2	0.008	434	55%	Y	0.0	219.7	7.2%	3.7	0.3	2.6	3054.1	266.0	13.2	0.010	502	61%	Y
TF23 Agricul_forestry_machinery	0.0	24.1	4.4%	0.7	0.0	0.4	543.9	69.6	7.0	0.009	244	30%	N	0.0	35.7	4.4%	1.0	0.0	0.8	805.5	82.3	7.8	0.009	313	38%	Y
TF24 Machine_tools	0.0	89.8	6.9%	1.6	0.0	0.9	1266.5	184.0	10.8	0.011	338	41%	Y	0.0	131.9	7.4%	2.2	0.0	1.3	1800.3	206.2	11.6	0.012	390	48%	Y
TF25 Spec_purp_machinery	0.0	145.5	4.0%	4.4	0.0	2.9	3602.1	57.1	6.2	0.008	466	57%	Y	0.0	122.8	2.7%	5.5	0.3	3.7	4493.7	31.9	4.9	0.007	522	65%	Y
TF26 Weapons_ammunition	0.0	8.7	6.0%	0.2	0.0	0.0	145.0	70.2	7.2	0.017	94	12%	N	0.0	13.1	6.5%	0.2	0.0	0.0	200.2	78.2	7.8	0.019	114	14%	N
TF27 Domestic_appliances	0.0	35.5	3.6%	1.2	0.0	0.8	981.2	38.8	5.3	0.009	300	37%	N	0.0	66.6	3.5%	2.3	0.0	1.6	1917.9	41.6	5.7	0.009	415	51%	N
TF28 Office_mach_computers	0.0	149.5	7.6%	2.4	0.0	0.9	1957.0	129.1	10.1	0.020	327	40%	N	0.0	556.6	11.9%	5.7	0.1	2.3	4884.7	325.6	15.7	0.024	489	60%	Y
TF29 Electric_motors_generators	0.0	17.6	6.2%	0.3	0.0	0.0	282.6	77.4	7.4	0.015	141	17%	N	0.0	39.5	7.0%	0.7	0.0	0.3	538.7	130.6	10.2	0.019	224	27%	N
TF30 Elec_distr_contr_wire_cable	0.0	35.1	4.4%	1.0	0.0	0.3	794.5	49.4	6.3	0.014	231	28%	N	0.0	41.6	4.4%	1.2	0.0	0.6	958.0	47.9	6.1	0.011	281	34%	N
TF31 Accumulators_battery	0.0	105.1	8.3%	0.2	0.0	0.0	127.2	140.3	9.4	0.018	96	12%	N	0.0	21.5	6.4%	0.4	0.0	0.2	338.1	94.3	8.5	0.016	180	22%	N
TF32 Lighting_equipment	0.0	14.1	8.3%	0.2	0.0	0.0	169.4	148.3	10.1	0.018	108	13%	N	0.0	29.7	8.2%	0.4	0.0	0.2	361.4	135.8	9.9	0.019	163	20%	N
TF33 Other_electr equip	0.0	36.7	6.0%	0.7	0.0	0.3	609.6	91.2	8.1	0.014	218	27%	N	0.0	46.6	5.2%	1.1	0.0	0.7	899.5	82.9	7.8	0.012	313	38%	N
TF34 Electr_components	0.0	132.3	11.8%	1.4	0.0	0.3	1211.1	199.3	12.7	0.033	245	30%	N	0.0	182.1	9.5%	2.4	0.0	0.9	1925.7	169.2	11.6	0.023	371	45%	Y
TF35 Signal_transm_telecom	0.0	160.1	7.7%	2.6	0.0	0.9	2092.8	106.3	9.1	0.020	326	40%	N	0.0	338.5	6.5%	6.4	0.1	2.3	5227.1	92.5	8.5	0.017	466	59%	Y
TF36 TV_radio_recv_audio	0.0	69.5	10.6%	0.8	0.0	0.2	655.4	176.5	11.6	0.027	181	22%	N	0.0	211.5	15.4%	1.7	0.0	0.4	1374.0	377.9	17.2	0.036	272	33%	N
TF37 Med_equipment	0.0	53.2	3.2%	2.0	0.0	1.2	1667.5	38.6	5.3	0.008	388	47%	Y	0.0	115.8	3.2%	4.4	0.2	2.9	3611.6	34.9	4.9	0.007	510	62%	Y
TF38 Measuring_instruments	0.0	89.9	4.4%	2.5	0.0	1.3	2031.9	59.7	6.5	0.010	382	47%	Y	0.0	175.8	4.4%	4.4	0.1	2.4	3605.3	82.8	7.4	0.010	489	60%	Y
TF39 Ind_proc_contr equip	0.0	19.2	5.1%	0.5	0.0	0.2	374.7	73.4	7.3	0.013	180	22%	N	0.0	52.8	7.8%	0.8	0.0	0.3	674.7	163.7	11.0	0.017	255	31%	N
TF40 Opti_instruments	0.0	48.9	5.4%	1.1	0.0	0.5	903.1	68.6	7.3	0.014	257	31%	N	0.0	170.5	12.2%	1.7	0.0	0.7	1399.9	370.2	16.8	0.023	324	40%	N
TF41 Watches_clocks	0.0	8.4	10.3%	0.1	0.0	0.0	81.8	112.8	9.6	0.037	47	6%	N	0.0	157.1	15.0%	0.2	0.0	0.0	157.1	132.2	12.8	0.057	60	7%	N
TF42 Motor_vehicles	0.0	251.8	9.7%	3.2	0.0	1.5	2562.5	263.3	13.7	0.018	391	48%	Y	0.0	232.9	13.2%	6.8	0.3	3.0	5571.6	412.4	18.0	0.025	501	61%	Y
TF43 Other_transp equip	0.0	24.3	3.8%	0.8	0.0	0.5	637.6	44.2	5.3	0.008	259	32%	N	0.0	44.3	4.1%	1.3	0.0	1.0	1076.8	61.1	6.4	0.008	353	43%	Y
TF44 Furniture_consum_goods	0.0	23.2	3.0%	1.0	0.0	0.7	780.3	38.0	5.3	0.008	288	35%	N	0.0	32.7	2.8%	1.6	0.0	1.3	1274.1	30.3	4.7	0.006	379	46%	Y
SUM_lightech	0.0	287.3	7.1%	4.9	0.0	1.8	4044.9	113.6	9.3	0.017	435	55%	Y	0.0	654.9	6.1%	13.0	0.4	5.1	10672.1	110.7	9.0	0.015	594	73%	Y
HT1_Aviation	0.0	12.1	7.3%	0.2	0.0	0.0	165.9	77.9	7.9	0.023	92	11%	N	0.0	40.2	12.8%	0.4	0.0	0.1	314.8	297.2	15.0	0.028	146	18%	N
HT2_Computer_office_mach	0.0	78.1	8.0%	1.2	0.0	0.4	971.4	124.8	9.9	0.022	244	30%	N	0.0	251.0	8.2%	3.7	0.0	1.4	3067.2	156.0	10.6	0.018	419	51%	N
HT3_Laser	0.0	16.8	12.3%	0.2	0.0	0.0	136.8	151.3	11.3	0.044	78	9%	N	0.0	10.1	6.0%	0.2	0.0	0.0	157.3	63.3	7.0	0.020	101	12%	N
HT4_Semiconductors	0.0	63.1	10.7%	0.7	0.0	0.1	589.5	153.6	11.2	0.033	168	21%	N	0.0	106.9	9.0%	1.4	0.0	0.4	1184.2	142.7	10.9	0.027	294	36%	N
HT5_Communication	0.0	119.0	7.3%	2.0	0.0	0.5	1639.4	96.2	8.9	0.022	275	34%	N	0.0	322.7	6.5%	6.0	0.0	1.7	4950.5	98.7	8.9	0.020	447	55%	Y
HT6_Microorgan_Genetics	0.0	23.2	3.5%	1.0	0.0	0.4	836.0	2																		

Table 3.2. Descriptives: EPO inventors by technology field

Technology Field	1990-1992 (mean value)										2002-2004 (mean value)															
	(1a) min nb	(2a) max nb	(3a) max reg share	(4a) mean nb	(5a) P30	(6a) P70	(7a) total nb	(8a) kurt nb	(9a) skew nb	(10a) HHI	(11a) regions ns-1 inventor	(12a) regions ns-1 inventor	(13a) high distrib.	(1a) min nb	(2b) max nb	(3b) max reg share	(4b) mean nb	(5b) P30	(6b) P70	(7b) total nb	(8b) kurt nb	(9b) skew nb	(10b) HHI	(11b) regions ns-1 inventor	(12b) regions ns-1 inventor	(13b) high distrib.
SUM_44_TF	0.0	1730.0	3.2%	65.7	3.0	38.9	5947.0	445.5	6.0	0.009	609	74%	Y	0.0	3637.7	4.4%	130.5	9.5	77.5	106866.0	50.8	5.9	0.008	717	83%	Y
TF1 Food beverages	0.0	84.3	7.8%	1.3	0.0	0.7	1065.7	184.1	11.0	0.014	155	19%	N	0.0	94.7	3.4%	2.4	0.0	0.0	1925.3	65.6	6.8	0.011	216	26%	N
TF2 Tobacco prod	0.0	12.0	18.3%	0.1	0.0	0.0	65.7	330.8	16.5	0.027	12	2%	N	0.0	22.0	22.0%	0.2	0.0	0.0	127.3	320.2	17.1	0.095	17	2%	N
TF3 Textiles	0.0	65.3	8.7%	0.9	0.0	0.3	752.7	129.3	10.5	0.057	98	12%	N	0.0	39.3	5.4%	0.9	0.0	0.3	723.3	76.9	7.5	0.014	110	13%	N
TF4 Wearing apparel	0.0	27.1	4.7%	0.1	0.0	0.0	56.3	445.5	6.0	0.018	12	1%	N	0.0	6.7	3.7%	0.2	0.0	0.0	180.3	36.6	3.5	0.011	39	5%	N
TF5 Leather articles	0.0	28.7	25.4%	0.1	0.0	0.0	113.0	546.9	22.0	0.080	16	2%	N	0.0	29.3	15.7%	0.2	0.0	0.0	187.0	382.2	17.6	0.037	29	4%	N
TF6 Wood prod	0.0	8.7	4.4%	0.2	0.0	0.0	198.7	49.3	5.8	0.010	47	6%	N	0.0	7.7	2.9%	0.3	0.0	0.3	266.0	22.9	4.1	0.008	60	7%	N
TF7 Paper	0.0	44.7	5.4%	1.0	0.0	0.3	823.0	74.2	7.8	0.021	118	14%	N	0.0	47.0	4.1%	1.4	0.0	0.7	1160.0	43.6	5.7	0.010	195	19%	N
TF9 Petrol prod_nucl fuel	0.0	30.0	6.0%	0.6	0.0	0.0	497.0	72.6	7.8	0.021	74	9%	N	0.0	51.7	6.9%	0.9	0.0	0.3	745.3	103.3	8.5	0.016	107	13%	N
TF10 Basic chemical	0.0	668.0	6.2%	13.2	0.3	5.7	10803.0	111.2	9.7	0.019	389	48%	Y	0.0	553.3	4.5%	15.0	0.7	8.3	12260.0	70.8	7.4	0.011	459	56%	Y
TF11 Pesticide_agrochem_prod	0.0	116.0	10.9%	1.3	0.0	0.3	1061.3	156.6	11.9	0.047	92	11%	N	0.0	108.3	10.8%	1.2	0.0	0.3	1007.3	129.1	10.8	0.041	103	13%	Y
TF12 Paints_varnishes	0.0	12.3	19.9%	0.1	0.0	0.0	62.0	341.1	16.5	0.063	11	1%	N	0.0	4.3	9.0%	0.1	0.0	0.0	48.3	96.6	8.2	0.027	13	2%	N
TF13 Pharmaceuticals	0.0	386.3	4.4%	10.7	0.0	3.5	8755.7	52.3	6.4	0.013	321	39%	N	0.0	448.0	2.5%	21.7	0.0	8.7	17735.3	22.1	4.4	0.009	456	56%	Y
TF14 Soaps_detergents	0.0	181.0	21.5%	1.0	0.0	0.0	843.0	441.6	19.2	0.064	79	10%	N	0.0	104.0	11.3%	1.1	0.0	0.0	922.7	166.1	11.7	0.035	95	12%	N
TF15 Other chemicals	0.0	128.0	7.7%	2.0	0.0	0.7	1673.0	126.3	9.9	0.019	172	21%	N	0.0	78.0	5.9%	1.7	0.0	0.7	1427.0	83.8	7.8	0.013	178	22%	N
TF16 Man-made fibres	0.0	14.3	7.7%	0.2	0.0	0.0	185.7	90.2	8.7	0.032	30	4%	N	0.0	10.0	5.2%	0.2	0.0	0.0	193.7	45.6	6.2	0.019	36	4%	N
TF17 Rubber_plastic_prod	0.0	100.0	2.8%	4.4	0.0	3.2	3595.7	32.6	4.9	0.007	342	42%	Y	0.0	127.3	3.0%	6.8	0.3	5.2	5566.3	33.4	4.8	0.007	412	42%	Y
TF18 Non-metal_mineral_prod	0.0	131.0	5.0%	3.2	0.0	2.2	2635.7	79.6	7.1	0.009	276	34%	N	0.0	108.7	3.0%	4.4	0.3	3.0	3833.7	33.4	4.8	0.007	342	42%	Y
TF19 Basic metals	0.0	90.0	4.7%	3.2	0.0	1.3	1897.0	75.9	7.4	0.011	218	27%	N	0.0	97.0	4.2%	2.8	0.0	1.7	2304.0	60.8	6.5	0.009	264	32%	N
TF20 Fabric_metal_prod	0.0	113.0	4.3%	3.2	0.0	2.3	2633.3	75.3	7.3	0.009	287	35%	N	0.0	207.0	4.7%	5.3	0.3	4.0	4380.3	94.7	7.9	0.008	382	47%	Y
TF21 Energy machinery	0.0	164.0	6.5%	3.1	0.0	1.7	5222.3	127.2	9.1	0.012	252	31%	N	0.0	363.7	6.5%	6.9	0.3	3.9	5634.7	120.4	12.0	0.012	342	42%	Y
TF22 Nonspc_machinery	0.0	148.7	3.8%	4.8	0.0	3.0	3912.3	56.8	6.4	0.009	336	41%	Y	0.0	426.7	7.5%	7.0	0.3	5.0	5726.3	255.6	13.3	0.011	396	48%	Y
TF23 Agricul_forestry_machinery	0.0	30.0	3.9%	0.9	0.0	0.7	761.0	55.2	6.0	0.008	144	18%	N	0.0	49.7	7.8%	1.6	0.0	2.3	3146.0	22.1	4.0	0.009	201	25%	N
TF24 Machine tools	0.0	180.3	8.8%	2.5	0.0	1.3	2051.3	287.3	14.1	0.014	235	29%	N	0.0	237.0	7.8%	3.8	0.0	2.3	3146.0	22.1	4.0	0.012	290	35%	Y
TF25 Spec_purp_machinery	0.0	305.0	5.1%	7.2	0.0	4.7	5929.3	93.0	7.9	0.010	385	47%	Y	0.0	244.7	3.9%	9.8	0.3	6.7	8857.3	35.5	5.0	0.007	438	53%	Y
TF26 Weapons_ammunition	0.0	17.7	7.0%	0.3	0.0	0.0	254.0	92.8	8.5	0.021	45	5%	N	0.0	15.7	4.0%	4.0	0.0	0.0	324.7	55.3	6.9	0.018	58	7%	N
TF27 Domestic appliances	0.0	55.7	3.7%	1.9	0.0	1.0	1518.3	43.4	5.7	0.010	201	25%	N	0.0	33.7	4.0%	4.0	0.0	2.7	3305.0	60.8	6.8	0.010	302	37%	N
TF28 Office_mach_computers	0.0	281.7	8.0%	4.3	0.0	1.7	3522.3	129.8	10.0	0.021	234	28%	N	0.0	85.4	9.0%	11.2	0.3	5.0	9179.0	216.8	12.5	0.018	393	48%	Y
TF29 Electric_motors_generators	0.0	39.0	7.7%	0.6	0.0	0.0	504.7	116.4	8.9	0.018	83	10%	N	0.0	83.7	7.8%	1.3	0.0	0.7	1077.7	156.3	11.1	0.020	144	18%	N
TF30 Elec_distr_ctrn_wire_cable	0.0	89.0	6.5%	1.7	0.0	0.7	1360.0	84.7	8.0	0.017	149	18%	N	0.0	82.3	4.4%	2.3	0.0	1.0	1851.3	49.6	6.3	0.012	198	24%	N
TF31 Accumulators_battery	0.0	21.3	8.3%	0.3	0.0	0.0	258.0	133.3	9.3	0.018	52	6%	N	0.0	48.3	5.7%	1.0	0.0	0.3	842.7	80.5	8.0	0.016	118	14%	N
TF32 Lighting equipment	0.0	23.0	8.7%	0.3	0.0	0.0	265.7	153.5	10.3	0.019	51	6%	N	0.0	59.3	9.3%	0.8	0.0	0.3	638.0	160.1	11.0	0.022	93	11%	N
TF33 Other_elec equip	0.0	77.7	7.3%	1.3	0.0	0.7	1062.0	120.7	9.2	0.016	143	17%	N	0.0	103.7	5.9%	2.1	0.0	1.3	1757.0	102.5	8.5	0.012	217	26%	N
TF34 Electr_components	0.0	265.0	12.0%	2.7	0.0	0.7	2216.7	196.6	12.6	0.033	173	21%	N	0.0	442.3	9.5%	5.5	0.0	2.0	4515.0	185.9	12.0	0.023	279	34%	N
TF35 Signal_transm_telecom	0.0	260.0	7.2%	4.4	0.0	1.3	3624.3	96.9	8.8	0.020	238	29%	N	0.0	595.7	5.8%	12.5	0.3	5.0	10865.3	81.6	7.9	0.015	383	47%	Y
TF36 TV_radio_recv_audio	0.0	129.7	12.1%	1.3	0.0	0.3	1073.3	210.9	12.8	0.032	108	13%	N	0.0	356.3	13.8%	3.2	0.0	1.0	2590.7	322.7	15.7	0.031	185	23%	N
TF37 Med equip	0.0	82.3	2.8%	3.6	0.0	2.3	2936.0	31.0	4.9	0.008	283	35%	N	0.0	219.0	3.0%	8.8	0.3	5.7	7221.7	33.1	4.9	0.007	416	51%	Y
TF38 Measuring_instruments	0.0	170.7	4.2%	4.9	0.0	2.7	4016.7	56.4	6.4	0.010	299	37%	N	0.0	381.7	4.6%	10.0	0.3	5.7	8216.7	76.6	7.1	0.010	394	48%	Y
TF39 Ind_proc_ctrn equip	0.0	46.3	6.4%	0.9	0.0	0.3	719.0	104.1	8.4	0.014	116	14%	N	0.0	110.3	7.9%	1.7	0.0	0.7	1401.7	184.7	11.8	0.018	182	20%	N
TF40 Opti_instruments	0.0	98.3	5.9%	2.0	0.0	1.0	1667.0	73.6	7.7	0.017	174	21%	N	0.0	436.0	14.4%	3.7	0.0	1.3	3018.3	439.0	18.8	0.029	233	28%	N
TF41 Watches_clocks	0.0	11.0	9.6%	0.1	0.0	0.0	114.3	103.5	9.1	0.033	22	3%	N	0.0	37.0	15.9%	0.3	0.0	0.0	233.0	236.7	13.4	0.052	31	4%	N
TF42 Motor_vehicles	0.0	527.0	12.1%	5.3	0.0	2.0	4345.3	356.3	16.5	0.023	292	36%	N	0.0	1406.7	13.7%	12.6	0.3	5.0	10300.7	418.0	18.2	0.027	395	48%	Y
TF43 Other_transp equip	0.0	44.7	4.3%	1.3	0.0	0.7	1034.0	57.7	6.0	0.009	154	19%	N	0.0	78.0	4.8%	2.2	0.0	1.3	1824.7	64.0	6.7	0.009	236	29%	N
TF44 Furniture_consum_goods	0.0	33.7	3.2%	1.3	0.0	1.0	1050.3	41.9	5.5	0.008	176	22%	N	0.0	48.0	2.8%	2.2	0.0	2.0	1842.7	31.3	4.8	0.007	265	32%	N
SUM_hightech	0.0	504.0	6.2%	9.9	0.0	3.7	8074.3	92.9	8.4	0.015	345	42%	Y	0.0	1173.0	5.1%	27.9	1.0	11.3	22832.3	83.5	7.8	0.013	513	63%	Y
HT1 Aviation	0.0	137.3	6.3%	0.3	0.0	0.0	676.7	118.2	7.6	0.022	162	4%	N	0.0	71.0	12.6%	0.7	0.0	0.3	562.7	294.2	14.8	0.028	81	10%	N
HT2 Computer_office_mach	0.0	29.3	10.2%	0.5	0.0	0.7	1706.0	112.2	10.3	0.041	41	5%	N	0.0	43.0	7.0%	7.6	0.0	3.0	6206.7	117.6	9.2	0.016	323	39%	N
HT3 Laser	0.0	111.0	9.3%	1.5	0.0	0.3	1195.0	129.8	10.4	0.031	112	14%	N	0.0	281.0	9.9%	3.5	0.0	1.0	2843.7	164.9	11.5	0.026	205	25%	N
HT4 Semiconductor	0.0	183.3	7.1%	3.3	0.0	1.0	2713.0	99.2	9.0	0.022	189	23%	N	0.0	541.7	5.7%	11.6	0.3	3.3	9486.7	81.7	8.1	0.018	347	42%	Y
HT5 Microorgan_Genetics	0.0	87.3	3.5%	3.0	0.0	1.0	2485.0	31.5	5.1	0.012	200	24%	N	0.0	231.3	4.8%	6.1	0.0	2.5	5063.0	52.2	6.1	0.011	289	35%	N

Source: own illustration. Notes: Fractional counting of applications; database covers 819 OECD Territorial Levels TL3 regions. For Belgium, Greece and the Netherlands, OECD TL3 corresponds to the EUROSTAT NUTS2 level. For Germany 97 "Raumordnungsregionen" are used. EPO patent application counting is based on fractional counting. Patent IDs are counted several times if the application ID correspond to several technology fields.

3.4.2.2. Regional Patenting Activity and EPO Inventors in Europe

3.4.2.2.1. Patent Applications by Technology Field

Another interesting picture can be generated from the regional structure of EPO patent applications and EPO inventors according to technology fields (see section 3.3 and appendix, tables B.2, B.3 and B.4 for methodological issues).

It is worth noting that, in the 1980s, almost each technology field within the regional population (819 TL3 regions) was dominated by only a small fraction of European regions with $n > 0$ EPO patent applications as illustrated in figure 3.11.³⁵⁹ Around 50 per cent of all 819 regions remain without a single patent application (fractional counting) in 32 technology fields, even in the year 2004, which supports the impression that research/inventorship activity is still highly concentrated across the population of 819 European regions. Figure 3.11 clearly highlights that the technology fields *TF12 Paints & varnishes*, *TF2 Tobacco*, *TF41 Watches & clocks*, *HT3 Laser* are only present in 8-10% of all 819 European regions in 2004. However, significant dispersion tendencies of EPO patent applications across the European landscape of regions can be observed since 1977, although the technology fields widely differ in their structural dynamics and overall geographic concentration. It has to be noted that the propensity to patent widely differs across the technology fields. Accordingly, all computed indices and measures for each technology field are hard to compare and are thus presented separately.

With respect to individual technology fields, the lowest dispersion tendencies and thus the highest concentration, in terms of regions with at least one single EPO patent application across the sample, can be observed for the following technology fields: *TF12 Paints & varnishes*, *TF41 Watches & clocks*, *TF2 Tobacco products*, *HT4 Laser*, *TF16 Man-made fibres*, *TF5 Leather articles*, *TF4 Wearing & apparel*, *TF26 Weapons & ammunition*, *TF6 Wood products* and *HT1 Aviation*. These technology fields are characterized by (i) a rather small amount of patent applications and (perhaps) (ii) a small propensity to patent.³⁶⁰ Thus, it has to be assumed that these two properties affect inequality/disparity measures.³⁶¹ In opposition to these highly concentrated technology fields, meaningful dispersion tendencies are observed for the following technology fields: *TF21 Energy machinery*, *TF35 Signal transm. & telecommunications*, *TF28 Office machinery & computers*, *TF38 Measuring instruments*, *TF42 Motor vehicles*, *TF22 Non-specific purpose machinery*, *TF37 Medical equipment*, *TF17 Rubber & plastic products*, *TF25 Special purpose machinery*, *TF13 Pharmaceuticals* and *TF10 Basic chemicals*. These technology fields are characterized by (i) larger shares of regions that show at least one single patent application ($n > 0$) and thus a higher dispersion across the 819 TL3 units, (ii) a larger number of IPC codes that form the technology field, (iii) a larger number of EPO patent applications, and (iv) potentially higher propensities to file patents at the EPO.³⁶² Moreover, as expected, high-technology

³⁵⁹ A value of $n > 0$ patent applications is possible due to the fractional counting methodology.

³⁶⁰ However note that (ii) is not the main research question of this study.

³⁶¹ It is clear that the market structure can have effects on the dispersion measures; industries and thus technology fields that consist of a small number of firms tend to be relatively more concentrated in space; although the inventor location information is used, inventors have a certain probability to cluster around the applicant location.

³⁶² Nevertheless, (iv) is not a central research question of this study.

Table 3.3. Descriptives: Change of EPO inventors and patent applications by TF

Technology Field	EPO patent applications by IPC and technology field						EPO inventors (unique inventor ID) by IPC and technology field					
	%change 1990/1992 - 2002/2004						%change 1990/1992 - 2002/2004					
	$\Delta(P70-P30)$ (6)-(5) %	Δ kurtosis (8) %	Δ skewness (9) %	Δ HHI (10) %	Δ regions with $n>0$ patents (11) %		$\Delta(P70-P30)$ (6)-(5) %	Δ kurtosis (8) %	Δ skewness (9) %	Δ HHI (10) %	Δ regions with $n>1$ inventors (11) %	
SUM_44_TF	72,0%	50,4%	15,5%	-5,6%	15,5%	+	84,6%	11,6%	-1,0%	-16,3%	17,8%	+
TF1_Food_beverages	71,6%	-52,4%	-27,7%	-10,9%	34,3%	++	100,0%	-64,4%	-38,4%	-21,7%	39,6%	++
TF2_Tobacco_prod	-	89,3%	61,1%	188,7%	30,0%	++	-	-3,2%	3,3%	68,6%	40,5%	++
TF3_Textiles	100,0%	-54,7%	-35,7%	-46,7%	13,1%	+	0,0%	-40,5%	-28,7%	-50,7%	11,9%	+
TF4_Wearing_apparel	-	-47,6%	-24,9%	-38,2%	159,1%	++++	-	-19,6%	-12,3%	-36,5%	227,8%	++++
TF5_Leather_articles	-	-3,3%	-5,4%	-49,8%	79,9%	+++	-	-30,1%	-19,9%	-53,1%	75,5%	+++
TF6_Wood_prod	-	-19,2%	-9,9%	-19,7%	31,5%	++	-	-53,5%	-27,2%	-24,0%	27,0%	++
TF7_Paper	0,0%	-31,2%	-18,6%	-19,7%	15,3%	+	100,0%	-41,3%	-26,0%	-32,1%	32,6%	++
TF9_Petrol_prod_nucl_fuel	-	-38,1%	-22,6%	-30,5%	34,7%	++	-	42,4%	8,7%	-24,2%	44,8%	++
TF10_Basic_chemical	16,9%	-37,9%	-24,1%	-36,1%	16,8%	+	43,8%	-36,4%	-23,6%	-40,0%	17,9%	+
TF11_Pesticide_agrochem_prod	66,7%	16,0%	3,7%	-7,1%	3,3%	+	0,0%	-17,6%	-9,2%	-11,2%	12,4%	+
TF12_Paints_varnishes	-	-85,5%	-61,5%	-57,3%	-5,8%	-	-	-71,7%	-50,0%	-57,5%	14,7%	+
TF13_Pharmaceuticals	118,1%	-46,2%	-24,7%	-24,6%	35,0%	++	126,4%	-57,7%	-32,0%	-29,9%	42,0%	++
TF14_Soaps_detergents	-	-51,8%	-31,3%	-36,4%	13,2%	+	-	-62,4%	-38,9%	-45,6%	20,2%	+
TF15_Other_chemicals	0,0%	-8,8%	-8,3%	-17,4%	-1,4%	-	0,0%	-33,6%	-21,1%	-31,3%	3,5%	+
TF16_Man_made_fibre	-	-7,1%	-10,1%	-36,7%	28,9%	++	-	-49,5%	-28,9%	-42,2%	18,7%	+
TF17_Rubber_plastic_prod	33,6%	10,0%	1,5%	-11,0%	21,2%	+	52,1%	-19,8%	-9,7%	-13,6%	21,1%	+
TF18_Non-metal_mineral_prod	23,9%	-47,1%	-24,8%	-23,5%	20,2%	+	21,2%	-58,0%	-32,6%	-28,3%	24,1%	+
TF19_Basic_metals	28,6%	-5,6%	-3,8%	-12,5%	14,8%	+	25,0%	-19,8%	-11,6%	-17,9%	21,1%	+
TF20_Fabric_metal_prod	40,8%	6,7%	2,5%	-6,5%	24,0%	+	57,1%	25,8%	9,0%	-7,9%	33,4%	++
TF21_Energy_machinery	61,7%	22,7%	12,1%	8,3%	31,7%	++	112,0%	-5,3%	-1,3%	2,1%	35,7%	++
TF22_Nonspec_machinery	21,4%	609,4%	154,8%	33,2%	15,7%	+	55,6%	367,4%	107,1%	21,6%	18,0%	+
TF23_Agricul_forestry_machinery	68,8%	18,2%	11,2%	0,3%	28,0%	++	50,0%	0,5%	5,9%	5,4%	39,9%	++
TF24_Machine_tools	41,2%	12,1%	7,4%	5,2%	15,5%	+	75,0%	-22,7%	-14,7%	-15,0%	23,7%	+
TF25_Spec_purp_machinery	15,0%	-44,2%	-22,1%	-13,3%	14,2%	+	35,7%	-61,9%	-36,0%	-23,9%	13,6%	+
TF26_Weapons_ammunition	-	11,3%	8,5%	9,2%	21,2%	++	-	-40,4%	-18,9%	-13,2%	23,7%	+
TF27_Domestic_appliances	106,3%	7,3%	6,3%	-0,5%	38,3%	++	166,7%	40,3%	17,8%	3,8%	50,2%	+++
TF28_Office_mach_computers	130,0%	152,2%	55,6%	17,1%	49,4%	+++	180,0%	67,0%	24,1%	-11,6%	68,0%	+++
TF29_Electric_motors_generators	-	68,7%	38,0%	22,3%	58,9%	+++	-	34,2%	24,4%	14,2%	73,2%	+++
TF30_Elec_distr_contr_wire_cable	93,7%	-2,9%	-3,6%	-16,4%	21,7%	+	50,0%	-41,2%	-21,3%	-26,0%	33,1%	++
TF31_Accumulators_battery	-	-32,8%	-10,3%	-10,4%	88,2%	+++	-	-39,7%	-14,0%	-11,2%	129,0%	++++
TF32_Lighting_equipment	-	-8,4%	-1,6%	3,9%	50,5%	+++	-	4,3%	6,6%	17,3%	81,8%	+++
TF33_Other_electr equip	98,1%	-9,1%	-3,6%	-17,6%	43,6%	++	100,0%	-15,1%	-7,2%	-23,5%	51,9%	+++
TF34_Electr_components	182,3%	-15,1%	-8,5%	-28,7%	51,3%	+++	200,0%	-6,4%	-4,8%	-30,4%	61,4%	+++
TF35_Signal_transm_telecom	152,0%	-13,0%	-7,5%	-17,1%	48,8%	++	250,0%	-15,8%	-9,9%	-22,5%	61,1%	+++
TF36_TV_radio_receiv_audio	72,6%	114,1%	48,1%	32,6%	50,6%	+++	200,0%	53,0%	22,4%	-1,1%	70,8%	++
TF37_Med_equipment	116,8%	-9,5%	-7,5%	-13,4%	31,4%	++	128,6%	6,9%	1,2%	-7,9%	46,9%	++
TF38_Measuring_instruments	70,1%	38,6%	13,6%	-3,5%	27,9%	++	100,0%	36,0%	12,0%	-6,8%	31,7%	++
TF39_Ind_proc_contr equip	100,0%	122,9%	51,3%	33,1%	41,9%	++	100,0%	77,5%	42,0%	29,5%	39,9%	++
TF40_Opti_instruments	47,8%	439,4%	131,3%	63,4%	26,1%	++	33,3%	496,8%	144,0%	76,0%	33,8%	++
TF41_Watches_clocks	-	71,3%	33,6%	56,3%	26,1%	++	-	119,0%	48,4%	56,4%	40,3%	++
TF42_Motor_vehicles	80,0%	56,6%	30,9%	41,3%	27,9%	++	133,3%	17,3%	10,3%	15,9%	35,5%	++
TF43_Other_transp equip	92,2%	38,3%	19,5%	2,6%	36,2%	++	100,0%	10,9%	12,2%	6,3%	53,1%	+++
TF44_Furniture_consum_good	100,0%	-20,1%	-10,5%	-17,1%	31,4%	++	100,0%	-25,4%	-12,5%	-18,1%	50,1%	+++
SUM_hightech	157,2%	-2,5%	-3,1%	-13,1%	36,7%	++	181,8%	-10,1%	-7,3%	-16,4%	48,7%	++
HT1_Aviation	-	281,6%	89,5%	21,1%	59,3%	+++	-	328,1%	96,2%	24,1%	96,0%	+++
HT2_Computer_office_mach	244,7%	25,0%	7,2%	-17,6%	71,6%	+++	350,0%	4,8%	-2,3%	-27,5%	99,4%	+++
HT3_Laser	-	-58,1%	-38,3%	-55,3%	40,1%	++	-	-21,5%	-19,4%	-50,2%	43,1%	++
HT4_Semiconductors	285,5%	-7,1%	-2,3%	-18,7%	75,0%	+++	200,0%	27,0%	10,9%	-15,0%	82,8%	+++
HT5_Communication	214,5%	2,6%	0,5%	-9,1%	62,5%	+++	200,0%	-17,6%	-9,7%	-20,2%	83,8%	+++
HT6_Microorgan_Genetics	120,9%	58,2%	19,3%	-2,6%	34,2%	++	153,3%	65,9%	20,9%	-3,5%	44,5%	++

Source: own illustration. Notes: Full counting of inventor IDs; database covers 819 OECD Territorial Levels TL3 regions. For Belgium, Greece and the Netherlands, OECD TL3 corresponds to the EUROSTAT NUTS2 level. For Germany, we make use of 97 "Raumordnungsregionen." Inventor counting is based on full counting. IDs are counted several times if inventor IDs correspond to several technology fields. EPO patent application counting is based on fractional counting method. Patent IDs are counted several times if the application ID correspond to several technology field aggregates.

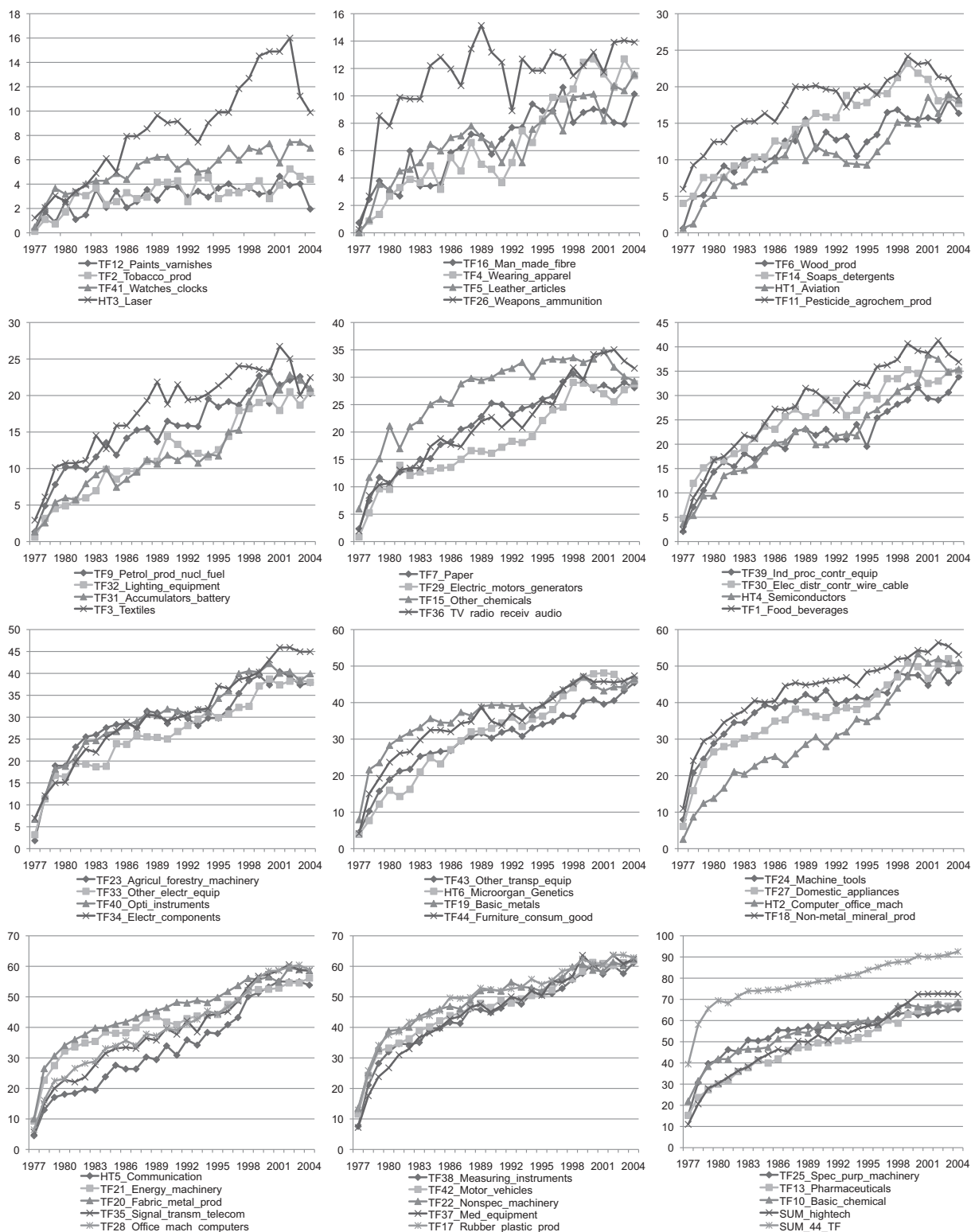


Fig. 3.11. Share of European regions with $n > 0$ patent applications by TF
Source: own calculations and illustration. *Notes:* Fractional counting, 1977-2004; the population covers 819 European TL3 regions. Patent data generated by mySQL OECD RegPAT (2009) extractions and application of ISI-SPRU-OST concordance. TL3 population data constructed from EUROSTAT REGIO, OECD, ESPON and BBR data. For Belgium, Greece and the Netherlands, OECD TL3 correspond to EUROSTAT NUTS2. For Germany, 97 “Raumordnungsregionen” are used (OECD, 2003).

fields, such as *HT3 Laser technology* and *HT1 Aviation technology*, are much more concentrated in space compared to *HT4 Semiconductors*, *HT6 Microorganisms & genetics*, *HT2 Computer & office machinery* or *HT5 Communication technology*. However, *HT3 Laser* and *HT1 Aviation* generally show a smaller number of EPO patent applications, which implicitly affects the measures. An alternative extraction shows that only a few European regions contribute with $n > 9$ EPO patent applications. Figure A.9 (appendix) highlights the computed share of regions within the entire population of European regions that have $n > 9$ yearly EPO patent applications since the 1980s. Generally, the overall picture that emerges from figure 3.11 remains, although the share of regions with $n > 9$ patent applications is much smaller compared to $n > 0$.

3.4.2.2.2. EPO Inventors by Technology Field

A similar picture, compared to the distribution of EPO patent applications presented in figure 3.11 (and A.9, appendix), is visualized in the following figure 3.12 (and A.10, appendix).

Figure 3.12 shows the share of regions that have at least one inventor ($n > 1$ heterogenous inventor IDs) according to technology field (respectively ten inventors in figure A.10, appendix). The larger the fraction of regions that correspond to this category, the more the technology field appears to be dispersed across the 819 European regions in terms of inventors; additionally, the TL3 regions can be thought of as being clusters (or agglomerations) of inventors. Figure 3.12 (and A.10, appendix) clearly depicts that (i) several technology fields are highly concentrated in space and (ii) that the utilization of inventor IDs also represents an admissible proxy for research activity in cluster and location studies.³⁶³ To conclude, the overall picture is one of dispersion as the number of regions with $n > 1$ registered EPO inventors has increased.

3.4.2.2.3. Revealed Technological Advantage by Technology Field

The previous extractions and computations only account for the absolute number of EPO patents and hence for absolute specialization. As a result, nothing can be said about relative specialization of regions. Therefore, alternative computations are applied: location quotients (LQ)/ revealed technological advantage (RTA) indices and modified Gini coefficients.

Relating to equation 3.4.4, figure 3.13 depicts the shares of European regions (%) by technology field with a location quotient $LQ > 1$, i.e., a revealed technological advantage $RTA > 1$. The figure clearly shows that the share (and number) of European regions with $RTA > 1$ within the entire population of 819 European regions has increased since the

³⁶³ Note that the fractions reported in figures 3.12 and 3.11 (and A.10 and A.9, appendix) can differ, because full counting of inventor IDs is applied in figure 3.12 (and A.10, appendix), whereas the calculated shares in figure 3.11 (and A.9, appendix) are based on fractional counting of patent applications. Although a region hosts three inventors of a patent, each of them holds one third of the patent. Accordingly, results from fractional and full counting are only identical when comparing the share of regions with $n > 0$ patent application with the share of regions with $n > 0$ inventor IDs.

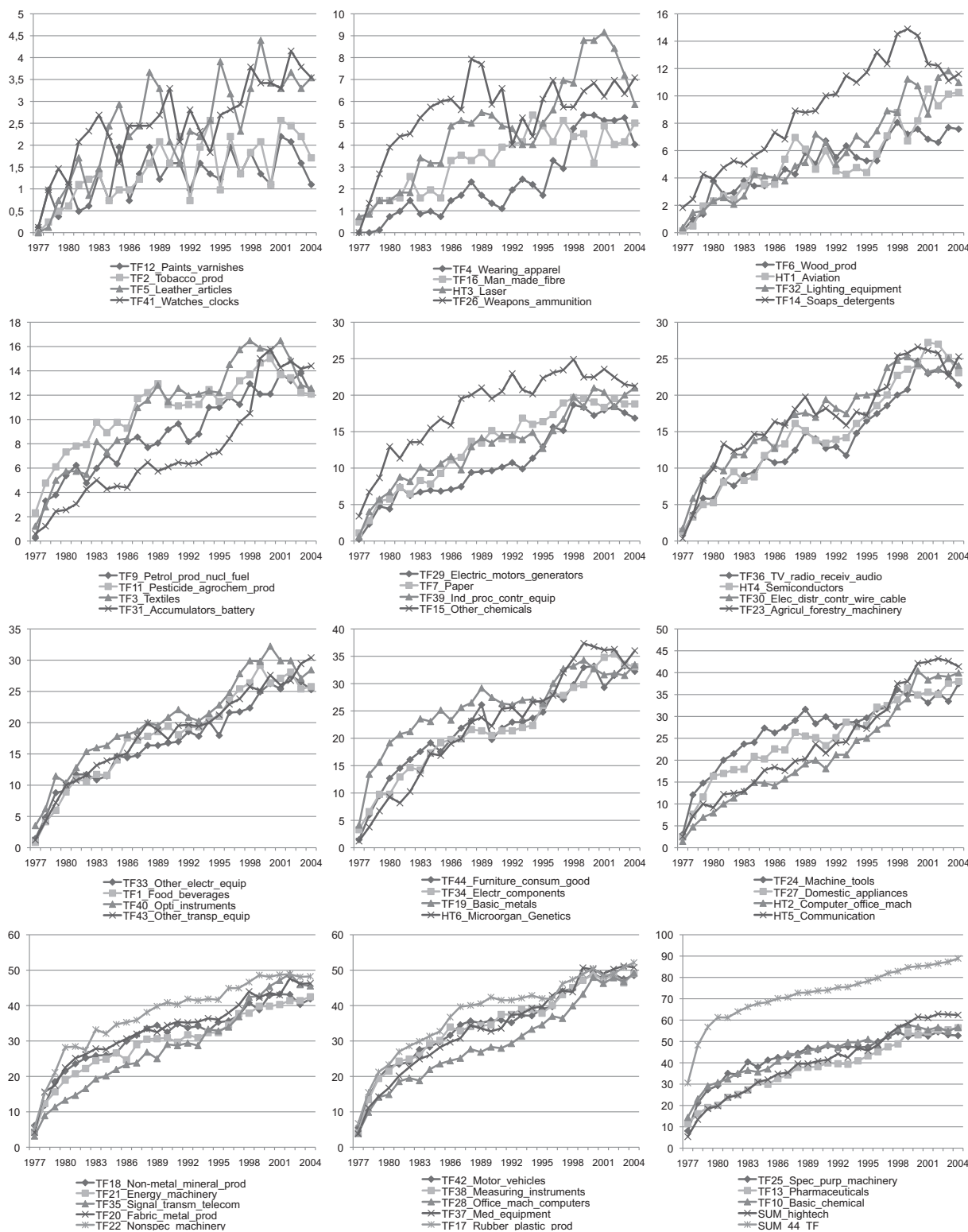


Fig. 3.12. Share of European regions with $n > 1$ inventor IDs by TF
Source: own calculations and illustration. *Notes:* Full counting, 1977-2004; the population covers 819 European TL3 regions. Patent data generated by MySQL OECD RegPAT (2009) extractions and application of ISI-SPRU-OST concordance. TL3 population data constructed from EUROSTAT REGIO, OECD, ESPON and BBR data. For Belgium, Greece and the Netherlands, OECD TL3 correspond to EUROSTAT NUTS2. For Germany, 97 “Raumordnungsregionen” are used (OECD, 2003).

year 1977. Further to this, figure 3.14 supports these findings and highlights the structural change of the share of regions with $RTA > 1$. An overall increase of specialized regions can be clearly observed.

The specialization analysis (i.e., LQ/ RTA) admittedly unveils that the share of regions with $RTA > 1$ in a technology field i is in general smaller compared to the share of regions that show at least a minimum EPO patenting activity ($n > 0$) as has been presented in figure 3.11. Hence, it can be concluded that the share of regions with a strong relative specialization ($RTA > 1$) is much smaller compared to the overall number of regions active in research ($n > 0$) as presented in figure 3.11 (and figure A.9, appendix). When analyzing figure 3.15 (and the alternative figure A.11, appendix), it is clearly visible that the numbers (and shares) of regions with $RTA > 1$ compared to the number (and share) of regions with $n > 0$ EPO patent applications has decreased during the last two decades (1988-90 vs. 2002-2004).³⁶⁴ These results indicate a relative decrease of specialized research locations and innovative places (TL3 regions) in the European research landscape.

The following conclusions have to be drawn from the previous findings: (i) the number of TL3 regions with strong specialization in a specific technology field ($RTA > 1$) has increased within the entire population of 819 TL3 regions; (ii) a larger share of European regions is involved in EPO patenting in the 2000s compared to the 1980s and 1990s; (iii) the share of regions with $RTA > 1$ within the population of European regions with $n > 0$ EPO patent applications (in a specific technology-field) has decreased, which means that Europe is characterized by ongoing dispersion and decreasing relative concentration and specialization as the average level of patenting has increased in almost all technology fields since the 1980s; (iv) high-technology fields have experienced very strong dispersion tendencies since the 1980s, except some technology fields that in general show lower patenting propensities (e.g., *HT4 Laser*, *HT1 Aviation*).

3.4.2.3. Regional Disparities of EPO Patenting Activity

3.4.2.3.1. Locational and Spatial Gini Coefficients by Technology Field

Besides the calculation of regional shares and other descriptives, modified Gini coefficients are used as they represent much more sophisticated inequality/disparity measures; moreover, they satisfy several axioms as presented in the last section (see section 3.4.1). Therefore, this section provides the results from the computation of spatial and locational Gini coefficients (G_{SPACE}^* , G_{LOC}^*). In this respect, the spatial distributional structure and the concentration/disparities of EPO patenting activity in all 51 technology field aggregates are analyzed.³⁶⁵ Figures 3.16 to 3.23 summarize the distributional characteristics of European research/ inventorship activity by means of population weighted (y_j) and areal surface weighted (z_j) Gini coefficients for the periods 1988-2004 (population weighted Gini) and 1977-2004 (areal surface weighted Gini).³⁶⁶

³⁶⁴ Yearly values for all 51 technology fields have been extracted and calculated since 1977.

³⁶⁵ For a complete overview and list of abbreviations of all 51 technology field aggregates used in the following graphs and tables see table B.4 (appendix).

³⁶⁶ Unfortunately, we are not able to calculate G_{LOC}^* for the full reference period from 1977 onwards due to population data constraints.

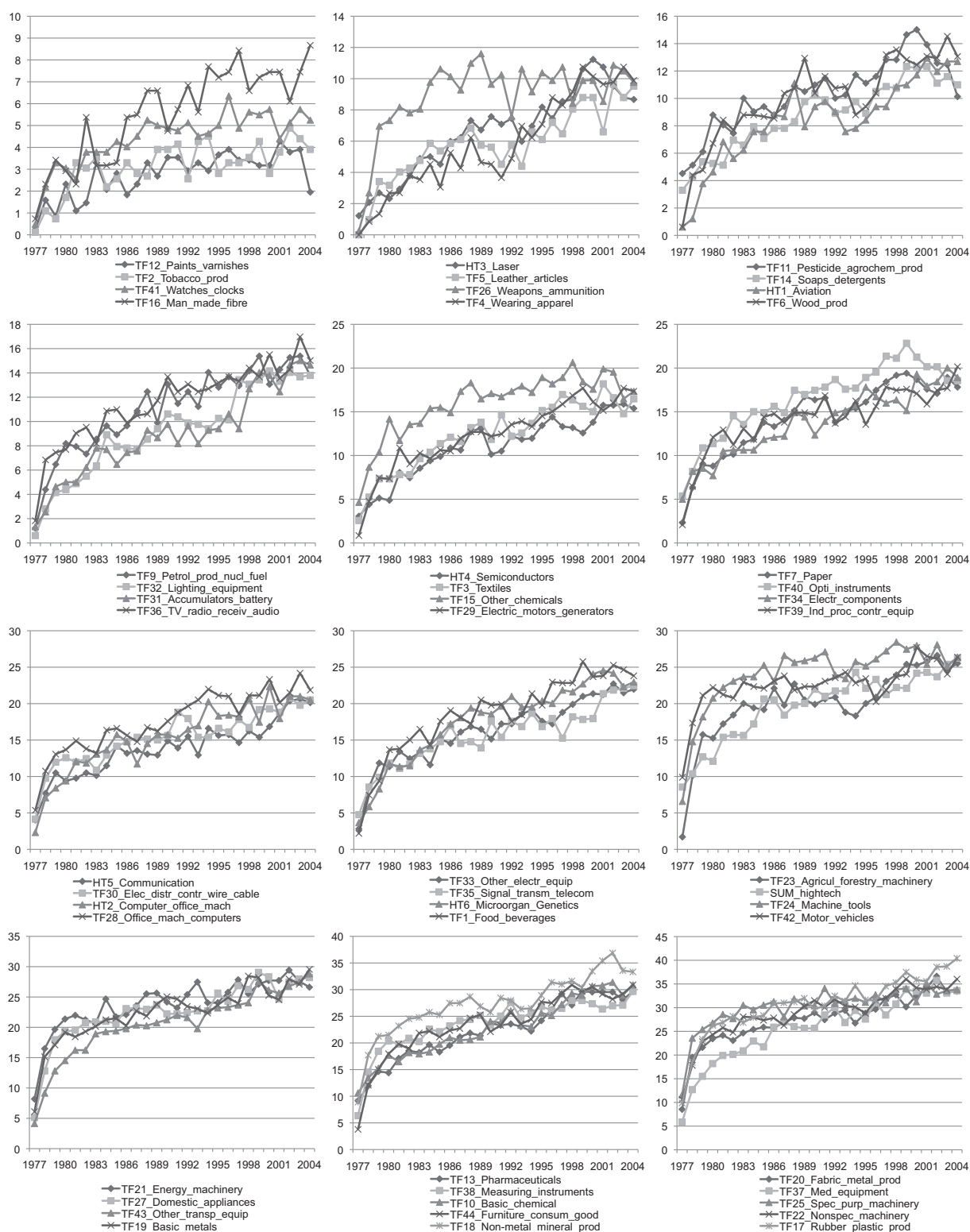


Fig. 3.13. Share of European regions with $RTA > 1$ by TF

Source: own calculations and illustration. *Notes:* $RTA > 1$ in EPO patent applications, 1977-2004; the population covers 819 European TL3 regions. Patent data generated by MySQL OECD RegPAT (2009) extractions and application of ISI-SPRU-OST concordance. TL3 population data constructed from EU-ROSTAT REGIO, OECD, ESPON and BBR data. For Belgium, Greece and the Netherlands, OECD TL3 correspond to EUROSTAT NUTS2. For Germany, 97 "Raumordnungsregionen" are used (OECD, 2003).

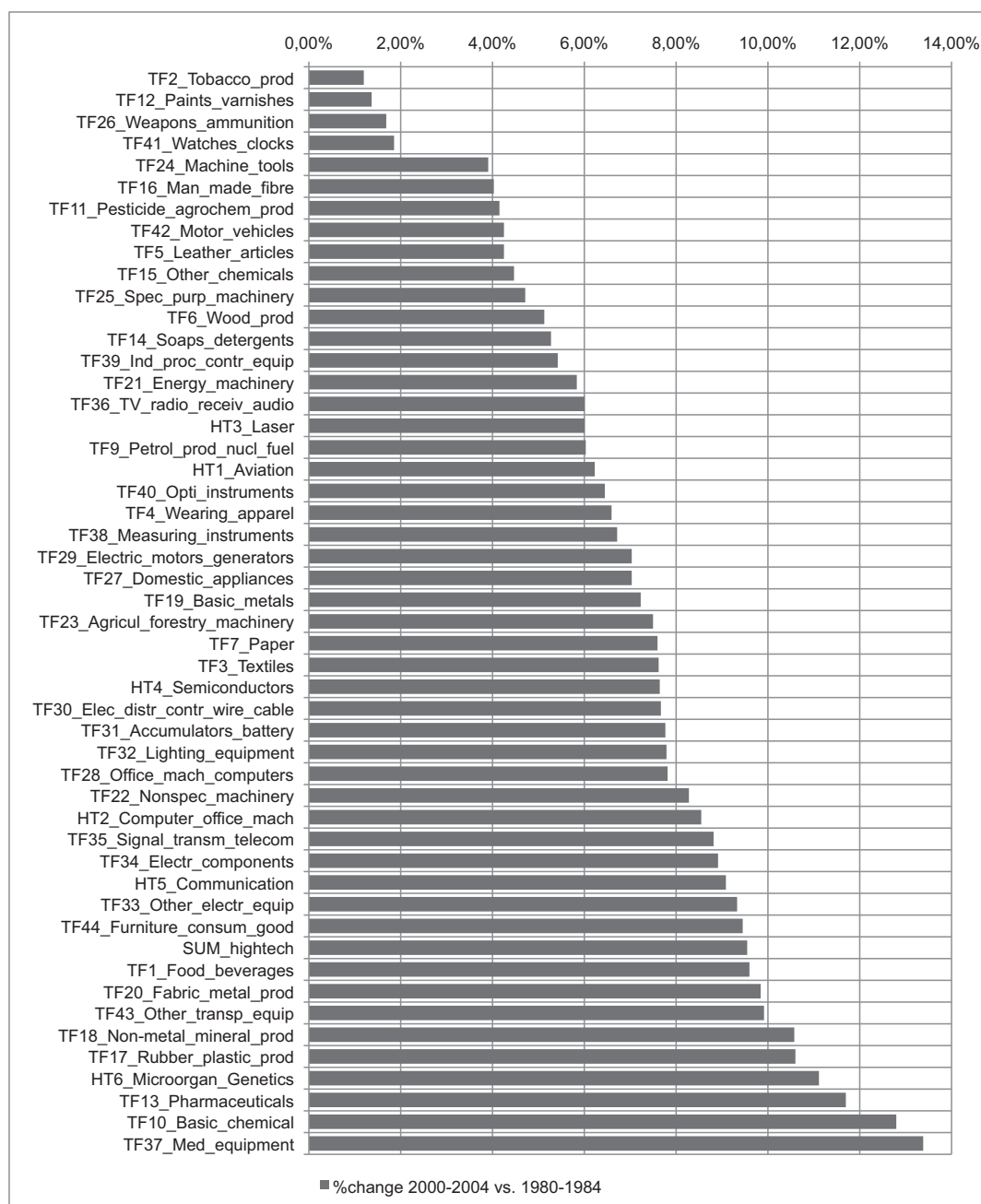


Fig. 3.14. Change (share) of European regions w/ RTA > 1 by TF: 1988-1990 vs. 2002-2004

Source: own calculations and illustration. *Notes:* Sample covers 819 regions; change 1988-1990 vs. 2002-2004; the population covers 819 European TL3 regions. Patent data generated by MySQL OECD RegPAT (2009) extractions and application of ISI-SPRU-OST concordance. TL3 population data constructed from EUROSTAT REGIO, OECD, ESPON and BBR data. For Belgium, Greece and the Netherlands, OECD TL3 correspond to EUROSTAT NUTS2. For Germany, 97 "Raumordnungsregionen" are used (OECD, 2003).

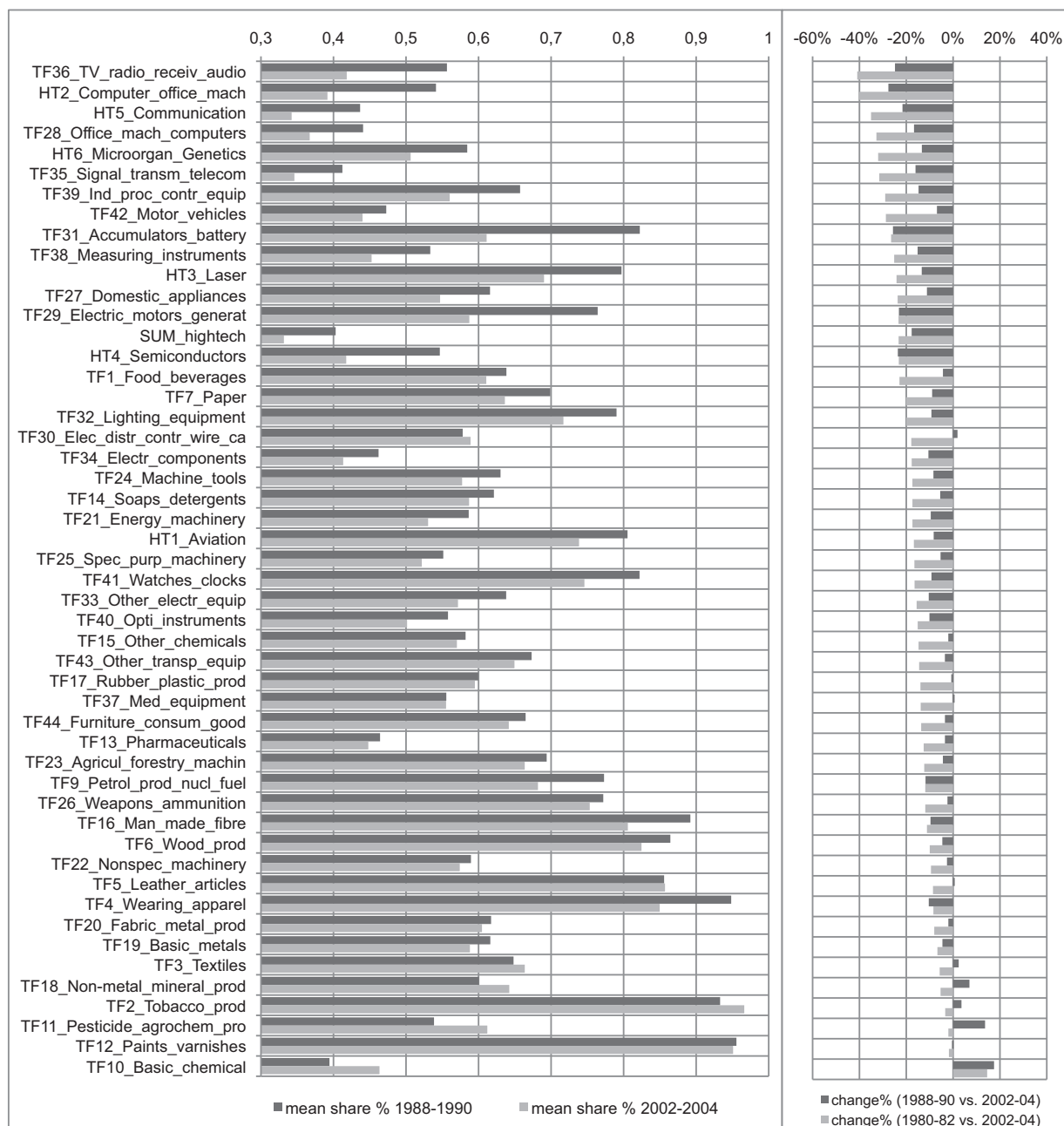


Fig. 3.15. Structure of European regions w/ RTA > 1 of regions w/ n > 0 patent applications

Source: own calculations and illustration. *Notes:* Calculations by technology field; change 1988-90 vs. 2002-04 and 1980-82 vs. 2002-04; the population covers 819 European TL3 regions. Patent data generated by MySQL OECD RegPAT (2009) extractions and application of ISI-SPRU-OST concordance. TL3 population data constructed from EUROSTAT REGIO, OECD, ESPON and BBR data. For Belgium, Greece and the Netherlands, OECD TL3 correspond to EUROSTAT NUTS2. For Germany, 97 "Raumordnungsregionen" are used (OECD, 2003).

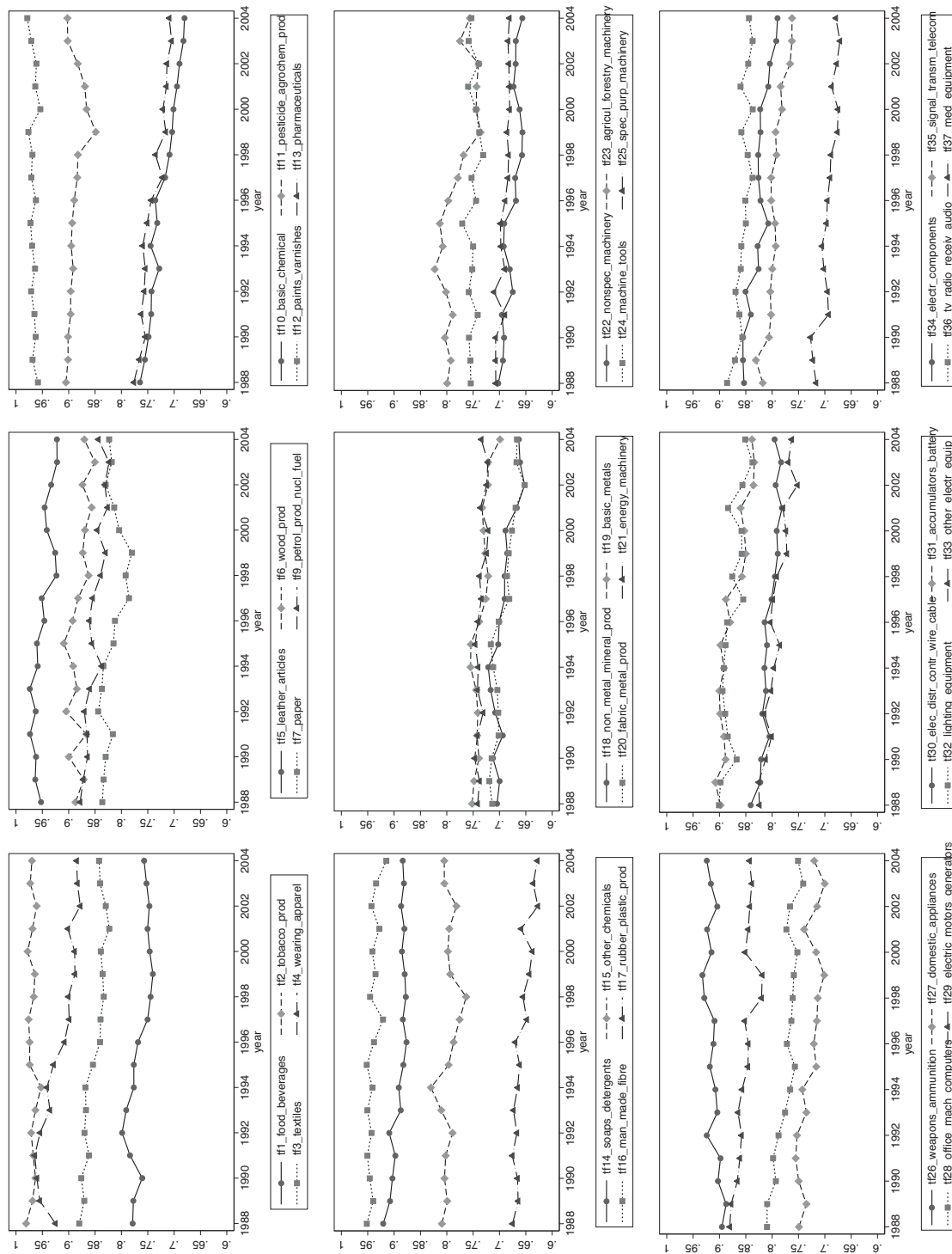


Fig. 3.16. Locational Gini: regional disparity of EPO patent applications by TF (EU-25, CH, NO) (a)
 Source: own calculations and illustration. Notes: G^*_{LOC} by technology field; the population covers 819 European TL3 regions (EU-25, CH, NO).

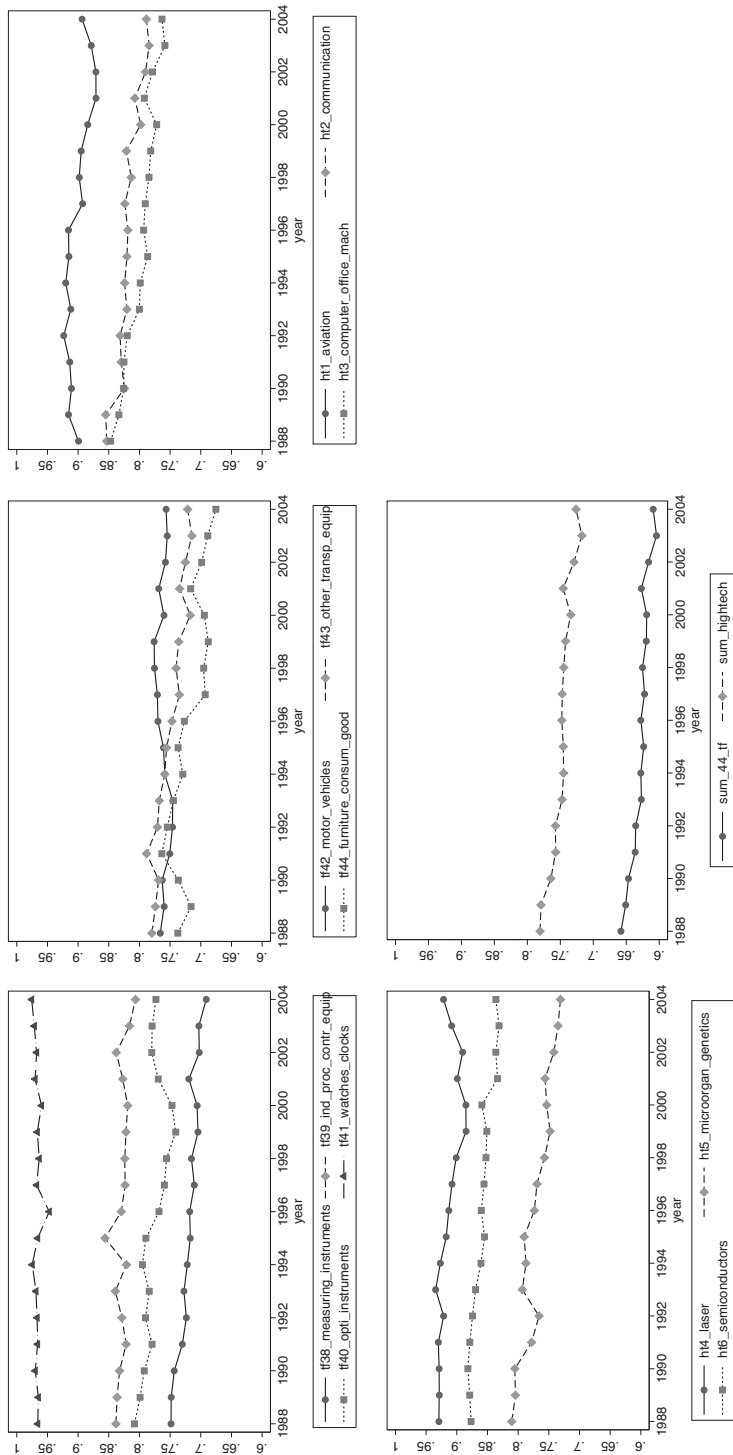


Fig. 3.17. Locational Gini: regional disparity of EPO patent applications by TF (EU-25, CH, NO) (b)
 Source: own calculations and illustration. Notes: G_{LOC}^* by technology field; the population covers 819 European TL3 regions (EU-25, CH, NO).

The following results can be reported: the technology fields *TF12 Paints & varnishes*, *TF2 Tobacco products*, *TF41 Watches & clocks*, *HT4 Laser*, *TF16 Man-made fibres*, *TF4 Wearing & apparel*, *TF5 Leather articles* and *TF26 Weapons & ammunition* show strong inequality (i.e., disparity) coefficients and thus strong spatial concentration within the population of 819 European regions. In comparison, *TF13 Pharmaceuticals* and *TF10 Basic chemicals* show much lower G_{LOC}^* values; accordingly, these fields exhibit much stronger dispersion within the regional population of regions (but also by a larger number of patent applications).³⁶⁷

Another important result of the G_{LOC}^* computation, as illustrated in figures 3.16 and 3.17, is that several technology fields are characterized by dispersion tendencies of inventorship activity since the 1980s (e.g., *TF10 Basic chemicals*; *TF13 Pharmaceuticals*; *TF28 Office machinery & computers*; *TF28 Electronic motors & generators*; *TF30-TF33*; *TF34 Electr. components*; *HT3 Computer & office machines*; *HT2 Communication technology*; *HT6 Semiconductors*). These tendencies are also identified by focusing on the two aggregates $\sum 44 TF$ and $\sum 6 high-TF$. However, several technology fields remain at a very high level of concentration, when the Gini computation controls for population size; e.g., *TF2 Tobacco*; *TF12 Paints & varnishes*; *TF26 Weapons & ammunition*; *TF41 Watches & clocks*; *TF42 Motor vehicles*; *HT1 Aviation*; *HT4 Laser*; *TF40 Optical instruments*; *TF39 Industr. proc. control equipm.*, among others. To conclude, G_{LOC}^* shows that the distribution of EPO patent applications converges in the course of time to the distribution of regional population for some technology fields. This development may result from a higher patenting activity in peripheral areas or from a stronger core-affinity of population, which causes shifts of the Lorenz curve; the latter case may mean that population has disproportionately moved towards European urban regions and metropolises. Furthermore, it should be noted that overall inequality persists at a very high level in many technology fields. Thus, there are still many technology field-specific research and innovation activities that are restricted to a minority of European regions as illustrated in figures 3.11, 3.16 and 3.17 ($n > 0$ patent applications). As a consequence, a large fraction of European regions is still not engaged in research/inventorship activity at all. In summary, especially with regard to figures 3.16 and 3.17, the technology field aggregates “ $\sum 44 TF$ ” and “ $\sum 6 high-TF$ ” show that (i) EPO patent applications are in general increasingly dispersed across the 819 European regions and that (ii) the aggregate of all 6 high technology fields shows similar dispersion tendencies across the 819 regions, although several technology fields remain highly concentrated (e.g., *HT4 Laser* and *HT1 Aviation*). Additional time series, descriptives, and national weighted Gini coefficients, e.g., for Austria, Belgium, France, Germany, Italy, the Netherlands, Sweden, Switzerland and the United Kingdom, are presented in the appendix. According to these additional computations, the above presented picture of a general increasing dispersion of research activity remains for the majority of countries and technology fields, although some of them show interesting deviations from the trend.

Finally, population weighted Gini indices (G_{LOC}^*) are highlighted for EPO patent applications in the 51 technology fields for two subgroups (NMS, EU-15+2) in figures 3.18, 3.19, 3.20 and 3.21. The figures present the yearly Gini indices (locational Gini). A comparison clearly exhibits differing developments of the population-weighted Gini coefficients; the

³⁶⁷ *TF28* and *HT3* are very similar with respect to IPC codes; thus the Gini coefficients and inequality dynamics are almost identical.

NMS show a stronger decrease in disparities in several technology fields; especially in the second half of the 1990s (see also the dynamic illustration in figure 3.27).

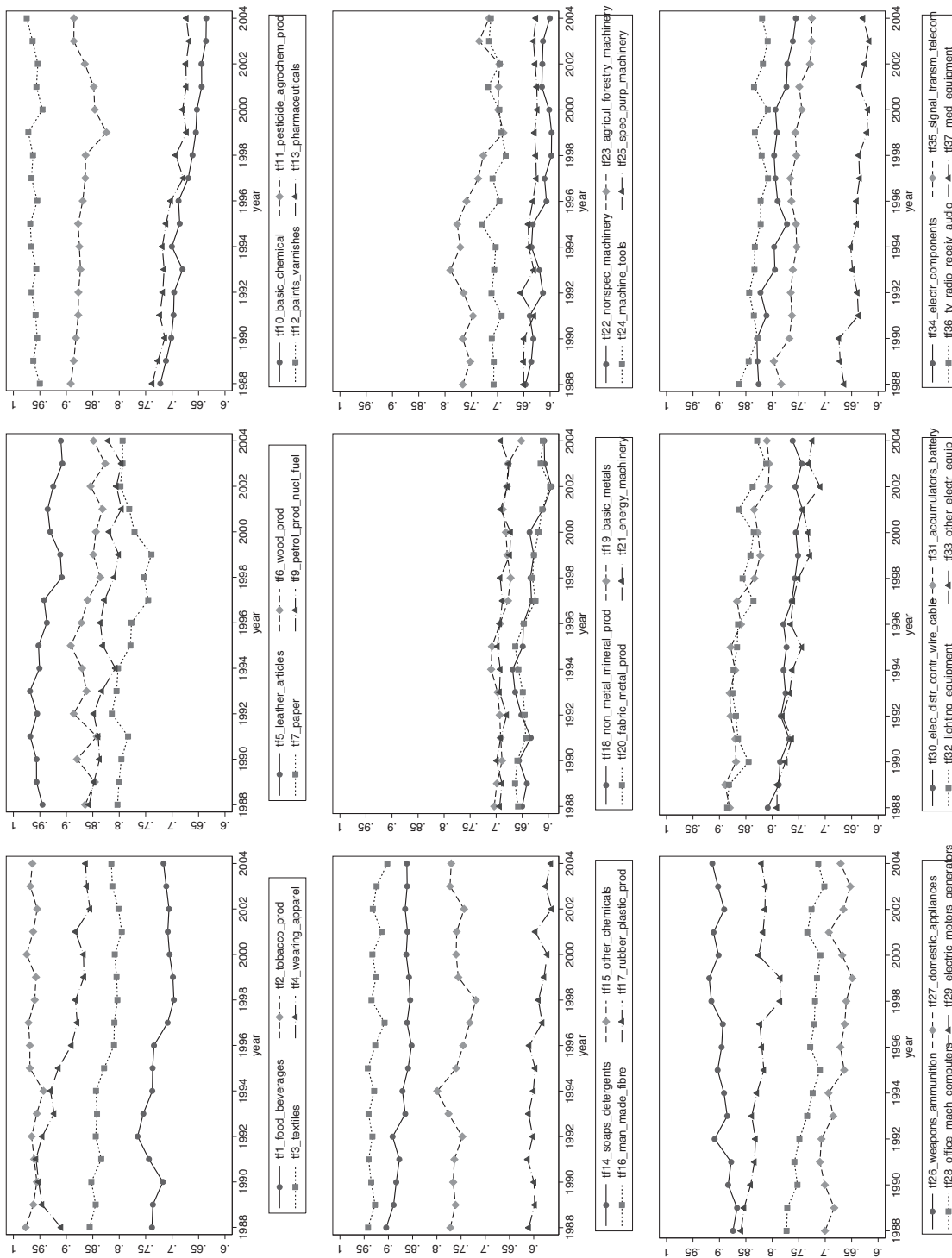


Fig. 3.18. Locational Gini: regional disparity of EPO patent applications by TF (EU-15) (a)
 Source: own calculations and illustration. Notes: G^*_{LOC} by technology field; the population covers 696 TL3 regions (EU-15, CH, NO).

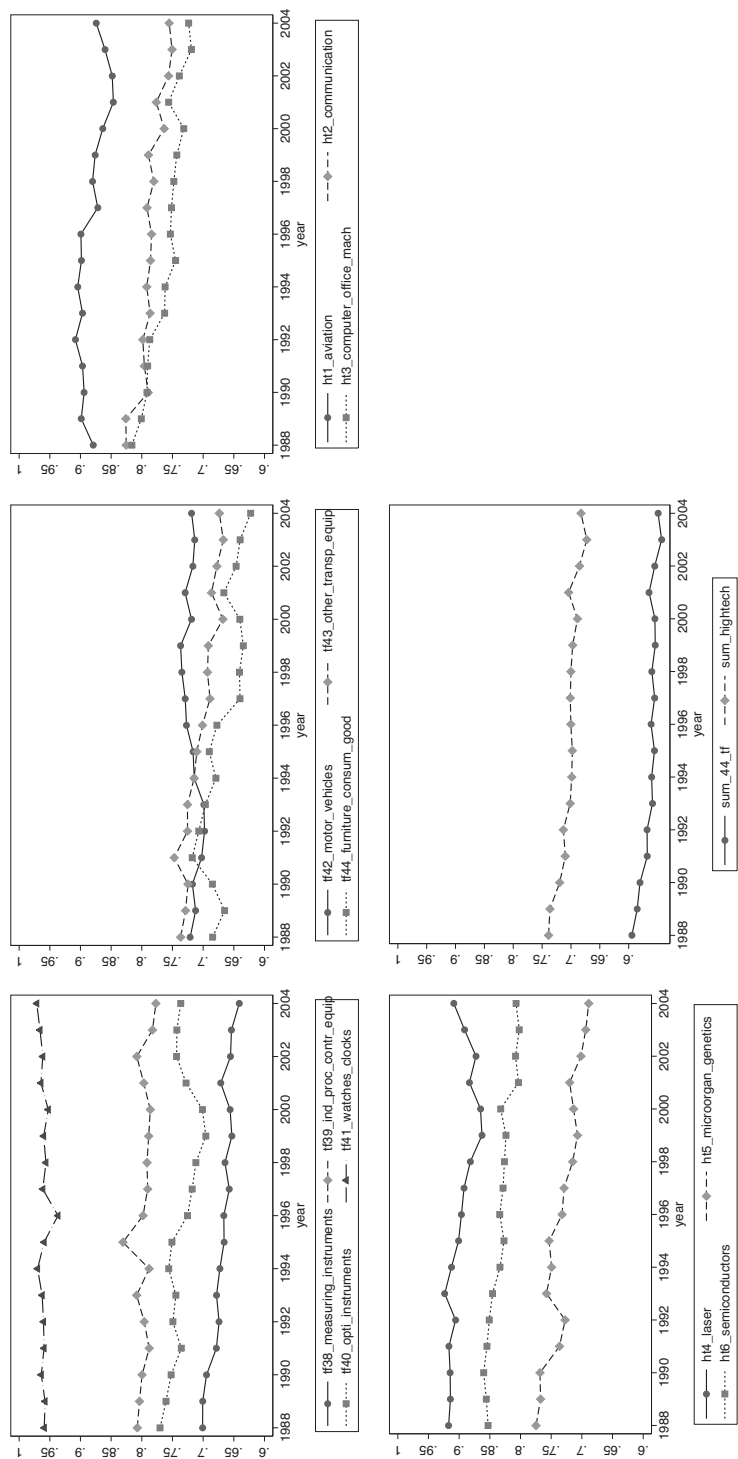


Fig. 3.19. Locational Gini: regional disparity of EPO patent applications by TF (EU-15) (b)
 Source: own calculations and illustration. Notes: G_{LOC}^* by technology field; the population covers 696 TL3 regions (EU-15, CH, NO).

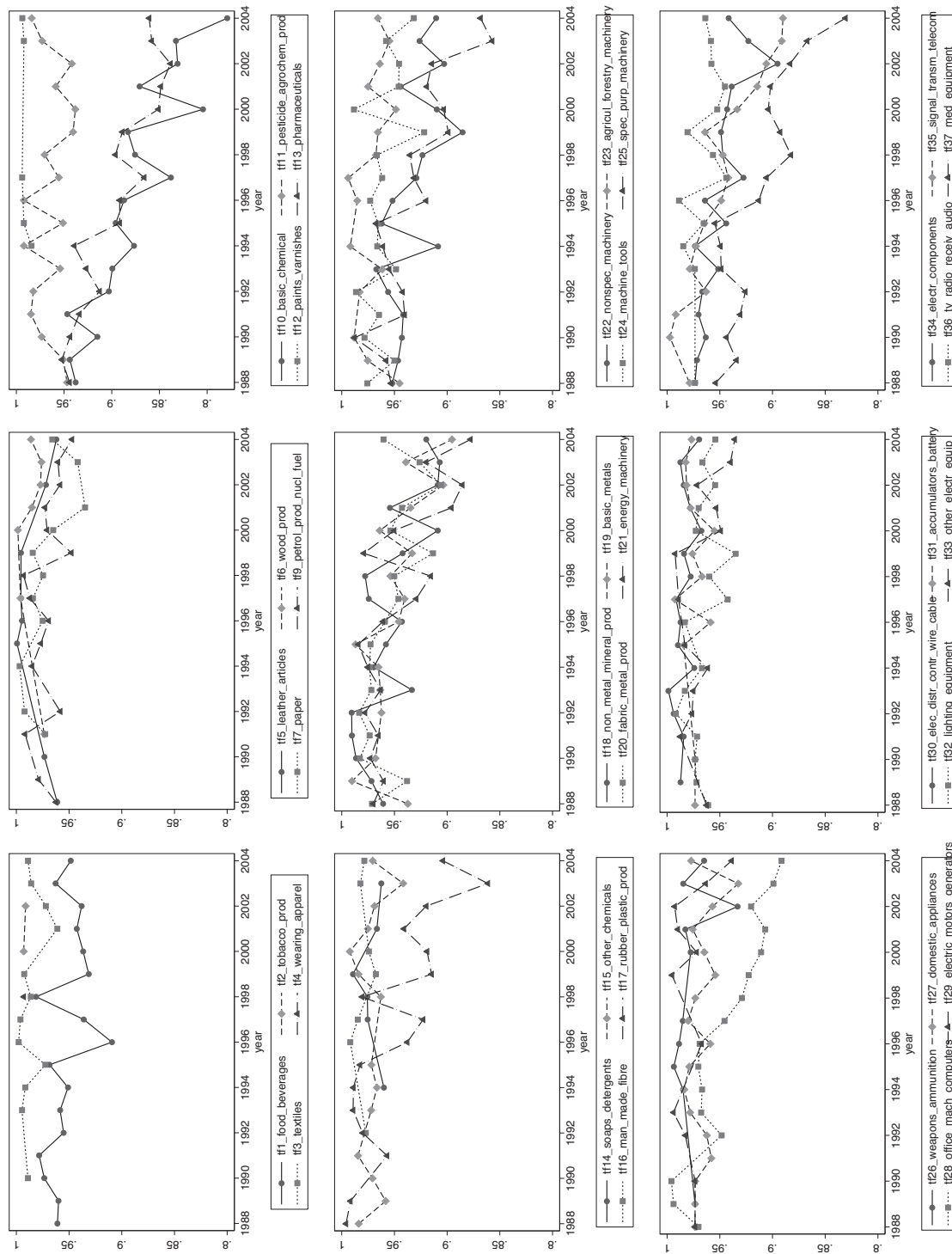


Fig. 3.20. Locational Gini: regional disparity of EPO patent applications by TF (NMS) (a)
 Source: own calculations and illustration. Notes: G^*_{Loc} by technology field; the population covers 123 TL3 regions (NMS).

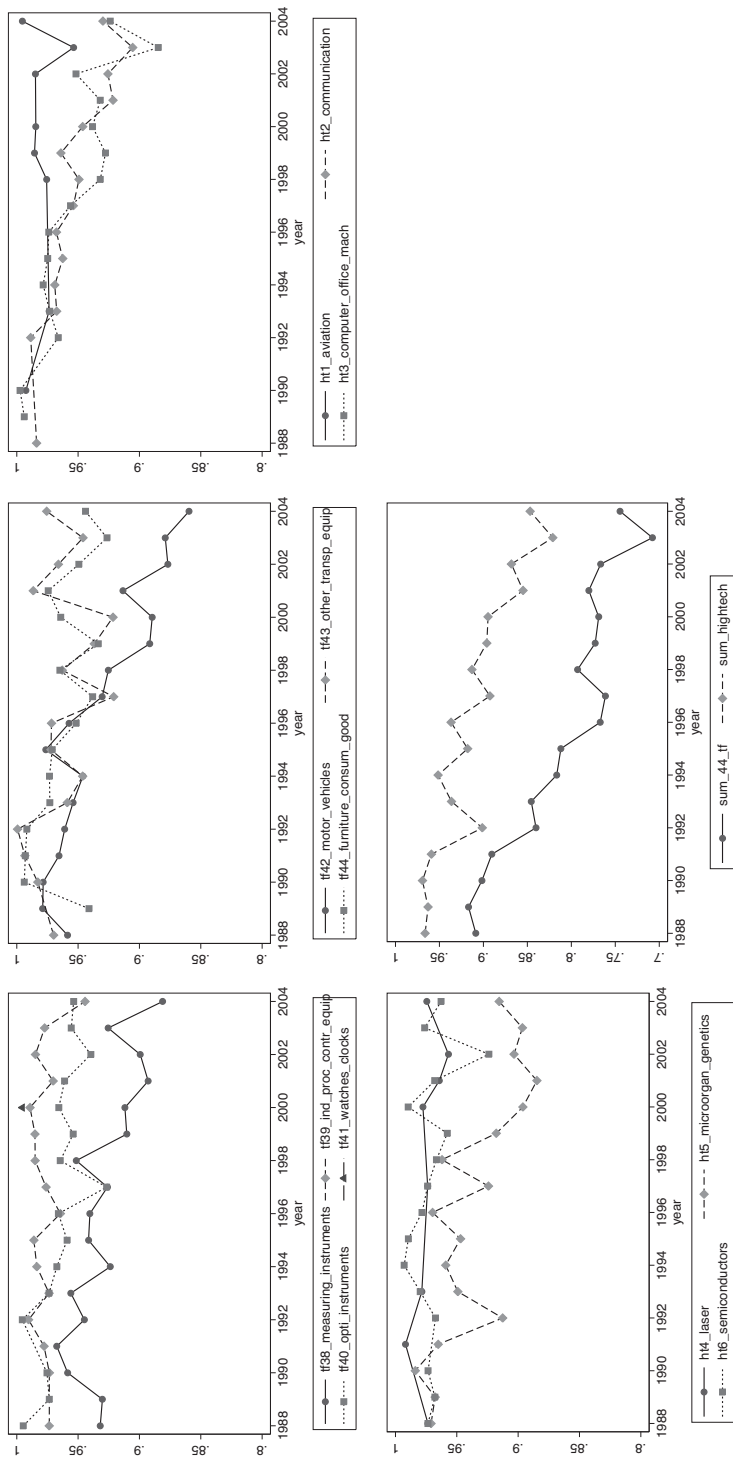


Fig. 3.21. Locational Gini: regional disparity of EPO patent applications by TF (NMS) (b)
 Source: own calculations and illustration. Notes: G_{LOC}^* by technology field; the population covers 123 TL3 regions (NMS).

Similar tendencies and conclusions can be reported for the areal surface weighted Gini coefficient. The computed G_{SPACE}^* coefficients are illustrated in figures 3.22 and 3.23. Although the levels and dynamics (%change) of G_{SPACE}^* differ to some extent from the population weighted alternative (G_{LOC}^*), the coefficients still support the structures and tendencies described above. Moreover, it can be concluded that higher levels of G_{SPACE}^* compared to G_{LOC}^* imply that population characteristics essentially differ from areal surface characteristics and may have changed since the 1980s. Areal surface, however, is time invariant (constant regional surface). Complementary to G_{LOC}^* , the G_{SPACE}^* values show strong decreases in the following technology fields: *TF1 Food & beverages*, *TF7 Paper*, *TF10 Chemicals*, *TF13 Pharmaceuticals*, *TF17 Rubber and plastics*, among others. The technology fields that remain concentrated at a constant level across the 819 European regions are the following: *TF2 Tobacco products*, *TF12 Paints & varnishes*, *TF41 Watches & clocks*, *HT4 Laser*, *HT1 Aviation*, *TF11 Pesticides & agrochemicals*, *TF6 Leather articles*, *TF14 Soaps & detergents*, among a few others.

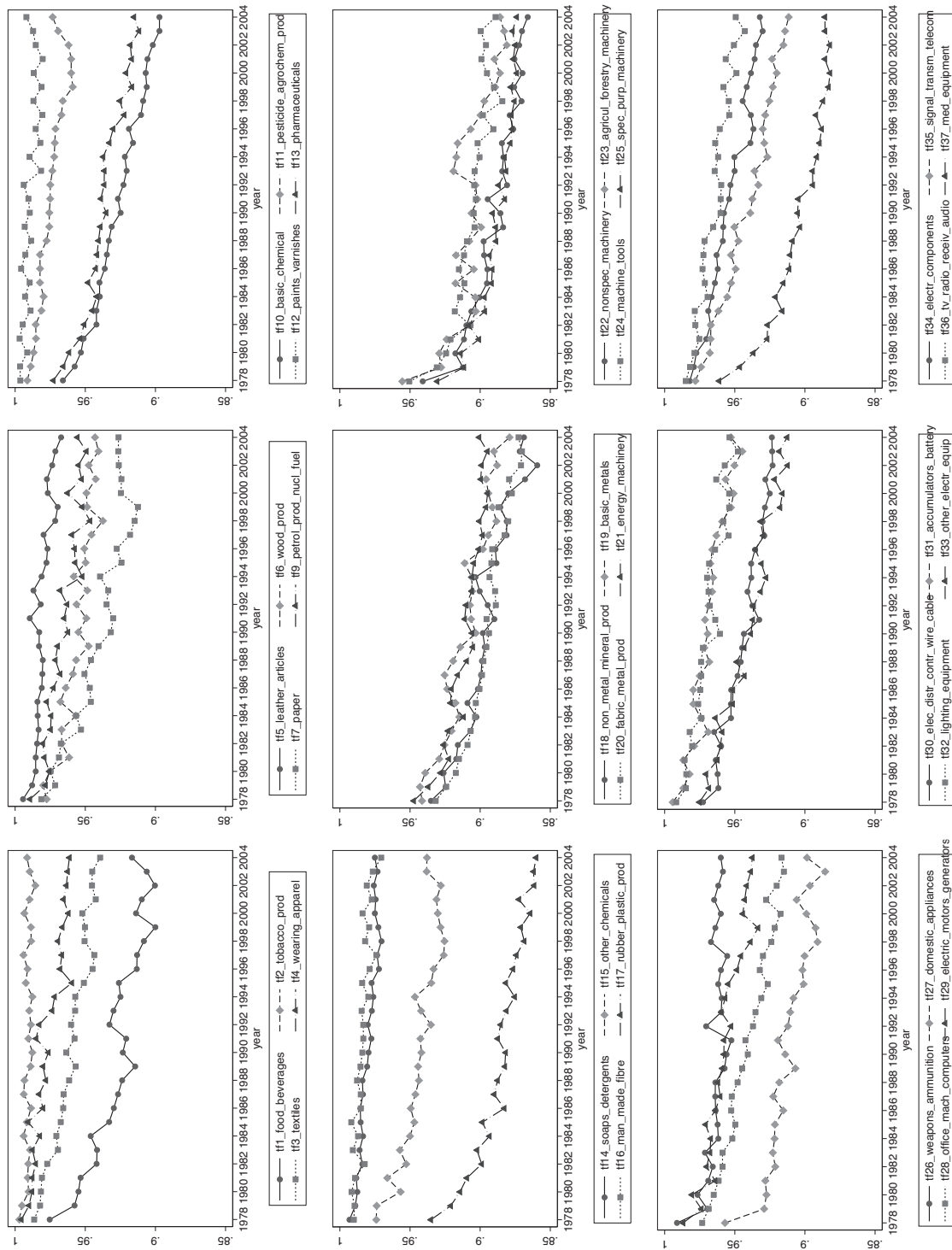


Fig. 3.22. Spatial Gini: regional disparity of EPO patenting by TF (EU-25, CH, NO) (a)
 Source: G_{SPACE}^* by technology field; the population covers 819 European TL3 regions (EU-25, CH, NO).

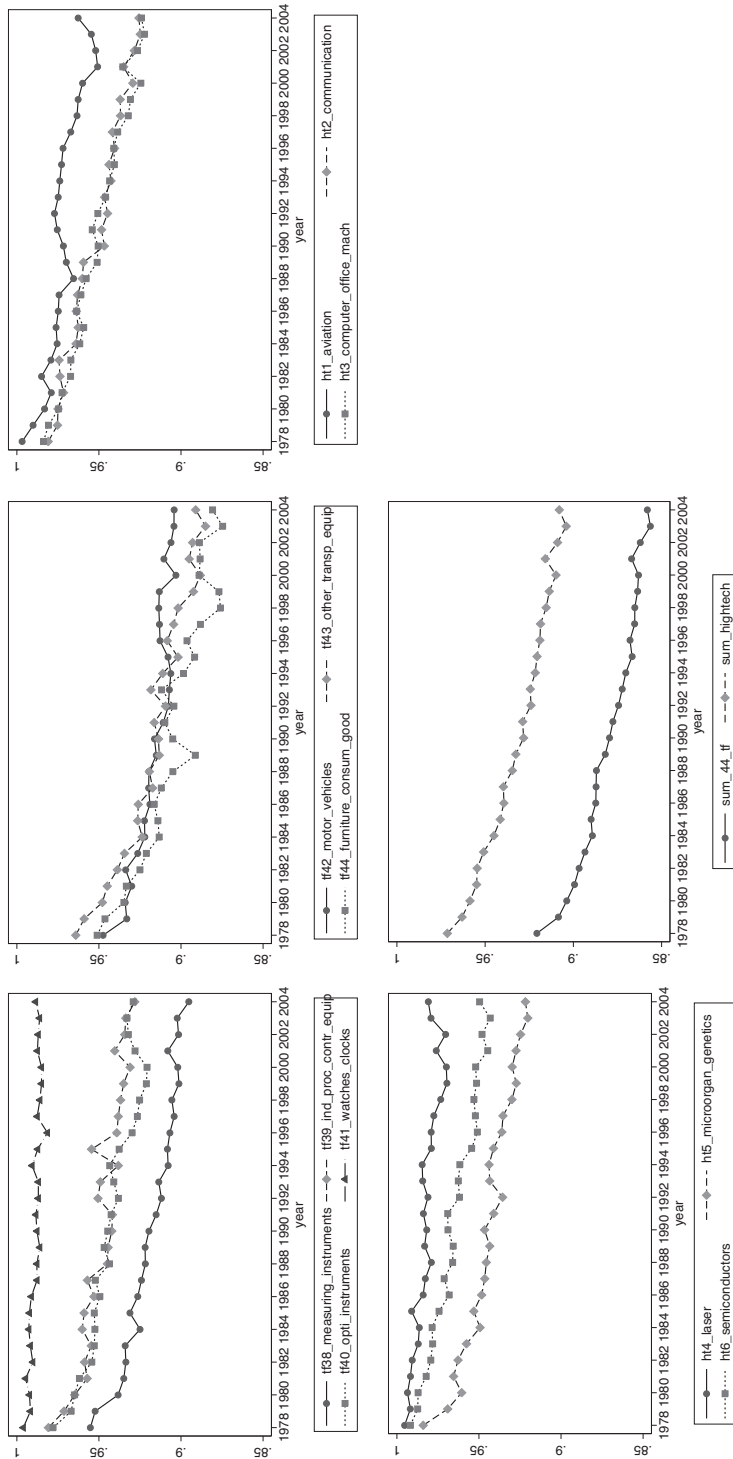


Fig. 3.23. Spatial Gini: regional disparity of EPO patenting by TF (EU-25, CH, NO) (b)
 Source: own calculations and illustration. Notes: G^*SPACE by technology field; the population covers 819 European TL3 regions (EU-25, CH, NO).

Finally, the intra-national distributional dynamics of European regional research activity, i.e., EPO patent application activity, are briefly described in the following figures 3.24 and 3.25. The dynamics of the whole aggregate are illustrated (“ $\sum 44$ TF”). It can be reasoned from the graphs in figures 3.24 and 3.25 that different national developments exist. Some European countries have experienced a strong decrease in spatial inequality/disparity of patenting activity (e.g., Austria, Germany, France, Italy, Ireland, Spain, Portugal, Slovenia, the Czech Republic, Poland, Latvia), whereas research distribution follows an opposite direction in several countries (Finland, Netherlands, Sweden, United Kingdom). The strongest decrease in inequality/disparity can be observed in the Czech Republic, Ireland, Poland, Portugal and Slovenia. This is what people generally expect from the past European enlargement rounds and the transformation processes. Moreover, other countries show a rather stable, almost static distribution of research activity (Norway, Slovakia, Malta, Belgium). Accordingly, it can be depicted from the graphs that different U-shaped and inverted U-shaped patterns exist at the national level (e.g., Belgium, United Kingdom, Hungary, Greece), which is quite similar to the distribution of GDP (see section 5.3 for an analysis of European income inequality dynamics).³⁶⁸ For comparison purpose, complete Gini calculations for selected EU-15 countries and all 51 technology fields are included in the appendix (see figures A.12 to A.29).

³⁶⁸ Following Martin (1998a), income differences among European Member States have been strongly narrowing in the last fifteen years even if the process of global dispersion has been accompanied by a significant widening of the inter-regional variance within single countries (see chapter 5). The same is said to hold for research activity (refer to figures 3.24 and 3.25).

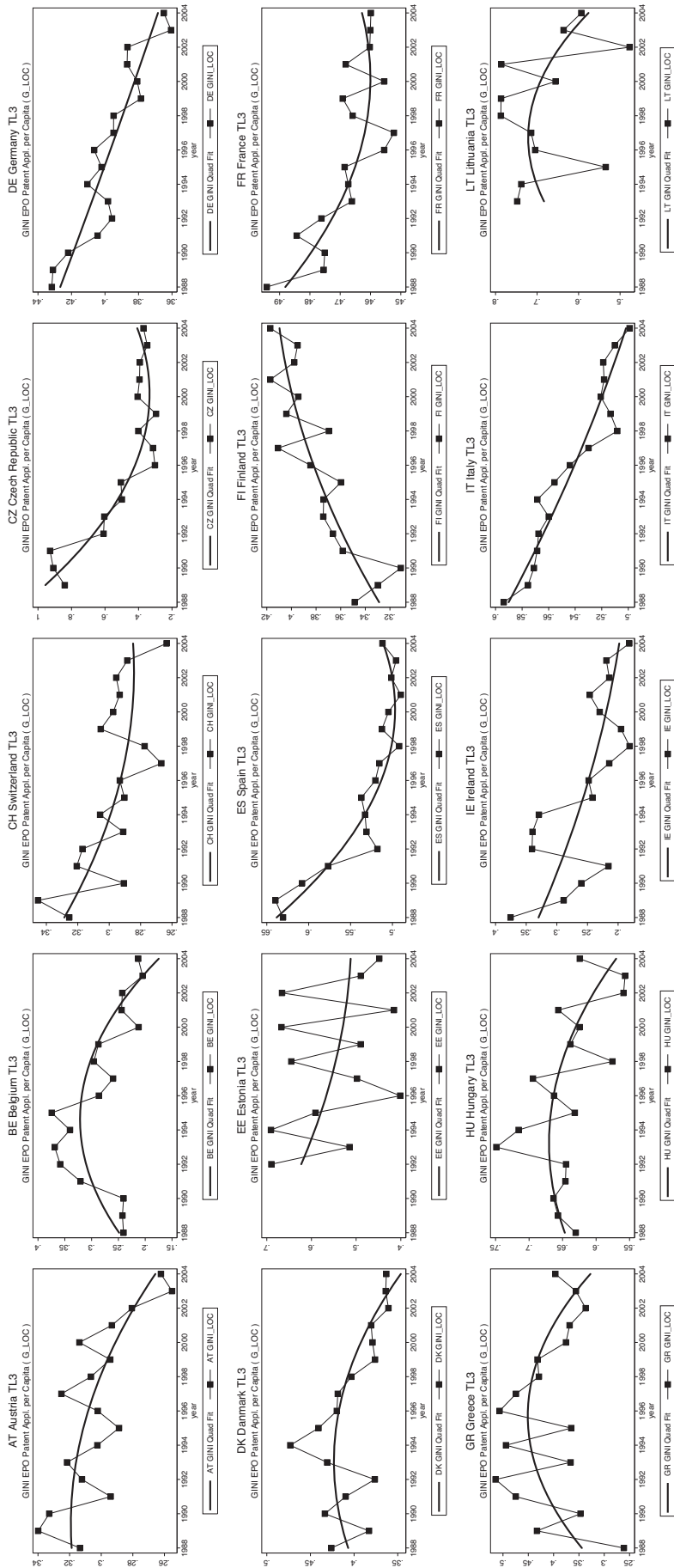


Fig. 3.24. Locational Gini: regional disparity of EPO patent applications (all IPC) (a)
Source: own calculations and illustration. *Notes:* G_{Loc}^* by country and technology field.

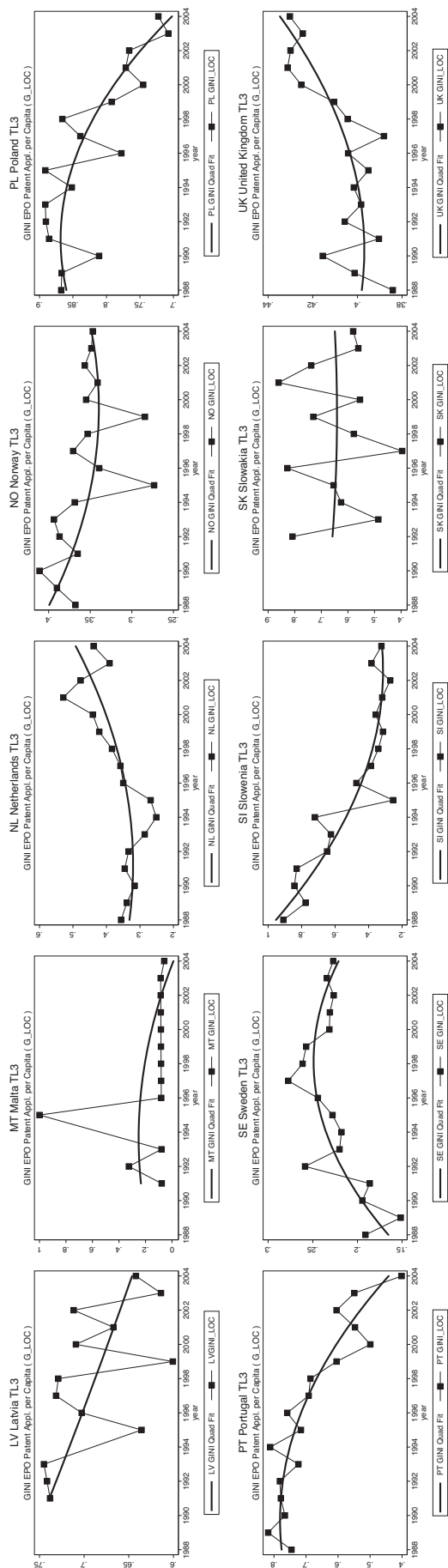


Fig. 3.25. Locational Gini: regional disparity of EPO patent applications (all IPC) (b)
 Source: own calculations and illustration. Notes: G_{Loc}^* by country and technology field.

3.4.2.3.2. Dynamics of Gini Coefficients by Technology Field

This section gives priority to the analysis of concentration/disparity dynamics of EPO patenting activity since the 1980s, as the European Research Area seems to have “physically” expanded at the regional level by means of EPO patent applications ($n > 0$) by region. The European Commission’s program is assumed to support convergence of regions and thus to induce a decrease in regional disparities of research activity. The subsequent figures 3.26 to 3.28 summarize technology-specific disparity/inequality dynamics in terms of changing Gini coefficients (% change) between the 1980s and 2000s. Time-averaging of the data reduces business cycle effects and depicts the structural change in regional disparities (Combes and Overman, 2004). The reported results support the computed Herfindahl-Hirschman measures for EPO patent applications and inventors (see tables 3.1 and 3.2).

Figure 3.26 highlights the dynamics of all 51 technology field aggregates under analysis (see table B.4, appendix, for an IPC-TF concordance). The figure presents the technology-specific G_{LOC}^* values ranked by their rate of change. The mean values of the yearly Gini coefficients are used for constructing two periods: 1988-1990 and 2002-2004. It is clearly visible that the strongest process of decreasing disparities and thus dispersion of research/inventorship activity across the population of 819 regions concerns the following technology fields: *TF10 Basic chemicals*, *HT3 Computer & office machines*, *TF20 Fabricated metal products*, *TF13 Pharmaceuticals*, *TF33 Other electrical equipment*, *TF43 Other transport equipment*, *TF34 Electronic components*, *TF31 Accumulators & battery*, *TF4 Wearing & apparel*, *HT2 Communication*, *TF35 Signal transmission & telecommunications* and *TF18 Non-metallic mineral products*. The skewed distribution of the technology fields *TF26 Weapons & ammunition*, *TF12 Paints & varnishes*, *TF41 Watches & clocks*, *TF2 Tobacco products*, among others, remains more or less unchanged.

In addition, the subsequent bar chart (see figure 3.27) summarizes the change in G_{LOC}^* for both the NMS and EU-15 group between 1988/1990 and 2002/2004. Complementary to the previous graphs, the chart clearly demonstrates a relatively stronger decrease in regional disparities in the NMS group in several technology fields, e.g., *TF10 Basic chemicals*, *TF17 Rubber & plastic products*, *TF21 Energy machinery*, *TF25 Spec. purp. machinery*, *TF37 Med. equipment*, *TF42 Motor vehicles*, *SUM hightech* (high-tech aggregate).

Similarly, the spatial Gini computation, G_{SPACE}^* , shows the same dispersion between 1988-1990 and 2002-2004, although inequality levels and thus the ranking of technology fields in terms of inequality coefficients differ from the G_{LOC}^* measure. The G_{SPACE}^* computations show (i) higher inequality levels and thus concentration in space compared to G_{LOC}^* and (ii) lower disparity dynamics (%change) due to a different reference distribution (regional surface z_j). The results are summarized in figure 3.28.

The change (%) in inequality/disparity for the technology fields under analysis, from 1988-1990 to 2002-2004, is highest for the following technology fields: *TF18 Non-metallic mineral products*, *TF35 Signal transmission & telecommunications*, *TF10 Basic chemicals*, *TF33 Other electrical equipment*, *HT2 Communication*, *HT3 Computer & office machines*, *HT5 Microorganisms & genetics*, *TF19 Basis metals*, *TF28 Office machinery & computers*. Quite the contrary, *TF26 Weapons & ammunition*, *TF41 Watches & clocks*, *TF2 Tobacco*

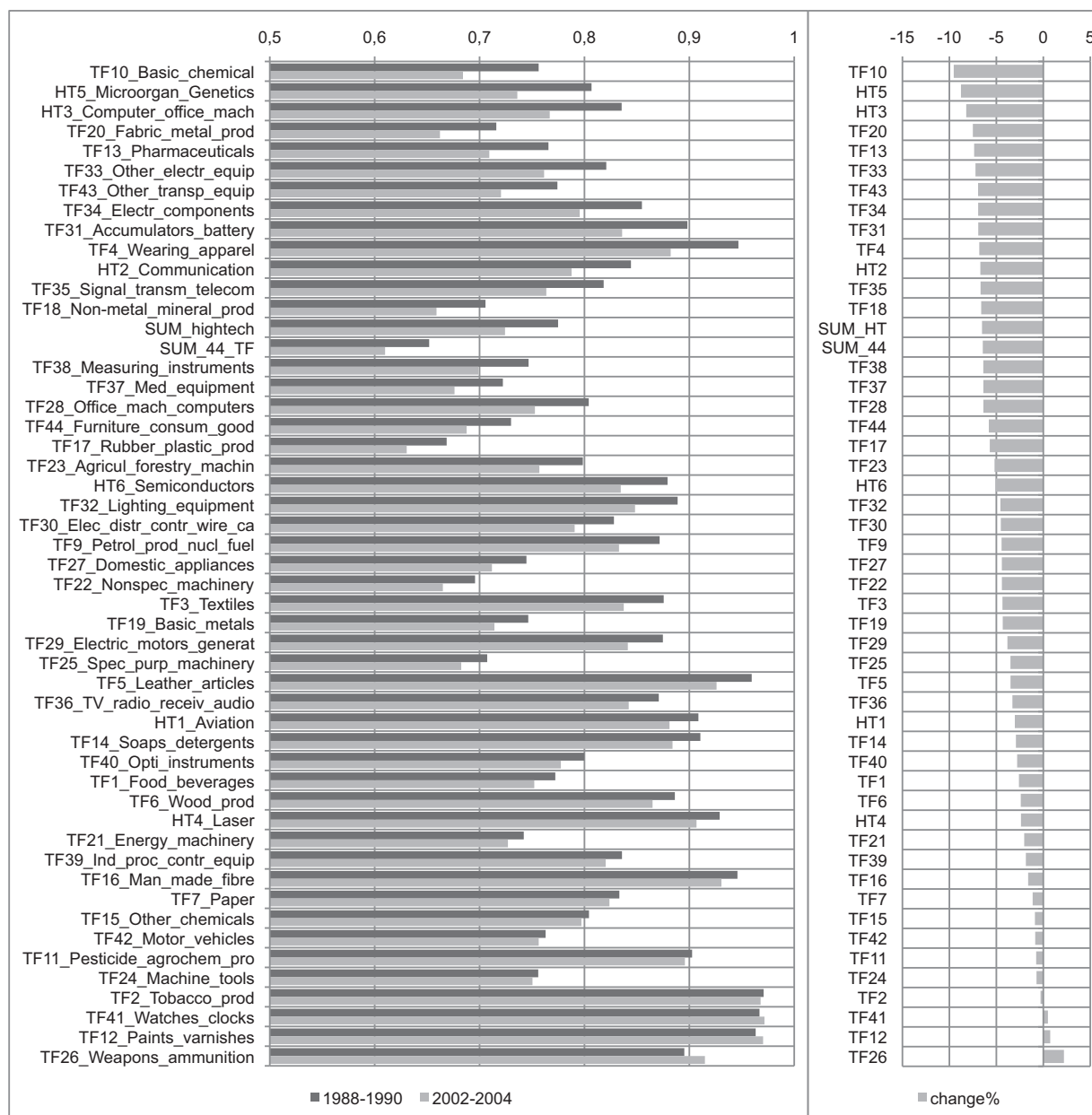


Fig. 3.26. Change (%) of locational Gini: regional disparities by TF (819 TL3)
 Source: own calculations and illustration. Notes: G^*_{LOC} coefficient dynamics by technology field 1988-1990 vs. 2002-2004; the population covers 819 European TL3 regions.

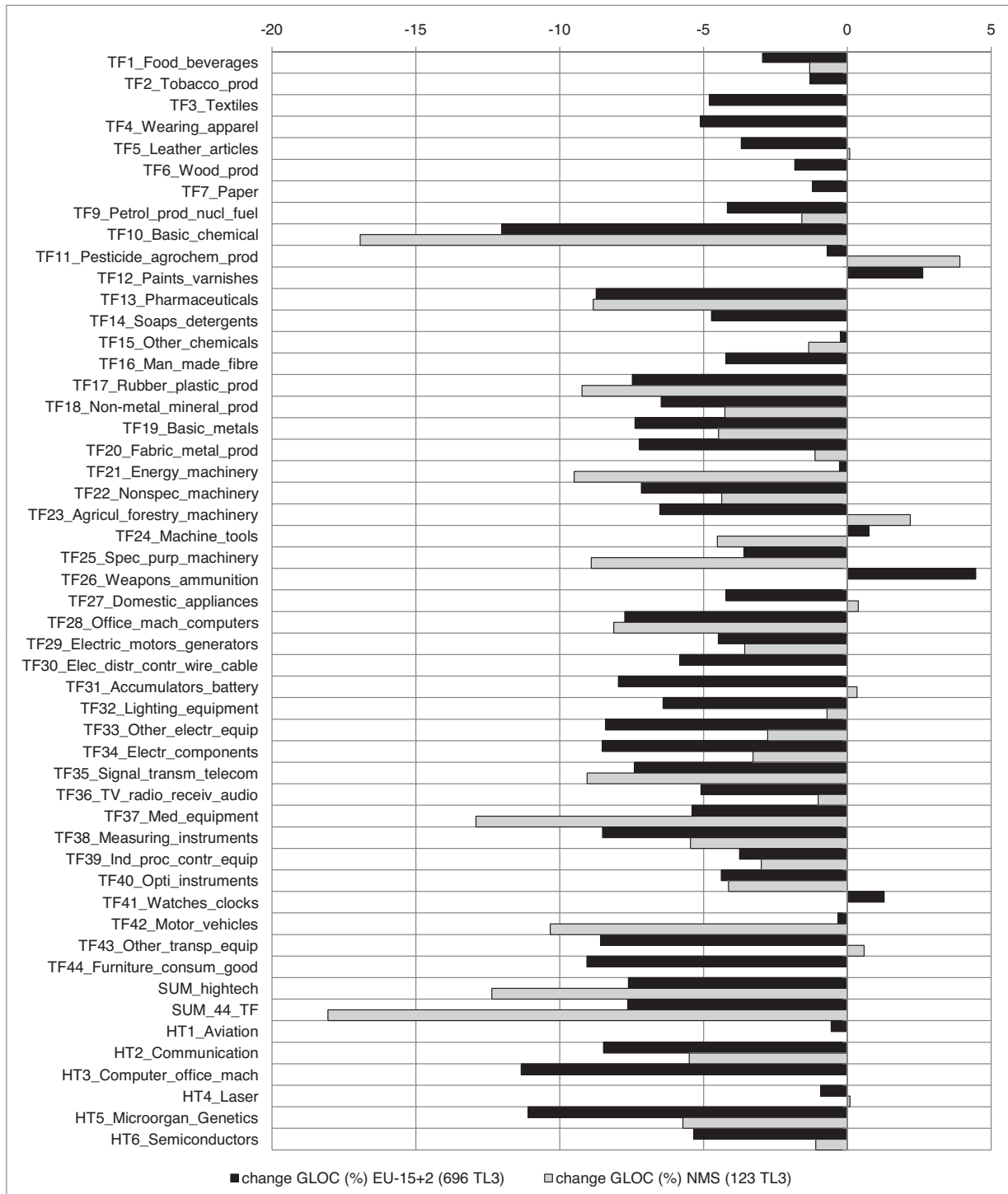


Fig. 3.27. Change (%) of locational Gini: regional disparities by TF in EU-15 and NMS
 Source: own calculations and illustration. Notes: G_{LOC}^* coefficient dynamics by technology field 1988-1990 vs. 2002-2004; the population covers 123 NMS regions and the regions of the EU-15, CH and NO.

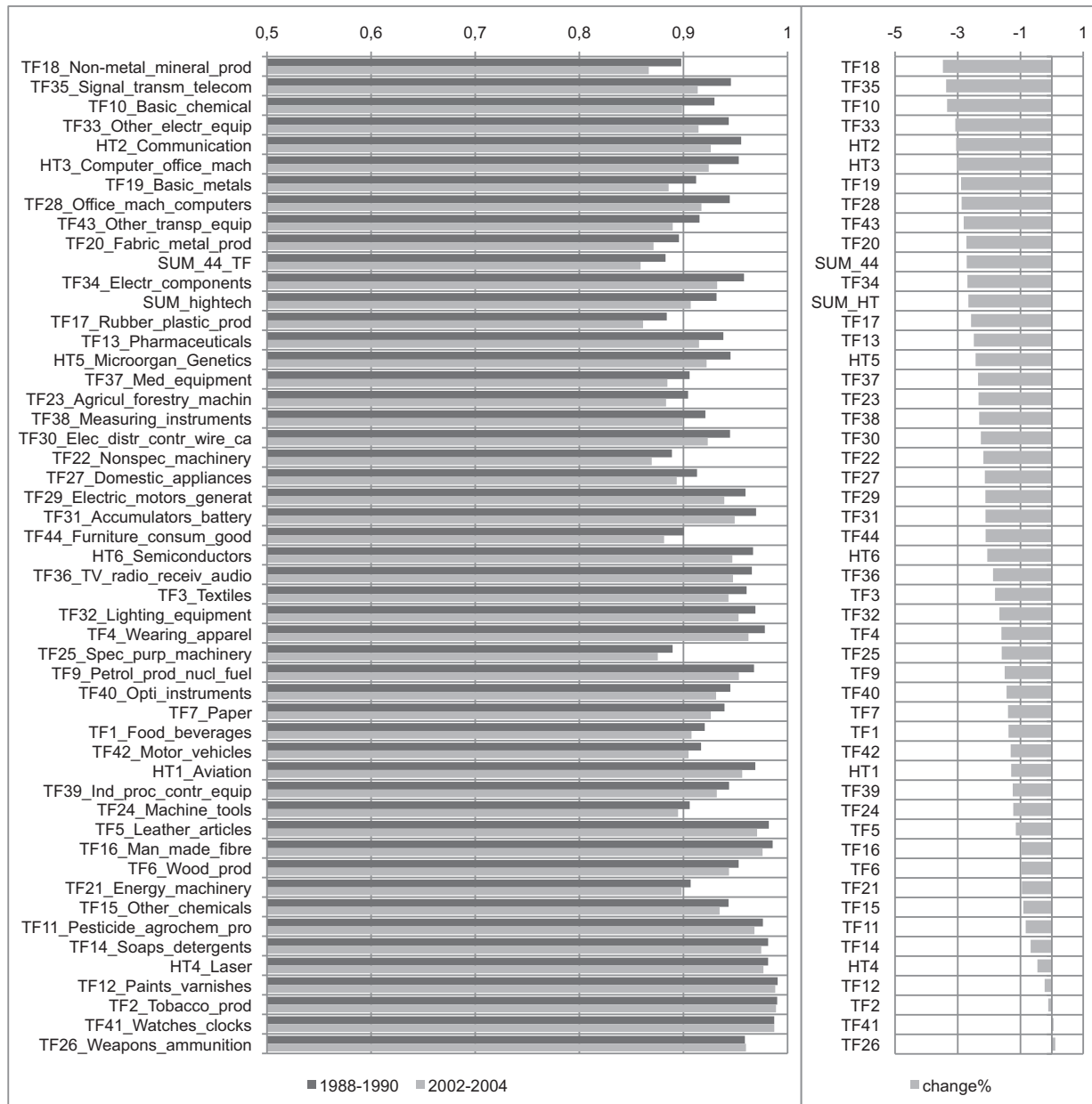


Fig. 3.28. Change (%) of spatial Gini: development of regional disparities by TF
 Source: own calculations and illustration. Notes: G_{SPACE}^* coefficient dynamics by technology field 1988-1990 vs. 2002-2004; the population covers 819 European TL3 regions.

products, *HT4 Laser*, *TF12 Paints & varnishes* and *TF14 Soaps, detergents* do not highlight decreasing dispersion across the 819 European regions.

With respect to single technology fields, several G_{LOC}^* indices have declined much more than their corresponding G_{SPACE}^* indices. This can be explained by the fact that population characteristics changed differently compared to areal surface characteristics (see also the explanation above). Areal surface is assumed to be constant (time invariant) for the whole period of analysis. If population, in general, shows migratory movements from rural (peripheral) areas to capital regions, whereas EPO patenting activity, in comparison, generally shows increasing dispersion, it can be assumed that the population weighted Gini coefficient decreases much stronger as opposed to its spatial counterpart.

To sum up, several conclusions can be drawn from the previous empirical analyses: (i) technology-field specific research/inventorship activities highly differ in their distribution across the entire population of 819 European regions; (ii) EPO patent applications and EPO inventors are similarly distributed across the European landscape of regions; (iii) the majority of regions only account for a few EPO patent applications and very small shares of EPO inventors; (iv) the majority of high-technology fields show, by and large, high levels of disparities and spatial concentration (i.e., Gini coefficients, HHI); (v) several high-technology fields show strong dispersion tendencies between the 1990s and the 2000s (i.e., 1988/1990 vs. 2002/2004); (vi) the population corrected Gini (G_{LOC}^*) in general shows stronger decreases opposed to the spatial Gini (G_{SPACE}^*), although dispersion tendencies in terms of G_{SPACE}^* were extraordinarily high in the 1980s; (vii) both weighted Gini alternatives clearly reveal a decline in regional disparities for a large fraction of the 51 technology field aggregates under analysis.

In presenting global disparity measures of EPO patenting activity for more than two decades at the regional level, the reported results of the concentration/ disparity analysis in this study offered detailed information about the distributional dynamics of patenting activity (and implicitly research activity) by technology field across the entire population of European regions. To conclude, the presented results clearly exhibit a decreasing disparity and ongoing dispersion of research activity across the 819 European regions. To complement these results, the following part of the chapter places special emphasis on the identification of individual research clusters in the European landscape of regions (section 3.5). Therefore, a comparable and harmonized quantitative measure for research clustering at the regional level is introduced. Furthermore, the subsequent analysis is conceptualized to offer a short study on co-location and co-agglomeration of technology field-specific research clusters.

3.5. Identifying Research Clusters and Co-Agglomeration in Europe

3.5.1. Research Clusters, Cities and Inventorship

The previous part of the chapter was dedicated to the global distributional characteristics of EPO patenting since 1977. Moreover, the previous analysis focused on the number of

regions that are engaged in research activities (EPO patent applications and inventors) by technology-field. The calculations of several weighted disparity measures demonstrated a meaningful dispersion of patenting activity across the 819 European regions. Additional descriptive measures supported the general picture of dispersion of research activity in Europe (and in the ERA).

However, the literature still lacks a harmonized research clustering measure at the regional level. Therefore, this section places the emphasis on the identification of research clustering and the analysis of co-agglomeration of research activities. The existence of multiple research clusters (i.e., co-agglomeration) in European regions will be analyzed in the following, i.e., the number of significant research clusters in terms of EPO patent applications by technology field. This analysis is considered to additionally support the identification of highly diversified European research clusters. Moreover, it is possible to identify such research clusters at a very disaggregated spatial level (TL3 regions), which offers several significant advantages compared with the aggregated NUTS1/2 levels. Thus, the central idea of this section is to explore if research activity is predominantly present in a few European research locations, which are determined by relative and absolute strength in various technology fields. Therefore, a quantitative identification of research clustering in the ERA and the analysis of structural dynamics of clusters take center stage.³⁶⁹ Related to the proposed research questions, a quantitative “top-down” clustering analysis is applied for several reasons. It enables us to identify and compare research clustering intensity for the entire population of 819 TL3 regions in Europe for each of the aforementioned technology fields.³⁷⁰ Moreover, the identified patenting activities (by inventor location) of every single region can be related to the regional settlement structure (capital, metro, urban, intermediate or rural region) (European Union, 2009; OECD, 2010). The analysis can be used to explore the structural changes of the distribution of the identified European research clusters in the course of time. Finally, the analysis helps to depict structural differences in research/ patenting activity between European core regions and the NMS.

3.5.2. The Research Cluster Index

3.5.2.1. Constructing a Research Cluster Index

In the following, a composite “research cluster index” (RCI_{ij}) for EPO patenting activities in 50 technology fields for 819 European regions is proposed, which measures and combines for each region its relative population (population corrected) patent density ($RPPD_{ij}$), its relative spatial (space corrected) patent density ($RSPD_{ij}$), the revealed technological advantage (RTA_{ij}), and its relative inventor density (RID_{ij}). The different (relative) coefficients are combined to the RCI_{ij} as presented in equation 3.5.1. The suggested methodology builds upon the contribution of Litzenberger and Sternberg (2005),

³⁶⁹ No qualitative approaches will be applied, e.g., qualitative regional studies of inventor or firm networks, in-depth case-studies on local knowledge bases, (half) structured interviews or regional knowledge diffusion studies. Furthermore, the study does not make use of econometrics to analyze the effects of research clustering.

³⁷⁰ It should be kept in mind that a top-down approach is applied and that the term “cluster” is used although the more accurate term would be “research agglomeration.”

Litzenberger and Sternberg (2006) and Litzenberger (2007), who have applied a similar composite cluster index to German employment data.³⁷¹

$$RCI_{ij} = \left[\left(\frac{pat_{ij}}{a_i} \right) / \left(\frac{\sum_{i=1}^n pat_{ij}}{\sum_{i=1}^n a_i} \right) \right] \times \left[\left(\frac{pat_{ij}}{pop_i} \right) / \left(\frac{\sum_{i=1}^n pat_{ij}}{\sum_{i=1}^n pop_i} \right) \right] \quad (3.5.1)$$

$$\times \left[\left(\frac{inv_{ij}}{pop_i} \right) / \left(\frac{\sum_{i=1}^n inv_{ij}}{\sum_{i=1}^n pop_i} \right) \right] \times \left[\left(\frac{pat_{ij}}{\sum_{j=1}^m pat_{ij}} \right) / \left(\frac{\sum_{i=1}^n pat_{ij}}{\sum_{i=1}^n \sum_{j=1}^m pat_{ij}} \right) \right]$$

pat_{ij} is the number of patent applications at the EPO by priority date of region i in technology field j ; $\sum_{i=1}^n pat_{ij}$ represents the number of all EPO patent applications in the spatial aggregate in technology field j ; inv_{ij} is the number of inventors in technology field j in region i ; a_i represents the size of the spatial unit in square kilometers; $\sum_{i=1}^n inv_{ij}$ is the number of heterogenous inventors in technology field j in the spatial aggregate; and pop_i is the regional population.

(1) the “relative spatial patent density” ($RSPD_{ij}$) of region i with respect to the spatial unit size a_i is

$$RSPD_{ij} = \left[\left(\frac{pat_{ij}}{a_i} \right) / \left(\frac{\sum_{i=1}^n pat_{ij}}{\sum_{i=1}^n a_i} \right) \right] \quad (3.5.2)$$

(2) the “relative population patent density” ($RPPD_{ij}$) of region i , which is relative patenting per capita, is

$$RPPD_{ij} = \left[\left(\frac{pat_{ij}}{pop_i} \right) / \left(\frac{\sum_{i=1}^n pat_{ij}}{\sum_{i=1}^n pop_i} \right) \right] \quad (3.5.3)$$

³⁷¹ Defining a descriptive measure for clustering, i.e., a composite index, is at least as subjective as measuring inequality, because clustering strength depends on the importance given to the chosen RCI components. At least, it can be assured that the presented composite index is a harmonized measure as the four RCI components are weighted identically. Unequal weights of the four RCI components did not significantly change the relative ranking position of regions.

(3) the “relative inventor density” (RID_{ij}) of region i is given by

$$RID_{ij} = \left[\left(\frac{inv_{ij}}{pop_i} \right) / \left(\frac{\sum_{i=1}^n inv_{ij}}{\sum_{i=1}^n pop_i} \right) \right] \quad (3.5.4)$$

(4) and the “revealed technological advantage” (RTA_{ij}) of region i is given by

$$RTA_{ij} = \left[\left(\frac{pat_{ij}}{\sum_{j=1}^m pat_{ij}} \right) / \left(\frac{\sum_{i=1}^n pat_{ij}}{\sum_{i=1}^n \sum_{j=1}^m pat_{ij}} \right) \right] \quad (3.5.5)$$

3.5.2.2. Interpretation of the Research Cluster Index

The four components, (1) relative spatial patent density ($RSPD_{ij}$), (2) relative population patent density ($RPPD_{ij}$), (3) relative inventor density (RID_{ij}) and (4) revealed technological advantage (RTA_{ij}) are multiplicatively combined. If $RPPD_{ij} = 1$, $RSPD_{ij} = 1$, $RTA_{ij} = 1$ and $RID_{ij} = 1$, then the research clustering index RCI_{ij} would be equal to one, meaning that the region under analysis has an identical cluster strength compared to the higher spatial aggregate (sum of all European regions). $RCI_{ij} > 0$ is observed in case that all four components are non-zero. *Ceteris paribus*, RCI_{ij} decreases with spatial unit size (a_i). Moreover, regions with $RPPD_{ij} > 1$, $RSPD_{ij} > 1$ and $RTA_{ij} > 1$ may suffer from low RID_{ij} values; $RID_{ij} < 1$ is observed in case that region i has a relatively smaller inventor density (per million population) compared to the spatial aggregate (i.e., the 819 TL3 regions in ERA); e.g., region θ_A and θ_B show identical $RPPD_{ij}$, $RSPD_{ij}$ and RTA_{ij} values; however, region θ_A has a smaller RCI_{ij} if the regional inventor density RID_{ij} is smaller compared to region θ_B , although this region may show a larger number of patent applications in the specific technology field compared to other regions. Thus, RCI_{ij} increases c.p. with the relative number of heterogenous EPO inventors (unique inventor IDs) in the region compared to the spatial aggregate, which is the European research area (819 TL3 regions). Consequently, the RCI computation penalizes regions when large numbers of patent applications stem from a relatively small number of inventors within the region, i.e., from a smaller population of researchers (Litzenberger and Sternberg, 2006; Litzenberger, 2007). This effect can be interpreted as an effective control for potential interaction between individuals. Thus, low RID_{ij} values penalize RCI because one has to assume that such regions have only low potentialities for interaction due to a small density (relative number) of researchers.

The lower threshold level of RCI_{ij} is defined for identifying regional technology field-specific research clustering with $1 < RCI \leq 16$; otherwise, $RCI_{ij} \geq 16$ with $RPPD_{ij} \geq 2$, $RSPD_{ij} \geq 2$, $RTA_{ij} \geq 2$ and $RID_{ij} \geq 2$ represents the threshold level for significant research clustering in European regions. Finally, if all coefficients are larger than three, then we have $RCI_{ij} > 81$, which is defined as relatively strong research clustering in the region (compared to the spatial aggregate). Following Litzenberger and Sternberg (2006),

$1 < RCI \leq 16$ represents potential research clustering. Therefore, only a few of the four components need to show values larger than one. Regions that fulfill $RCI > 1$ with RCI values close to one are considered to show at least research clustering potentialities. Regions with RCI values that are significantly different from the threshold level $RCI = 1$ may be interpreted as stronger research clusters if their RCI values fulfill $1 < RCI \leq 16$. $16 < RCI \leq 81$ and $RCI > 81$ finally represent very strong cluster regions as several coefficients within RCI have to be larger than one.

Furthermore, the RCI-based cluster study analyzes if urban and metropolitan regions tend to host a much larger variety of technology field-specific research clusters compared to their rural counterparts. Therefore, the analysis proceeds in linking the RCI to a regional settlement typology (European Union, 2009; OECD, 2010). First, the 819 European TL3 regions are classified into five categories: (1) urban regions, (2) intermediate regions, (3) rural regions, (4) capital regions and (5) metropolitan regions.³⁷² Second, the absolute number of heterogeneous technology-specific research clusters, with $1 < RCI \leq 16$, $16 < RCI \leq 81$ and $RCI > 81$, is calculated for each of the 819 European regions. It is expected that metropolitan, capital and urban regions show much higher numbers of research clustering, and thus a higher diversity of technology fields, compared to rural regions, which turns cities, capital regions and urban areas into “multi-technology-hubs” (i.e., diversified research clusters). The results are presented in the next section.

3.5.3. Patent Data, Regional Typology and Technology Fields

In order to tackle the proposed research questions (see section 3.1 and chapter 1), a quantitative approach is applied which makes use of data on EPO patent applications and EPO inventors for the period 1977-2004 at the level of OECD TL3 regions (see section 3.3 and the appendix for more details). The patent data extractions and calculations are based upon OECD RegPAT, January 2009 (Maraut *et al.*, 2008). The analysis approaches the spatial distribution of research clusters in the ERA (incl. Switzerland and Norway) by explicitly measuring relative densities, intensities and specialization for each of the 819 European regions in 43 standard technology fields (Schmoch *et al.*, 2003) and 6 high-technology fields (EUROSTAT, 2009). However, it has to be clarified that the analysis is solely using EPO patent application and EPO inventor data (1990-1994 and 2000-2004) to compute and identify research clustering at the TL3 level of regions. Neither employment data, nor input-output data, nor network data at the firm-level are used in this chapter. Moreover, inter-regional or intra-regional relationships, based upon relational data, are not challenged in this section. An alternative analysis based upon employment data or product announcement data for the same period would maybe lead to differing results, as clustering, in general, can also mean a significant concentration of production and employment without any research activity. Thus, the methodology and data in this study completely ignore clustering of non-knowledge intensive activities and tasks. The results are interpreted as the outcome of an alternative quantitative top-down analysis, which nevertheless gives a global picture of European technology-specific research clustering and

³⁷² Regions are first related to urban, intermediate and rural areas; second, these regions can additionally fulfill the criteria for being a capital and/or metropolitan region.

helps to identify and compare research clustering across the entire population of 819 European regions. Finally, it is argued that case-specific analysis represents the only possible way to obtain a complete picture and an in-depth understanding of regional set-ups, intra-regional firm structures, employment and production structures, of the economic history of a region (path dependency), of formal and informal relationships, and of changing and time-invariant characteristics. However, such a qualitative analysis is beyond the scope of this study as the performed analysis incorporates more than 800 regions. Accordingly, a top-down approach is preferred, which implements a harmonized quantitative research clustering analysis that is based upon EPO patent applications and additional regional data.

3.5.4. Research Clusters in Europe by Technology Field

3.5.4.1. Global Statistics: Research Clusters by Technology Field and Country

As the analysis of EPO patent densities and revealed technological advantage indices (RTA) is considered to be unsuited for controlling for relative concentration, relative density and the relative number of inventors at the same time, an alternative measure is needed. The alternative has to combine information of several coefficients. Therefore, the RCI computation, according to equation 3.5.1, helps to identify research clustering at the regional level as it controls for relative densities and relative technological advantage at the same time. In view of this, global clustering statistics are presented in the following.³⁷³

Concerning the absolute number and share of existing research clusters in the ERA by RCI, the following figures 3.29 and 3.30 highlight the computational results for the predefined technology field aggregates for the periods 1990-1994 and 2000-2004. The figures present absolute numbers and (shares) of research clusters; large numbers are identified in the following technology fields: *TF44 Furniture & consum. good*, *TF17 Rubber & plastic prod.*, *TF18 Non-metal mineral prod.*, *TF25 Spec. purp. machinery*, *TF20 Fabricated metal prod.*, *TF22 Nonspec. machinery*, *TF43 Other transp. equip.*, *TF37 Med. equipment*, *TF6 Wood prod.*, and *TF19 Basic metals*. In opposition, the technology fields *TF2 Tobacco prod.*, *TF41 Watches & clocks*, *TF11 Pesticides & agrochem. prod.*, *TF14 Soaps & detergents*, *TF12 Paints & varnishes*, *TF36 TV & radio receiv. & audio* and *TF42 Motor vehicles* represent the aggregates with a rather small number of research clusters.

In taking a more dynamic perspective, figure 3.31 summarizes the changing number of research cluster regions by technology field between the 1990s and 2000s. It is obvious that the absolute number of clusters has grown considerably across most technology fields, e.g., *TF3 Textiles*, *TF4 Wearing & apparel*, *TF5 leather articles*, *TF6 Wood products*, *TF15 Other chemicals*, *TF30 Electr. distr. contr. wire cable*, *TF31 Accumulators & battery*, *TF32 Lighting equipment*, *TF33 Other electr. equip.*, *TF34 Electr. components*, *TF10 Basic chemicals*, *TF11 Pesticides & agrochem. prod.*, *TF12 Paints & varnishes*, *TF13 Pharmaceuticals*, *TF14 Soaps & detergents*, *TF34 Electric components*, *TF44 Furniture*

³⁷³ For a complete overview and list of abbreviations of all 51 technology field aggregates used in the following graphs and tables see table B.4 (appendix).

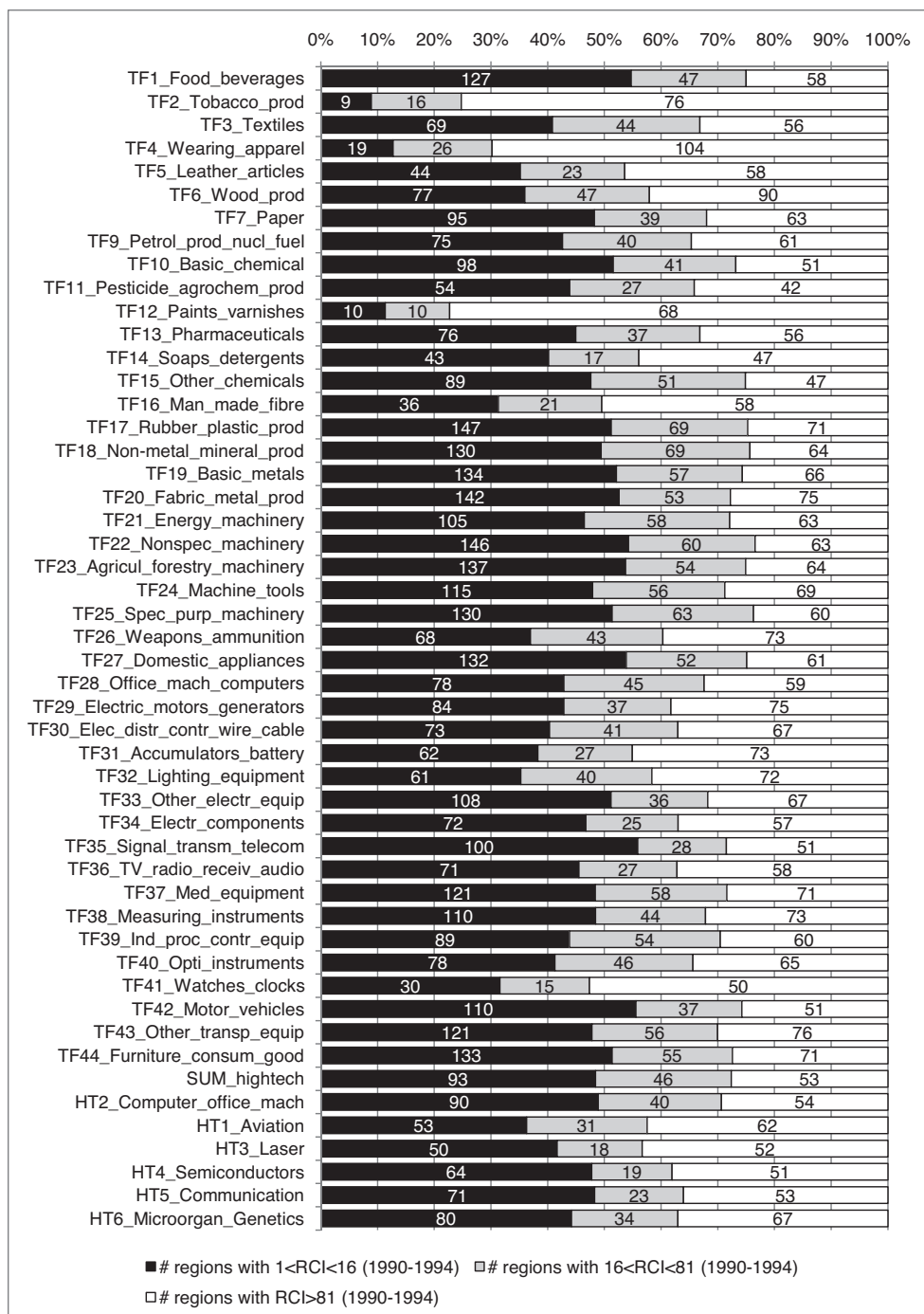


Fig. 3.29. Structure of research clusters by TF and RCI class, 1990-1994

Source: own calculations and illustration. *Notes:* share and number of research clusters by TF and TL3 region of all regions with $1 < RCI \leq 16$, $16 < RCI \leq 81$ and $RCI > 81$; calculations based upon OECD RegPAT (2009) database extractions and application of the ISI-SPRU-OST concordance.

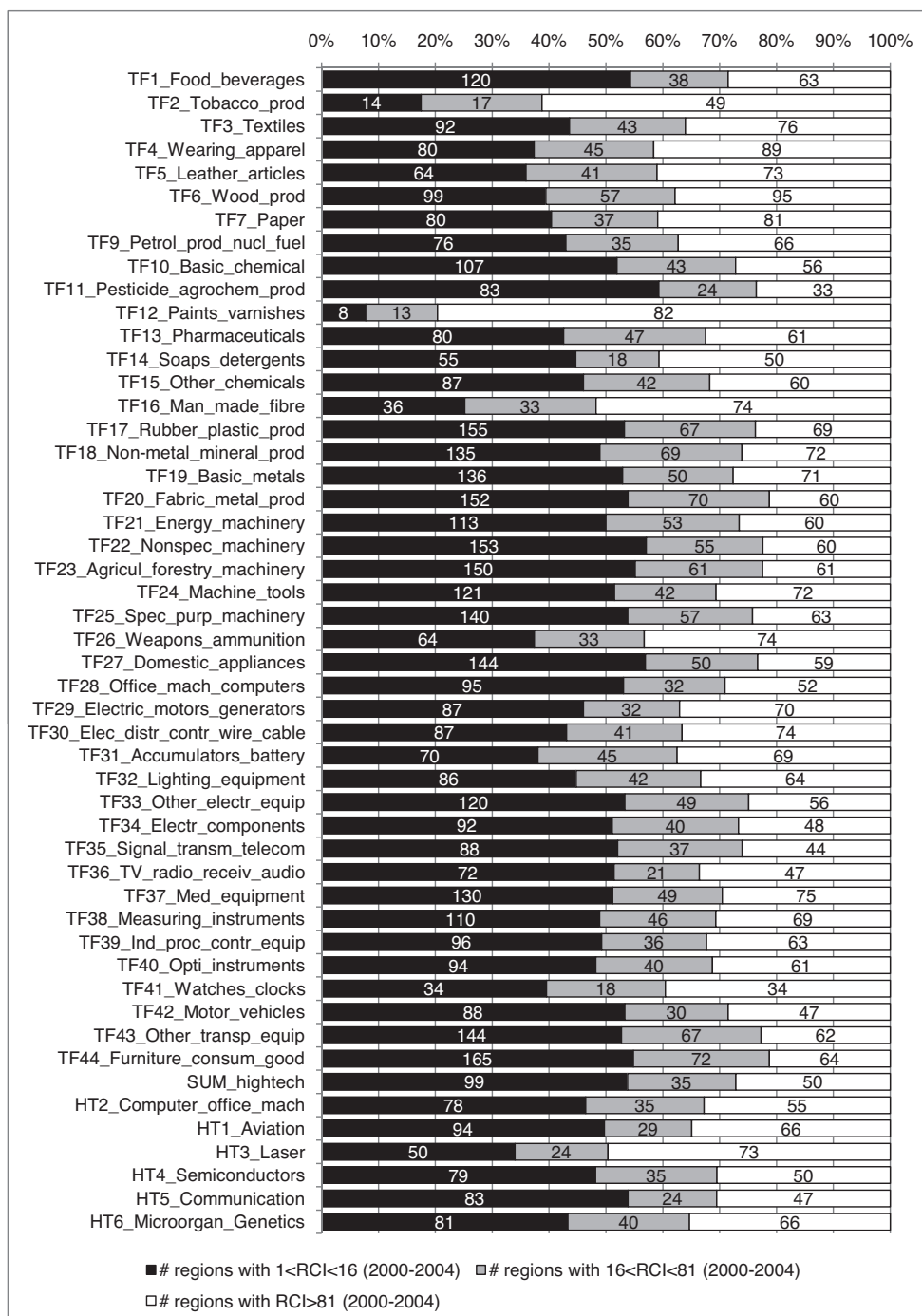


Fig. 3.30. Structure of research clusters by TF and RCI class, 2000-2004

Source: own calculations and illustration. *Notes:* share and number of research clusters by TF and TL3 region of all regions with $1 < RCI \leq 16$, $16 < RCI \leq 81$ and $RCI > 81$; calculations based upon OECD RegPAT (2009) database extractions and application of the ISI-SPRU-OST concordance.

& consumer goods, HT1 Aviation, and HT3 Laser. In comparison, some technology fields show a significant decrease in the absolute number of research clusters; e.g., TF1 Food & beverages, TF2 Tobacco products, TF22 Nonspec. machinery, TF26 Weapons & ammunition, TF27 Domestic appliances, TF28 Office mach. & computers, TF35 Signal transm. telecom., TF36 TV & radio receiv. & audio, TF38 Measuring instruments, TF39 Ind. proc. contr. equip., TF41 Watches & clocks, TF42 Motor vehicles, SUM hightech (i.e., 6 high-technology fields) and HT2 Computer & office mach.

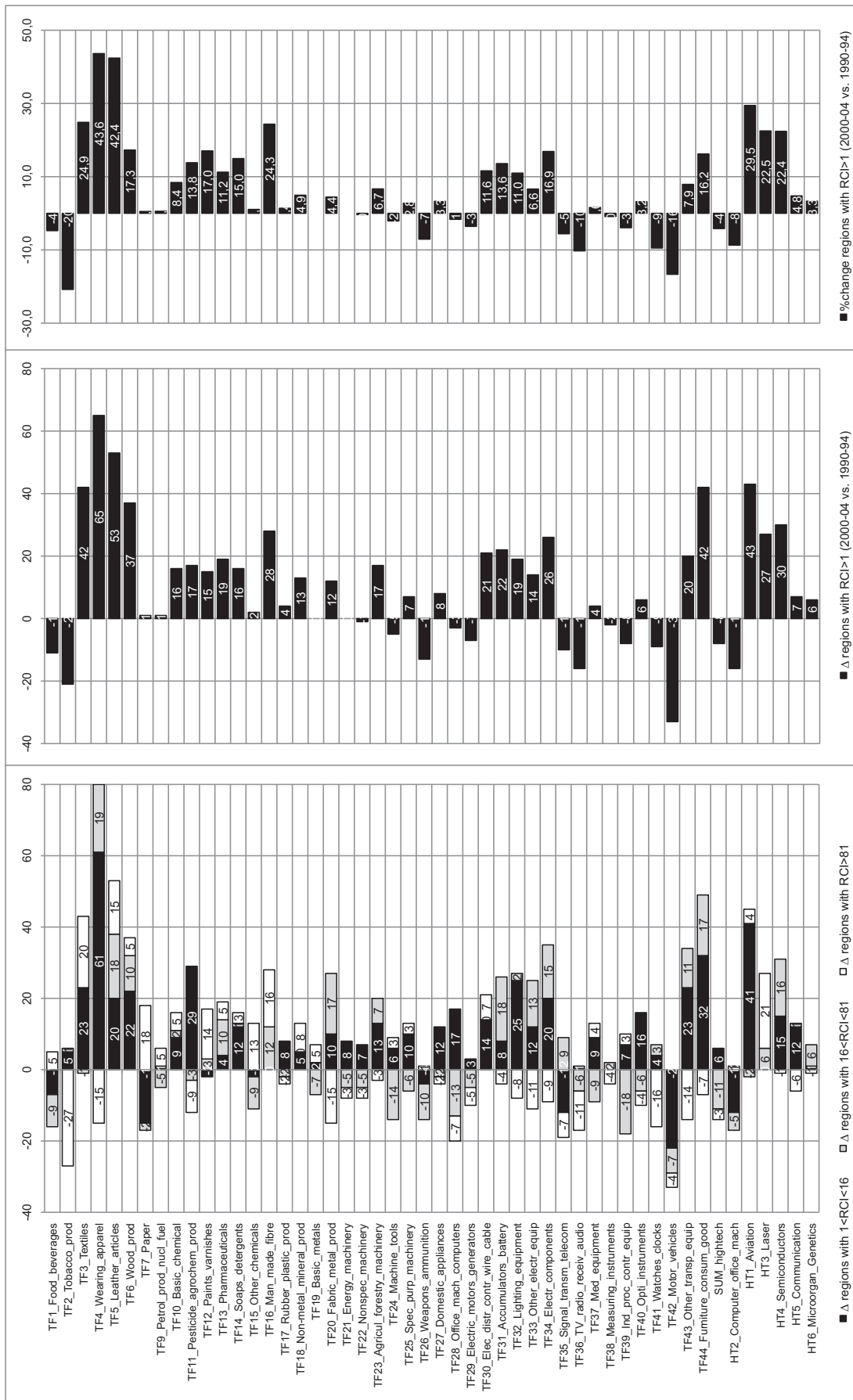


Fig. 3.31. Change of research clusters by TF and RCI class, 2000-2004 vs. 1990-1994
 Source: own calculations and illustration. Notes: change of number of research clusters by technology field and RCI class, $1 < RCI \leq 16$, $16 < RCI \leq 81$ and $RCI > 81$; 2000-2004 vs. 1990-1994; calculations based upon OECD RegPAT (2009) database extractions and application of the ISI-SPRU-OST concordance.

With respect to higher RCI classes, the number of regions with $RCI > 16$ could be interpreted as a threshold level for strong(er) research clusters. Figure 3.32 illustrates the absolute number of technology field-specific clusters across the 819 European regions (first graph), the share of the 819 European regions with $RCI > 16$ (second graph), the change in absolute numbers, i.e. Δ regions with $RCI > 16$ (third graph), and the growth rate (change %) of regions with $RCI > 16$ (graph on the right). The strongest increase in absolute numbers can be observed for the following technology fields: *TF3 Textiles*; *TF5 Leather articles*; *TF6 Wood prod.*; *TF7 Paper*; *TF12 Paints & varnishes*; *TF13 Pharmaceuticals*; *TF16 Man-made fibre*; *TF31 Accumulators & battery*; *TF44 Furniture & consum. good*; *HT3 Laser*; *HT4 Semiconductors*. However, the strongest decrease in absolute numbers is observed for *TF2 Tobacco prod.*; *TF11 Pesticides & agrochem. prod.*; *TF21 Energy machinery*; *TF22 Nonspec. machinery*; *TF24 Machine tools*; *TF26 Weapons & ammunition*; *TF28 Office mach. & computers*; *TF36 TV & radio receiv. & audio*; *TF39 Ind. proc. contr. equip.*; *TF40 Optical instruments*; *TF41 Watches & clocks*; *TF42 Motor vehicles*; *SUM hightech*. This picture is quite similar to the previously described development of the number of regions with $16 < RCI \leq 81$ and $RCI > 81$ in figure 3.31.

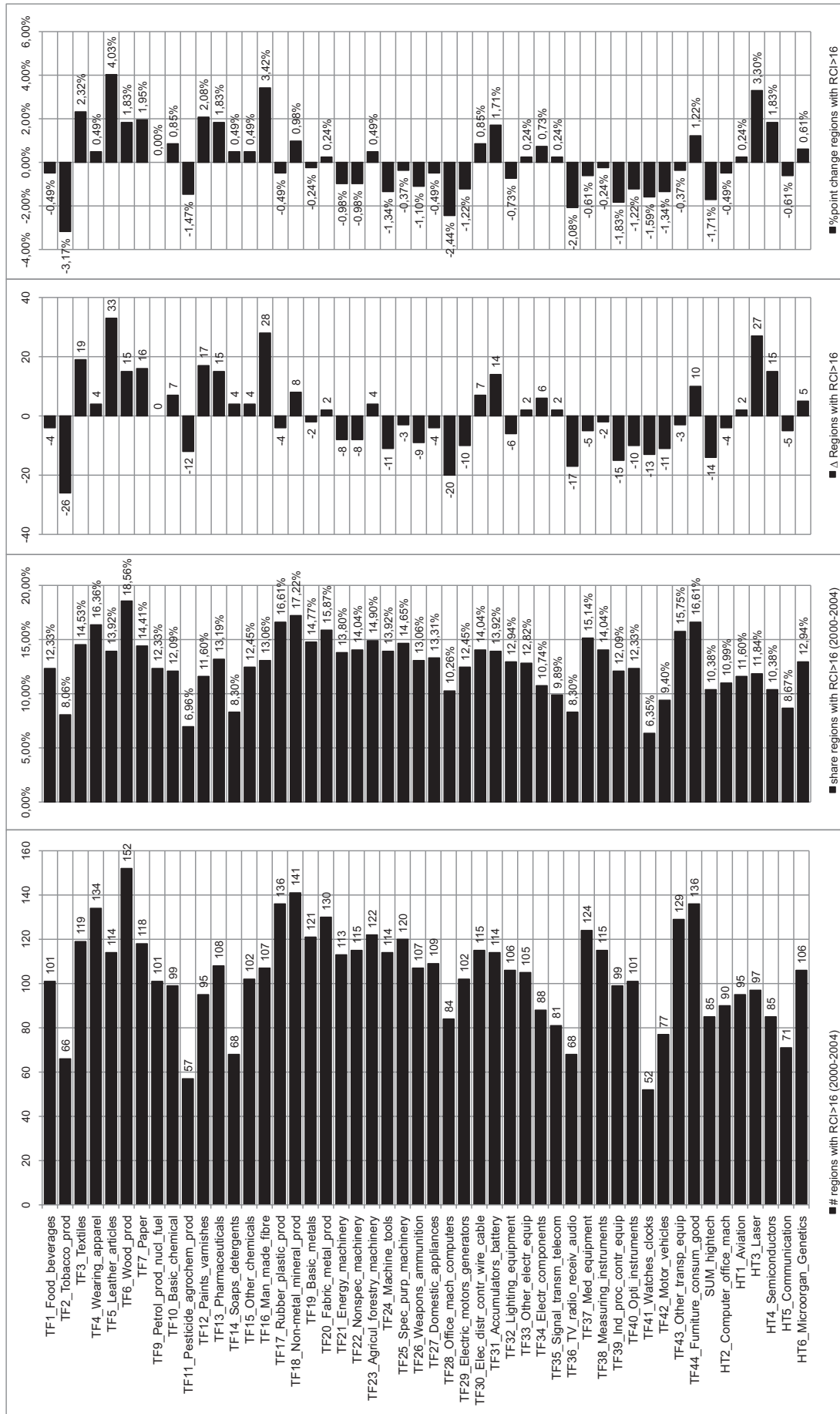


Fig. 3.32. Structure and change of research clusters by TF with RCI > 16, 2000-2004 vs. 1990-1994
 Source: own calculations and illustration. Notes: research clusters by technology field, 2000-2004 vs. 1990-1994; calculations based upon OECD RegPAT (2009) database extractions and application of the ISI-SPRU-OST concordance.

The study also offers RCI calculations for each European country (incl. Switzerland and Norway). Absolute numbers of existing technology field-specific research clusters are calculated for every country and different RCI classes: $RCI > 1$, $1 < RCI \leq 16$, $16 < RCI \leq 81$ and $RCI > 81$. The definition/ grouping helps to enrich our understanding with respect to the strength of research clustering at the regional level (see the methodological issues of RCI computation in section 3.5.2). The subsequent table 3.4 (and table B.6, appendix) and figure 3.33 summarize all identified research clusters in Europe and the ERA by country and technology field.³⁷⁴

It is obvious from the following table 3.4 (period 2000-2004) that the majority of research clusters (including tendencies) across the 819 European regions with $RCI > 1$ are located in the highly industrialized EU-15 group. For the calculations for the period 1990-1994 see table B.6 (appendix). The leading countries (2000-2004) are Germany (2622 cluster), France (1110), the Netherlands (264), Switzerland (970), Italy (884) and the United Kingdom (1957). Ireland (42), Luxembourg (18) and Norway (145) show an intermediate number of research clusters. Greece (5), Portugal (17) and Spain (107) represent rather weak research cluster tendencies due to the small number of regions with $RCI > 1$. In the NMS, the Czech Republic (23), Slovenia (88), Poland (27), Malta (8), Hungary (24) and Latvia (4) show small numbers of research clusters with $RCI > 1$ across the 50 analyzed technology fields (compared to the EU-15), being at a level similar to Greece (5) and Portugal (17). Estonia (2), Lithuania (3), Cyprus (2) and the Slovak Republic (5) do not host any single significant research cluster that fulfills $RCI > 1$ in the 1990s. In the 2000s, the only countries in the NMS group with a remarkable number of research clusters in different technology fields are the Czech Republic, Poland, Slovenia and Hungary. Estonia, Cyprus, Latvia, Lithuania and the Slovak Republic are characterized by very small numbers of research clusters.³⁷⁵ Nevertheless, changing the extraction criterion from $RCI > 1$ to $RCI > 16$ or $RCI > 81$ leads to a strong reduction of the overall number of European research clusters as $RCI > 1$ also includes “weak” clusters and clustering “tendencies.”

Regarding stronger research clusters (i.e., $RCI > 16$), table 3.5 summarizes the share of each country by technology field. First, the overall number of research clusters is significantly smaller compared to the previous tables. Nevertheless, in the 2000s, Germany (1551), Switzerland (677), France (547), Italy (399) and the UK (875) host the majority of cluster regions (with $RCI > 16$). For the calculations for the period 1990-1994 see table B.7 (appendix).

³⁷⁴ The number of identified research clusters is endogenous to the chosen RCI threshold level. The higher the RCI threshold level, the smaller the number of national research clusters. Further information is available upon request from the author. All regions with $RCI > 1$ and $RCI \geq 81$ are reported. The other classes may also represent strong research clustering. However, $RCI > 1$ is the lowest threshold level of RCI (the index of the four multiplicatively combined coefficients has only to be larger than one).

³⁷⁵ For a full description of country abbreviations see table B.3, appendix.

Table 3.4. Research clusters by TF and country with $RCI > 1$, 2000-2004

Technology Field	AT	BE	CH	CY	CZ	DE	DK	EE	ES	FI	FR	GR	HU	IE	IT	LT	LU	LV	MT	NL	NO	PL	PT	SE	SI	SK	UK	Σ	
TF1_Food beverages	2%	4%	10%	0%	0%	18%	5%	0%	4%	2%	15%	0%	1%	0%	10%	0%	0%	0%	0%	5%	4%	0%	0%	2%	0%	0%	16%	221	
TF2_Tobacco prod	3%	1%	10%	0%	0%	26%	3%	0%	5%	0%	9%	0%	3%	0%	11%	0%	0%	0%	0%	4%	0%	1%	0%	4%	0%	0%	20%	80	
TF3_Textiles	5%	4%	10%	0%	0%	21%	3%	0%	0%	2%	16%	0%	0%	0%	13%	0%	0%	0%	0%	2%	0%	1%	2%	2%	0%	0%	16%	211	
TF4_Wearing apparel	4%	2%	5%	0%	0%	22%	2%	0%	3%	2%	18%	0%	0%	1%	12%	0%	0%	0%	0%	2%	2%	0%	0%	3%	0%	0%	21%	214	
TF5_Leather articles	8%	1%	5%	0%	1%	19%	2%	0%	3%	0%	12%	0%	0%	1%	25%	0%	0%	0%	1%	1%	2%	1%	0%	4%	0%	0%	15%	178	
TF6_Wood prod	8%	3%	6%	0%	1%	25%	3%	0%	4%	3%	8%	0%	0%	1%	13%	0%	0%	0%	0%	3%	2%	0%	1%	3%	0%	0%	12%	251	
TF7_Paper	6%	3%	12%	0%	1%	23%	2%	0%	0%	7%	7%	0%	0%	0%	7%	0%	0%	0%	0%	5%	1%	1%	0%	4%	0%	0%	22%	198	
TF9_Petrol_prod_nucl_fuel	4%	3%	3%	0%	1%	21%	2%	0%	1%	3%	11%	0%	1%	0%	7%	0%	0%	1%	0%	5%	3%	0%	0%	2%	0%	0%	28%	177	
TF10_Basic_chemical	4%	4%	12%	0%	0%	26%	2%	0%	0%	1%	11%	0%	0%	0%	7%	0%	0%	0%	0%	4%	1%	0%	0%	2%	0%	0%	22%	206	
TF11_Pesticide_agrochem_prod	3%	3%	9%	0%	1%	26%	3%	0%	2%	1%	11%	0%	1%	0%	9%	0%	1%	0%	0%	4%	0%	1%	0%	1%	0%	0%	27%	140	
TF12_Paints_varnishes	9%	4%	7%	0%	0%	36%	7%	0%	2%	8%	8%	1%	0%	0%	4%	0%	1%	0%	0%	3%	1%	0%	4%	2%	0%	0%	0%	100%	103
TF13_Pharmaceuticals	4%	4%	11%	0%	1%	21%	3%	0%	1%	2%	12%	0%	1%	1%	6%	0%	0%	1%	0%	4%	1%	0%	0%	2%	2%	1%	24%	188	
TF14_Soaps_detergents	4%	4%	10%	0%	0%	21%	3%	0%	1%	0%	9%	0%	0%	1%	11%	0%	0%	0%	0%	4%	0%	0%	0%	0%	0%	0%	33%	123	
TF15_Other_chemicals	4%	4%	12%	0%	0%	29%	2%	0%	0%	2%	15%	0%	0%	0%	5%	0%	0%	0%	0%	3%	1%	0%	1%	3%	0%	0%	19%	189	
TF16_Man_made fibre	5%	6%	5%	1%	0%	21%	2%	0%	3%	1%	13%	0%	0%	0%	13%	0%	1%	0%	0%	5%	3%	3%	0%	0%	0%	0%	20%	143	
TF17_Rubber_plastic_prod	5%	3%	9%	0%	0%	24%	3%	0%	1%	1%	12%	0%	0%	0%	11%	0%	0%	0%	0%	3%	1%	0%	0%	2%	0%	0%	22%	291	
TF18_Non-metal_mineral_prod	9%	4%	8%	0%	0%	28%	5%	0%	1%	2%	11%	0%	0%	0%	11%	0%	0%	0%	0%	3%	1%	0%	0%	3%	2%	0%	13%	276	
TF19_Basic_metals	9%	4%	10%	0%	0%	25%	2%	0%	1%	3%	14%	0%	0%	0%	6%	0%	0%	0%	0%	2%	3%	0%	0%	5%	0%	0%	14%	257	
TF20_Fabric_metal_prod	9%	2%	9%	0%	0%	26%	3%	0%	1%	1%	12%	0%	0%	0%	12%	0%	0%	0%	0%	3%	0%	0%	0%	4%	3%	0%	14%	282	
TF21_Energy_machinery	6%	1%	10%	0%	0%	34%	5%	0%	0%	0%	10%	0%	0%	0%	11%	0%	0%	0%	0%	1%	1%	0%	0%	3%	0%	0%	16%	226	
TF22_Nonspec_machinery	7%	1%	9%	0%	0%	29%	4%	0%	0%	4%	9%	0%	0%	0%	12%	0%	0%	0%	0%	4%	2%	0%	0%	3%	1%	0%	15%	268	
TF23_Agriul_forestry_machinery	7%	3%	4%	0%	0%	20%	5%	0%	1%	3%	11%	0%	0%	1%	10%	0%	0%	0%	0%	4%	4%	0%	0%	4%	1%	0%	21%	272	
TF24_Machine_tools	7%	0%	11%	0%	0%	34%	2%	0%	1%	3%	10%	0%	0%	0%	13%	0%	0%	0%	0%	1%	1%	0%	0%	5%	0%	0%	12%	235	
TF25_Spec_purp_machinery	8%	3%	10%	0%	0%	27%	3%	0%	0%	4%	7%	0%	0%	0%	13%	0%	0%	0%	0%	3%	2%	0%	0%	5%	0%	0%	15%	260	
TF26_Weapons_ammunition	8%	2%	9%	0%	2%	26%	3%	0%	0%	2%	13%	0%	0%	1%	8%	0%	0%	0%	0%	1%	2%	1%	0%	5%	1%	0%	14%	171	
TF27_Domestic_appliances	6%	2%	8%	0%	0%	24%	3%	0%	2%	1%	13%	0%	0%	0%	15%	0%	0%	0%	0%	3%	0%	0%	0%	3%	2%	0%	17%	253	
TF28_Office_machn_computers	3%	3%	13%	0%	0%	25%	3%	0%	1%	3%	10%	0%	1%	1%	3%	2%	0%	0%	0%	1%	1%	0%	0%	3%	0%	0%	28%	179	
TF29_Electric_motors_generators	7%	0%	12%	0%	1%	32%	3%	0%	0%	2%	11%	0%	0%	0%	10%	0%	0%	0%	0%	2%	1%	0%	2%	2%	1%	0%	16%	189	
TF30_Elec_distr_cont_wire_cable	5%	1%	11%	0%	0%	35%	2%	0%	1%	2%	15%	0%	0%	0%	8%	0%	0%	0%	0%	2%	1%	0%	0%	1%	4%	0%	9%	202	
TF31_Accumulators_battery	4%	2%	11%	0%	1%	34%	3%	0%	2%	1%	12%	0%	0%	0%	5%	0%	1%	0%	1%	2%	1%	1%	0%	1%	1%	0%	19%	184	
TF32_Lighting_equipment	6%	3%	10%	0%	1%	29%	3%	0%	1%	2%	10%	1%	1%	1%	11%	0%	0%	0%	0%	1%	2%	1%	0%	1%	3%	0%	15%	192	
TF33_Other_elec equip	8%	1%	9%	0%	0%	29%	2%	0%	1%	3%	12%	0%	0%	0%	9%	0%	0%	0%	0%	3%	2%	0%	0%	3%	1%	0%	20%	225	
TF34_Elec_components	6%	3%	14%	0%	0%	29%	1%	0%	0%	1%	9%	0%	1%	1%	7%	0%	0%	0%	0%	2%	1%	1%	0%	3%	0%	0%	21%	180	
TF35_Signal_transm_telecom	5%	3%	12%	0%	0%	27%	3%	0%	0%	4%	9%	0%	1%	1%	2%	0%	0%	0%	0%	2%	2%	0%	0%	5%	1%	0%	24%	169	
TF36_TV_radio_receiv_audio	2%	3%	15%	0%	0%	25%	5%	0%	0%	4%	10%	0%	1%	0%	3%	0%	0%	0%	0%	3%	2%	1%	0%	2%	0%	0%	25%	140	
TF37_Med equipment	4%	3%	10%	0%	0%	24%	4%	0%	0%	1%	8%	0%	0%	0%	7%	0%	0%	0%	0%	4%	1%	0%	0%	3%	0%	0%	30%	254	
TF38_Measuring_instruments	3%	4%	11%	0%	0%	31%	3%	0%	0%	2%	8%	0%	0%	0%	4%	0%	0%	0%	0%	2%	1%	0%	0%	3%	1%	0%	27%	225	
TF39_Ind_proc_contr equip	6%	2%	11%	0%	1%	31%	4%	0%	0%	3%	8%	0%	0%	1%	8%	0%	1%	0%	1%	3%	1%	0%	0%	4%	0%	0%	18%	195	
TF40_Opt_instruments	4%	4%	12%	0%	0%	29%	3%	0%	0%	1%	11%	0%	1%	0%	6%	0%	0%	0%	0%	3%	1%	0%	0%	2%	1%	0%	25%	195	
TF41_Watches_clocks	2%	2%	23%	0%	0%	30%	5%	0%	2%	2%	13%	0%	0%	0%	5%	0%	0%	0%	1%	1%	0%	0%	0%	0%	0%	0%	13%	86	
TF42_Motor_vehicles	7%	2%	4%	0%	0%	39%	1%	0%	2%	1%	19%	0%	0%	0%	6%	0%	1%	0%	1%	1%	0%	0%	0%	3%	0%	0%	15%	165	
TF43_Other_transp equip	7%	1%	8%	0%	0%	25%	1%	0%	2%	1%	13%	0%	0%	0%	9%	0%	0%	0%	0%	3%	4%	0%	0%	4%	2%	0%	19%	273	
TF44_Furniture_consum good	8%	2%	8%	0%	0%	19%	3%	0%	1%	1%	10%	0%	0%	0%	14%	0%	0%	0%	0%	3%	2%	0%	0%	4%	2%	0%	21%	301	
SUM_hightech	3%	3%	13%	0%	0%	28%	3%	0%	0%	3%	9%	0%	1%	1%	2%	0%	0%	0%	0%	4%	1%	0%	0%	2%	0%	0%	27%	184	
HT2_Computer_office_mach	3%	3%	14%	0%	0%	24%	3%	0%	1%	3%	10%	0%	1%	1%	4%	0%	1%	0%	0%	2%	1%	0%	0%	3%	0%	0%	27%	168	
HT1_Aviation	3%	3%	5%	0%	1%	26%	3%	0%	3%	1%	16%	0%	1%	0%	5%	0%	1%	0%	0%	2%	2%	0%	0%	3%	0%	0%	27%	189	
HT3_Laser	5%	1%	12%	0%	0%	23%	3%	0%	1%	2%	8%	0%	0%	0%	10%	0%	0%	0%	0%	1%	1%	1%	1%	1%	0%	0%	29%	147	
HT4_Semiconductors	7%	4%	15%	0%	0%	30%	2%	0%	0%	1%	9%	0%	0%	1%	7%	0%	0%	0%	0%	2%	1%	0%	0%	2%	0%	0%	21%	164	
HT5_Communication	2%	3%	11%	0%	0%	25%	4%	0%	0%	5%	10%	0%	1%	1%	2%	0%	0%	0%	0%	4%	2%	0%	0%	5%	1%	0%	26%	154	
HT6_Microorgan_Genetics	3%	4%	10%	0%	0%	26%	4%	1%	2%	2%	11%	0%	1%	1%	2%	0%	0%	1%	0%	4%	1%	1%	0%	2%	1%	0%	25%	187	
Σ cluster regions	551	273	970	2	23	2622	305	2	107	212	1110	5	24	42	884	3	18	4	8	264	145	27	17	292	88	5	1957	9980	
share cluster regions	6%	3%	10%	0%	0%	26%	3%	0%	1%	2%	11%	0%	0%	0%	9%	0%	0%	0%	0%	3%	1%	0%	0%	3%	1%	0%	20%	100%	

Source: own calculations and illustration. Notes: regions with $RCI > 1$, 2000-2004.

Table 3.5. Research clusters by TF and country with $RCI > 16$, 2000-2004

Technology Field	AT	BE	CH	CY	CZ	DE	DK	EE	ES	FI	FR	GR	HU	IE	IT	LT	LU	LV	MT	NL	NO	PL	PT	SE	SI	SK	UK	Σ
TF1_Food_beverages	1%	5%	16%	0%	0%	18%	9%	0%	1%	2%	14%	0%	0%	0%	9%	0%	0%	0%	0%	11%	3%	1%	0%	2%	0%	0%	9%	101
TF2_Tobacco_prod	3%	2%	11%	0%	0%	24%	2%	0%	6%	0%	9%	0%	3%	2%	12%	0%	0%	0%	0%	2%	0%	2%	0%	3%	0%	0%	21%	66
TF3_Textiles	4%	5%	12%	0%	0%	24%	4%	0%	1%	1%	13%	0%	0%	0%	11%	0%	0%	0%	0%	1%	0%	0%	1%	3%	3%	0%	18%	119
TF4_Wearing_apparel	7%	1%	7%	0%	0%	19%	4%	0%	3%	1%	14%	0%	0%	1%	13%	0%	0%	0%	0%	1%	0%	0%	1%	2%	0%	0%	26%	134
TF5_Leather_articles	10%	1%	6%	0%	0%	18%	2%	0%	2%	0%	11%	0%	0%	0%	28%	0%	0%	0%	1%	1%	3%	1%	0%	4%	0%	0%	14%	114
TF6_Wood_prod	11%	2%	9%	1%	0%	22%	5%	0%	5%	3%	3%	0%	1%	0%	14%	0%	0%	0%	3%	3%	1%	1%	1%	4%	4%	0%	13%	152
TF7_Paper	6%	2%	19%	0%	0%	25%	2%	0%	0%	8%	8%	0%	0%	0%	3%	0%	0%	0%	0%	3%	3%	1%	0%	6%	2%	0%	16%	118
TF9_Petrol_prod_nucl_fuel	2%	5%	3%	0%	0%	20%	3%	0%	1%	1%	12%	0%	0%	0%	7%	0%	0%	0%	0%	5%	4%	2%	0%	1%	0%	0%	35%	101
TF10_Basic_chemical	2%	6%	14%	0%	0%	28%	4%	0%	0%	1%	8%	0%	0%	0%	5%	0%	1%	0%	0%	4%	2%	0%	0%	1%	0%	0%	23%	99
TF11_Pesticide_agrochem_prod	2%	4%	7%	0%	0%	35%	5%	0%	0%	0%	9%	0%	0%	0%	4%	0%	0%	0%	0%	4%	0%	2%	0%	0%	0%	0%	30%	57
TF12_Paints_varnishes	9%	4%	6%	0%	0%	35%	7%	0%	2%	7%	7%	1%	0%	0%	4%	0%	1%	0%	0%	3%	1%	0%	4%	1%	5%	0%	30%	95
TF13_Pharmaceuticals	3%	5%	12%	0%	0%	19%	4%	0%	1%	1%	10%	0%	1%	0%	5%	0%	0%	0%	0%	5%	1%	0%	0%	3%	4%	0%	28%	108
TF14_Soaps_detergents	1%	10%	9%	0%	0%	26%	4%	0%	1%	0%	12%	0%	0%	0%	9%	0%	0%	0%	0%	3%	0%	0%	0%	0%	0%	0%	24%	68
TF15_Other_chemicals	4%	5%	16%	0%	0%	30%	1%	0%	1%	13%	0%	0%	0%	0%	4%	0%	0%	0%	0%	6%	1%	0%	0%	1%	0%	0%	19%	102
TF16_Man_made_fibre	6%	7%	6%	1%	0%	20%	2%	0%	2%	2%	12%	0%	0%	0%	12%	0%	1%	0%	0%	6%	3%	4%	0%	0%	0%	0%	19%	107
TF17_Rubber_plastic_prod	3%	4%	16%	0%	0%	35%	3%	0%	0%	1%	13%	0%	0%	0%	10%	0%	1%	0%	0%	1%	0%	0%	1%	0%	0%	0%	13%	136
TF18_Non-metal_mineral_prod	13%	5%	16%	0%	0%	34%	4%	0%	1%	2%	9%	0%	0%	0%	8%	0%	1%	0%	0%	1%	0%	0%	0%	1%	1%	0%	5%	100
TF19_Basic_metals	11%	4%	15%	0%	0%	32%	2%	0%	0%	3%	9%	0%	0%	0%	6%	0%	1%	0%	0%	1%	3%	0%	0%	0%	0%	0%	10%	121
TF20_Fabric_metal_prod	8%	2%	16%	0%	0%	37%	3%	0%	1%	1%	8%	0%	0%	0%	10%	0%	0%	0%	0%	1%	0%	0%	0%	2%	3%	0%	8%	130
TF21_Energy_machinery	5%	0%	9%	0%	0%	49%	3%	0%	0%	0%	11%	0%	0%	0%	7%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	14%	113
TF22_Nonspec_machinery	8%	0%	17%	0%	0%	41%	4%	0%	0%	1%	5%	0%	0%	0%	13%	0%	1%	0%	0%	3%	2%	0%	0%	2%	1%	0%	3%	115
TF23_Agricul_forestry_machinery	6%	2%	4%	0%	0%	20%	7%	0%	1%	1%	10%	0%	0%	0%	10%	0%	0%	0%	0%	7%	4%	0%	0%	5%	0%	0%	23%	122
TF24_Machine_tools	8%	0%	20%	0%	0%	43%	0%	0%	1%	0%	4%	0%	0%	0%	11%	0%	0%	0%	0%	0%	0%	0%	0%	5%	0%	0%	7%	114
TF25_Spec_pump_machinery	6%	3%	18%	0%	0%	39%	4%	0%	0%	3%	5%	0%	0%	0%	14%	0%	0%	0%	0%	2%	1%	0%	0%	3%	0%	0%	3%	120
TF26_Weapons_ammunition	8%	2%	8%	0%	2%	30%	3%	0%	2%	13%	0%	0%	0%	0%	7%	0%	0%	0%	0%	1%	0%	0%	0%	7%	0%	0%	16%	107
TF27_Domestic_appliances	2%	1%	12%	0%	0%	30%	3%	0%	4%	0%	15%	0%	0%	0%	17%	0%	0%	0%	1%	2%	0%	0%	0%	2%	0%	0%	12%	109
TF28_Office_mach_computers	4%	1%	19%	0%	0%	24%	2%	0%	0%	2%	12%	0%	0%	1%	1%	0%	0%	0%	0%	2%	1%	0%	0%	2%	0%	0%	27%	84
TF29_Electric_motors_generators	5%	0%	15%	0%	0%	39%	3%	0%	3%	12%	0%	0%	0%	0%	8%	0%	0%	0%	0%	0%	0%	0%	0%	2%	3%	0%	11%	102
TF30_Elec_distr_contr_wire_cable	4%	0%	16%	0%	0%	41%	3%	0%	1%	2%	17%	0%	0%	0%	6%	0%	1%	0%	1%	2%	0%	0%	0%	1%	4%	0%	2%	100
TF31_Accumulators_battery	3%	1%	13%	0%	0%	39%	4%	0%	3%	0%	12%	0%	0%	0%	5%	0%	0%	0%	0%	2%	1%	0%	0%	0%	1%	0%	16%	114
TF32_Lighting_equipment	8%	2%	9%	0%	0%	36%	4%	0%	1%	2%	9%	1%	1%	0%	9%	0%	0%	0%	0%	1%	2%	0%	0%	0%	5%	0%	9%	106
TF33_Other_electr equip	7%	1%	13%	0%	0%	35%	2%	0%	0%	5%	12%	0%	0%	0%	4%	0%	0%	0%	0%	1%	0%	0%	0%	4%	1%	0%	15%	105
TF34_Electr_components	6%	2%	18%	0%	0%	35%	1%	0%	0%	0%	10%	0%	0%	0%	5%	0%	0%	0%	0%	1%	0%	0%	0%	3%	0%	0%	18%	88
TF35_Signal_transm_telecom	1%	4%	10%	0%	0%	25%	5%	0%	0%	5%	13%	0%	0%	1%	2%	0%	0%	0%	0%	1%	1%	0%	0%	5%	0%	0%	25%	81
TF36_TV_radio_receiv_audio	1%	1%	20%	0%	0%	16%	7%	0%	0%	4%	13%	0%	0%	0%	0%	0%	0%	0%	0%	1%	3%	0%	0%	4%	0%	0%	26%	68
TF37_Med_equipment	3%	2%	20%	0%	0%	26%	4%	0%	0%	1%	5%	0%	0%	0%	3%	0%	0%	0%	0%	3%	1%	0%	0%	4%	0%	0%	26%	124
TF38_Measuring_instruments	3%	2%	17%	0%	0%	34%	3%	0%	0%	2%	7%	0%	0%	0%	1%	0%	0%	0%	0%	2%	1%	0%	0%	3%	0%	0%	25%	115
TF39_Ind_proc_contr equip	2%	0%	15%	0%	0%	42%	5%	0%	0%	2%	8%	0%	0%	0%	5%	0%	1%	0%	1%	1%	2%	0%	0%	1%	0%	0%	14%	99
TF40_Opti_instruments	2%	3%	20%	0%	0%	31%	4%	0%	0%	1%	10%	0%	0%	0%	2%	0%	0%	0%	0%	4%	0%	0%	0%	1%	0%	0%	23%	101
TF41_Watches_clocks	0%	2%	37%	0%	0%	23%	2%	0%	0%	4%	13%	0%	0%	0%	4%	0%	0%	0%	2%	2%	0%	0%	0%	0%	0%	0%	12%	52
TF42_Motor_vehicles	5%	1%	1%	0%	0%	62%	0%	0%	0%	0%	16%	0%	0%	0%	3%	0%	1%	0%	0%	0%	0%	0%	0%	4%	0%	0%	6%	77
TF43_Other_transp equip	8%	1%	11%	0%	0%	26%	2%	0%	1%	2%	16%	0%	0%	0%	8%	0%	0%	0%	0%	2%	5%	0%	0%	2%	2%	0%	16%	129
TF44_Furniture_consumm good	13%	1%	15%	0%	0%	22%	4%	0%	1%	0%	7%	0%	0%	1%	18%	0%	0%	0%	0%	2%	2%	0%	0%	1%	0%	0%	12%	136
SUM_hightech	2%	6%	13%	0%	0%	22%	4%	0%	0%	5%	13%	0%	0%	1%	1%	0%	0%	0%	0%	2%	1%	0%	0%	4%	0%	0%	25%	85
HT2_Computer_office_mach	2%	2%	19%	0%	0%	22%	2%	0%	0%	3%	11%	0%	0%	1%	3%	0%	0%	0%	0%	2%	2%	0%	0%	3%	0%	0%	26%	90
HTT_Aviation	3%	2%	3%	0%	0%	27%	2%	0%	4%	0%	21%	0%	0%	0%	2%	0%	0%	0%	0%	0%	1%	0%	0%	0%	3%	0%	31%	95
HT3_Laser	5%	1%	14%	0%	0%	23%	3%	0%	1%	1%	9%	0%	0%	0%	6%	0%	1%	0%	0%	1%	1%	1%	1%	1%	0%	0%	30%	97
HT4_Semiconductors	6%	4%	19%	0%	0%	38%	0%	0%	0%	0%	9%	0%	0%	0%	4%	0%	0%	0%	0%	1%	0%	0%	0%	2%	0%	0%	18%	100
HT5_Communication	1%	3%	8%	0%	0%	20%	7%	0%	0%	7%	17%	0%	0%	0%	3%	0%	0%	0%	0%	1%	1%	0%	0%	6%	0%	0%	25%	71
HT6_Microorgan_Genetics	5%	5%	8%	0%	0%	25%	5%	0%	0%	2%	8%	0%	0%	0%	6%	1%	0%	0%	0%	6%	1%	0%	0%	3%	0%	0%	29%	106
Σ cluster regions	278	133	677	2	2	1551	176	0	47	96	547	2	5	11	399	0	11	0	5	120	58	13	9	127	50	0	875	5194
share cluster regions	5%	3%	13%	0%	0%	30%	3%	0%	1%	2%	11%	0%	0%	0%	8%	0%	0%	0%	0%	2%	1%	0%	0%	2%	1%	0%	17%	100%

Source: own calculations and illustration. Notes: regions with $RCI > 16$, 2000-2004.

In taking a more dynamic perspective (i.e., a cross-country analysis), the change in the number of clusters between the 1990s and 2000s has been calculated. Figure 3.33 highlights the absolute change of research clusters across the 819 European regions but also the growth rates of technology field-specific clusters by country and RCI group. It is obvious, that especially the highly developed and formerly central industrialized European countries exhibit decreasing numbers, e.g., the UK and France. On the contrary, the largest increases of research clusters are observed in Poland, Slovenia, Spain, Latvia and the Czech Republic (although at a very low level). Regarding absolute numbers, the strongest increases can be observed in Austria, Belgium, Germany, Denmark, Spain, Finland, Italy and Slovenia (see figure 3.33). Nevertheless, the majority of emerging clusters do not reach beyond the $RCI > 16$ or $RCI > 81$ threshold level. The described dynamics are also illustrated for each of the 50 technology field aggregates by country and $RCI > 1$ in tables 3.6 (change in share) and B.8 (change in number, see appendix). The strongest relative decreases (national share) are observed in leading European countries; e.g., Germany, Switzerland, France, the Netherlands, Sweden, the United Kingdom and Italy. Moreover, the calculations clearly demonstrate that especially France and the UK suffered from a significant decrease in the share of research clusters with $RCI > 1$ between the 1990s and 2000s. Nevertheless, the UK has experienced an absolute increase in research cluster regions since the 1990s in almost all technology fields (see table B.8, appendix). However, the share of European research clusters in the UK has decreased in the period (percentage points) due to a higher average growth in the number of clusters in other European countries (see table 3.6).³⁷⁶ With regard to higher threshold levels of RCI (i.e., $RCI > 16$ and $RCI > 81$), tables 3.7 and 3.8 summarize the change (percentage points) in country shares between the 1990s and 2000s. France and the UK are characterized by a relatively stronger decrease in the shares, compared to Switzerland, Germany or Italy. Italy could increase its share in several technology fields, similar to Denmark, Belgium, Austria, Norway, Finland and Spain. Within the NMS group, only Slovenia, Poland, Malta and Hungary show technology field-specific dynamics. Accordingly, the presented tables clearly highlight the differing levels of regional development within the NMS group, irrespective of the RCI class ($RCI > 1$, $RCI > 16$, $RCI > 81$). To conclude, Cyprus, Estonia, the Slovak Republic, Lithuania and Latvia are characterized by a slower growth in research clustering compared to the other countries. Furthermore, the tables clearly demonstrate a persistent north-south gradient; Greece and Portugal still host only small numbers of clusters. Nevertheless, in opposition to Greece, Portugal shows a growing number (and share) of research clusters (see tables 3.6, 3.7 and 3.8).

³⁷⁶ Nevertheless, one has to bear in mind that $RCI > 1$ represents a rather modest threshold level for research cluster identification.

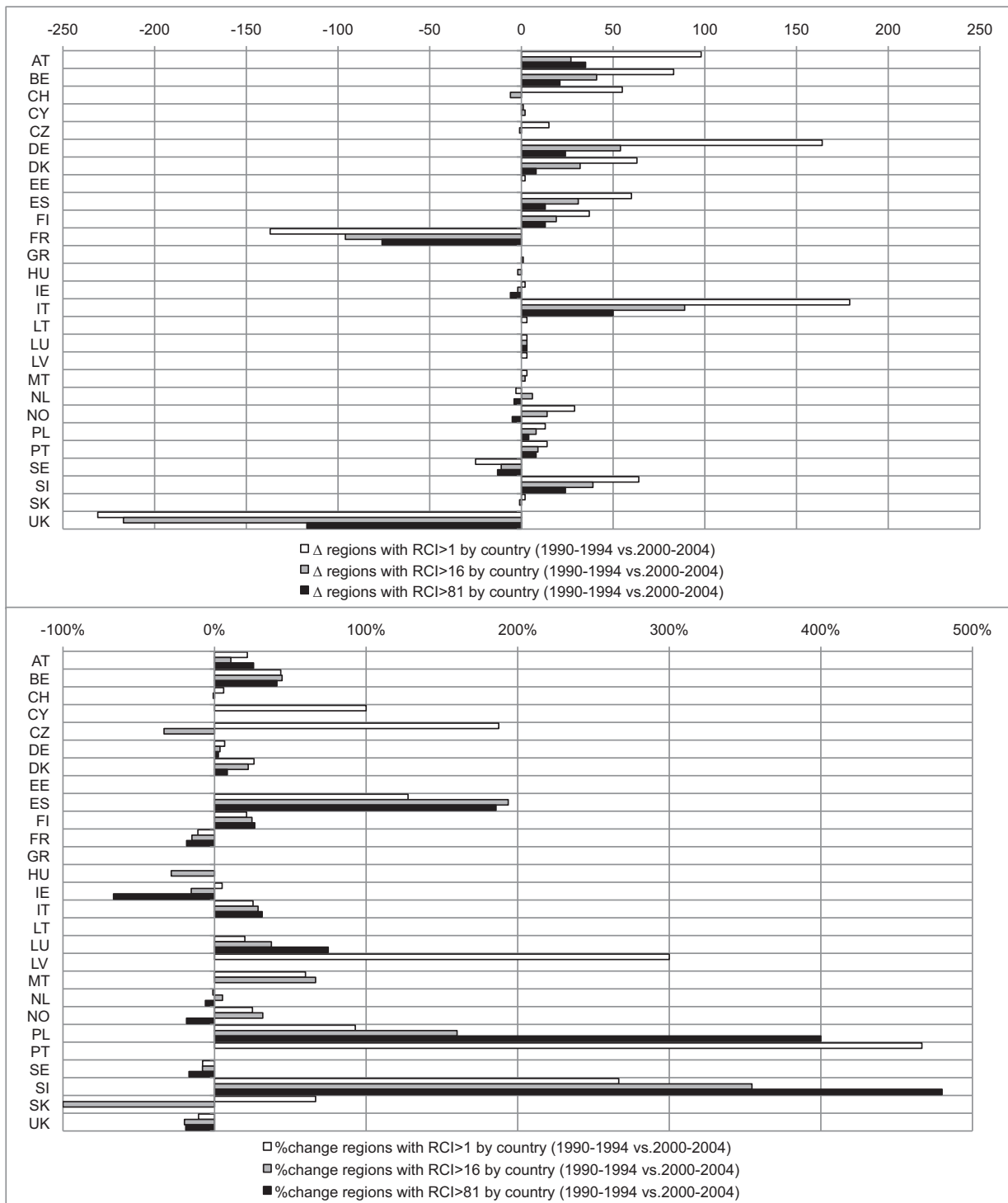


Fig. 3.33. Change of research clusters by TF and country, 2000-2004 vs. 1990-1994

Source: own calculations and illustration. Notes: number and structure 2000-2004 vs. 1990-1994; calculations based upon OECD RegPAT (2009) database extractions and application of the ISI-SPRU-OST concordance.

Table 3.6. Changing share of research clusters by TF and country with $RCI > 1$, 2000-2004 vs. 1990-1994

Technology Field	AT	BE	CH	CY	CZ	DE	DK	EE	ES	FI	FR	GR	HU	IE	IT	LT	LU	LV	MT	NL	NO	PL	PT	SE	SI	SK	UK
TF1_Food_beverages	-1%	1%	2%	0%	0%	-3%	0%	0%	3%	1%	-3%	0%	0%	0%	3%	0%	0%	0%	0%	1%	2%	0%	0%	1%	0%	0%	-6%
TF2_Tobacco_prod	0%	-1%	-1%	0%	0%	1%	2%	0%	1%	0%	0%	-1%	3%	0%	3%	0%	0%	0%	0%	0%	1%	0%	1%	2%	0%	0%	-11%
TF3_Textiles	1%	1%	3%	0%	-1%	-8%	-1%	0%	1%	1%	5%	0%	0%	0%	3%	0%	0%	0%	0%	0%	1%	0%	1%	1%	1%	0%	-8%
TF4_Wearing_apparel	0%	0%	-4%	0%	0%	1%	-2%	0%	2%	1%	2%	0%	0%	0%	0%	0%	0%	0%	0%	-2%	1%	0%	0%	-3%	0%	0%	3%
TF5_Leather_articles	-3%	1%	-1%	0%	1%	-9%	0%	0%	1%	0%	-2%	0%	-1%	1%	5%	0%	0%	0%	1%	0%	0%	1%	0%	0%	0%	0%	5%
TF6_Wood_prod	0%	0%	2%	0%	1%	-2%	-2%	0%	2%	0%	-8%	0%	0%	0%	6%	0%	0%	0%	0%	-1%	0%	0%	1%	-3%	3%	0%	0%
TF7_Paper	1%	1%	3%	0%	1%	1%	-1%	0%	-1%	1%	-4%	0%	-1%	3%	3%	0%	0%	0%	0%	0%	0%	-1%	1%	-1%	2%	0%	-5%
TF9_Petrol_prod_nucl_fuel	-1%	1%	-1%	0%	0%	-4%	-1%	0%	1%	2%	-6%	-1%	1%	-1%	1%	0%	-1%	1%	0%	1%	-1%	3%	0%	0%	0%	0%	4%
TF10_Basic_chemical	1%	1%	-2%	0%	0%	-1%	0%	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%	-3%
TF11_Pesticide_agrochem_prod	0%	-1%	0%	0%	1%	8%	0%	0%	1%	-1%	-4%	-1%	0%	0%	5%	0%	0%	0%	0%	1%	0%	0%	0%	1%	0%	0%	0%
TF12_Paints_varnishes	5%	3%	3%	0%	0%	0%	1%	0%	1%	1%	4%	1%	0%	0%	-1%	0%	1%	0%	0%	-2%	1%	0%	4%	-7%	5%	0%	-11%
TF13_Pharmaceuticals	0%	1%	1%	0%	1%	1%	1%	0%	0%	1%	1%	0%	-1%	0%	0%	0%	0%	1%	0%	0%	-1%	-1%	0%	0%	2%	1%	-6%
TF14_Soaps_detergents	1%	-2%	4%	0%	0%	0%	-1%	0%	0%	1%	-2%	0%	0%	0%	2%	0%	-1%	0%	0%	1%	0%	0%	0%	-1%	0%	0%	0%
TF15_Other_chemicals	1%	-1%	0%	0%	0%	2%	1%	0%	0%	1%	1%	0%	-1%	0%	4%	0%	0%	0%	0%	-1%	1%	0%	1%	0%	0%	0%	0%
TF16_Man_made_fibre	-1%	4%	-1%	1%	0%	-9%	0%	0%	3%	-3%	4%	0%	0%	0%	0%	0%	0%	0%	0%	1%	3%	1%	0%	0%	0%	0%	-8%
TF17_Rubber_plastic_prod	0%	1%	0%	0%	0%	-1%	0%	0%	1%	0%	-1%	0%	0%	0%	3%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-1%
TF18_Non-metal_mineral_prod	2%	0%	-2%	0%	0%	0%	2%	0%	1%	0%	-1%	0%	0%	0%	5%	0%	0%	0%	0%	0%	0%	0%	0%	-1%	2%	0%	-8%
TF19_Basic_metals	2%	1%	0%	0%	0%	0%	0%	0%	0%	0%	-1%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	-7%
TF20_Fabric_metal_prod	1%	1%	0%	0%	0%	0%	1%	0%	1%	0%	-2%	0%	0%	0%	2%	0%	0%	0%	0%	0%	1%	0%	0%	-1%	3%	0%	-5%
TF21_Energy_machinery	2%	1%	1%	0%	0%	4%	1%	0%	0%	-1%	-5%	0%	0%	0%	3%	0%	0%	0%	0%	0%	0%	0%	0%	-1%	0%	0%	-5%
TF22_Nonspec_machinery	2%	0%	0%	0%	0%	1%	1%	0%	0%	0%	-4%	0%	0%	0%	4%	0%	0%	0%	0%	0%	1%	0%	0%	0%	-2%	1%	-4%
TF23_Agricul_forestry_machinery	1%	1%	-2%	0%	0%	-2%	0%	0%	1%	1%	-6%	0%	0%	-1%	5%	0%	0%	0%	0%	-1%	1%	0%	0%	-2%	1%	0%	-4%
TF24_Machine_tools	0%	0%	0%	0%	0%	5%	0%	0%	1%	1%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	3%
TF25_Spec_purp_machinery	1%	0%	0%	0%	1%	-2%	1%	0%	0%	1%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-8%
TF26_Weapons_ammunition	3%	2%	2%	0%	2%	4%	2%	0%	-1%	0%	-6%	0%	0%	-1%	3%	0%	0%	0%	0%	-1%	-3%	1%	0%	0%	0%	0%	-8%
TF27_Domestic_appliances	0%	2%	-2%	0%	0%	-2%	0%	0%	0%	0%	-2%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%
TF28_Office_mach_computers	1%	2%	1%	0%	0%	0%	2%	0%	1%	1%	0%	0%	1%	1%	-2%	0%	0%	0%	0%	0%	-2%	0%	0%	1%	-2%	0%	-4%
TF29_Electric_motors_generators	0%	-1%	0%	0%	0%	-1%	0%	0%	-1%	0%	0%	0%	0%	0%	0%	0%	0%	-1%	0%	1%	0%	0%	0%	0%	2%	1%	-1%
TF30_Elec_distr_contr_wire_cable	2%	-1%	-2%	0%	0%	2%	1%	0%	2%	1%	-3%	0%	0%	-1%	2%	0%	0%	0%	0%	0%	0%	0%	0%	-2%	2%	0%	-6%
TF31_Accumulators_battery	-1%	0%	1%	0%	1%	6%	0%	0%	2%	0%	0%	-1%	0%	0%	-4%	0%	0%	0%	1%	0%	-1%	1%	0%	-3%	1%	0%	-1%
TF32_Lighting_equipment	1%	0%	3%	0%	0%	1%	1%	0%	-1%	2%	-6%	1%	-1%	1%	2%	0%	0%	0%	0%	-1%	0%	0%	0%	-2%	3%	0%	3%
TF33_Other_electr equip	2%	0%	-1%	0%	0%	2%	1%	0%	1%	1%	-4%	0%	0%	1%	3%	0%	0%	0%	0%	-1%	0%	0%	0%	-2%	-1%	0%	-3%
TF34_Electr components	0%	2%	2%	0%	0%	0%	0%	0%	0%	1%	-5%	0%	0%	1%	1%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	-4%
TF35_Signal_transm_telecom	2%	0%	-1%	0%	0%	0%	1%	0%	-1%	1%	-1%	0%	1%	0%	-1%	0%	0%	0%	0%	-1%	2%	0%	0%	2%	0%	0%	-4%
TF36_TV_radio_recv_audio	-2%	0%	3%	0%	0%	0%	2%	0%	0%	1%	-2%	0%	0%	0%	-3%	0%	0%	0%	0%	1%	2%	0%	0%	2%	-1%	0%	4%
TF37_Med equip	2%	1%	0%	0%	0%	2%	2%	0%	0%	0%	-4%	0%	0%	1%	0%	0%	0%	0%	0%	0%	-1%	0%	0%	0%	0%	0%	-1%
TF38_Measuring_instruments	1%	2%	0%	0%	0%	3%	0%	0%	0%	0%	-2%	0%	0%	0%	0%	0%	0%	0%	0%	-1%	0%	0%	0%	0%	0%	0%	-3%
TF39_Ind_proc_contr equip	3%	1%	2%	0%	1%	2%	2%	0%	0%	1%	-5%	0%	0%	1%	-1%	0%	0%	0%	1%	0%	-1%	1%	0%	1%	0%	0%	-7%
TF40_Opt instruments	0%	2%	-1%	0%	0%	2%	0%	0%	0%	0%	-1%	0%	0%	-1%	0%	0%	0%	0%	0%	0%	0%	-1%	0%	0%	0%	0%	-3%
TF41_Watches_clocks	-4%	-1%	2%	0%	0%	4%	5%	0%	1%	1%	1%	0%	0%	0%	-6%	0%	0%	0%	1%	1%	-1%	0%	0%	-2%	0%	0%	-2%
TF42_Motor_vehicles	3%	1%	-5%	0%	0%	6%	-1%	0%	2%	1%	2%	0%	0%	0%	0%	0%	0%	0%	1%	-1%	0%	0%	0%	-1%	0%	0%	-7%
TF43_Other_transp equip	-1%	1%	0%	0%	0%	0%	0%	0%	1%	-1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-1%	0%	0%	0%	1%	0%	-2%
TF44_Furniture_consum_good	1%	1%	-2%	0%	0%	-4%	-1%	0%	0%	-1%	-4%	0%	0%	0%	3%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	-4%
SUM_hightech	0%	1%	1%	0%	0%	2%	1%	0%	0%	0%	0%	0%	1%	0%	-3%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	3%
HT2_Computer_office_mach	1%	1%	5%	0%	2%	2%	2%	0%	1%	1%	-2%	0%	0%	0%	0%	0%	0%	0%	0%	-2%	1%	0%	0%	0%	-2%	0%	-5%
HT1_Aviation	0%	2%	2%	-1%	1%	0%	1%	0%	3%	0%	-5%	0%	1%	0%	0%	0%	1%	0%	0%	0%	1%	0%	0%	0%	0%	0%	-2%
HT3_Laser	1%	1%	-3%	0%	0%	1%	1%	0%	1%	2%	-4%	0%	0%	1%	1%	0%	0%	0%	0%	-1%	1%	0%	1%	-2%	0%	0%	1%
HT4_Semiconductors	2%	2%	2%	0%	0%	-2%	1%	0%	0%	1%	2%	0%	0%	0%	-2%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	-1%
HT5_Communication	0%	0%	-3%	0%	0%	2%	1%	0%	-1%	0%	-1%	0%	1%	1%	-1%	0%	0%	0%	0%	0%	1%	2%	0%	0%	0%	0%	-5%
HT6_Microorgan_Genetics	-1%	0%	2%	0%	-1%	9%	0%	1%	0%	0%	1%	-1%	0%	1%	-2%	0%	0%	0%	0%	0%	0%	-1%	1%	0%	0%	0%	-8%

Source: own calculations and illustration. Notes: change share (percentage points) of regions with $RCI > 1$, 2000-2004 vs. 1990-1994.

Table 3.7. Changing share of research clusters by TF and country with $RCI > 16$, 2000-2004 vs. 1990-1994

Technology Field	AT	BE	CH	CY	CZ	DE	DK	EE	ES	FI	FR	GR	HU	IE	IT	LT	LU	LV	MT	NL	NO	PL	PT	SE	SI	SK	UK	
TF1 Food beverages	-2%	2%	2%	0%	0%	3%	-1%	0%	1%	1%	-1%	0%	-1%	0%	4%	0%	0%	0%	0%	3%	1%	1%	0%	1%	0%	0%	-14%	
TF2 Tobacco prod	0%	-1%	-1%	0%	0%	3%	0%	0%	2%	0%	0%	-1%	3%	0%	5%	0%	0%	0%	0%	0%	-1%	0%	2%	0%	1%	0%	0%	-11%
TF3 Textiles	1%	2%	4%	0%	0%	-6%	-2%	0%	1%	-1%	0%	0%	0%	0%	1%	0%	-1%	0%	0%	1%	0%	-1%	0%	3%	2%	0%	-4%	
TF4 Weaving apparel	1%	-1%	-2%	0%	0%	1%	-2%	0%	3%	-1%	0%	0%	0%	0%	1%	0%	0%	0%	0%	-2%	-1%	0%	1%	-5%	0%	0%	7%	
TF5 Leather articles	-6%	1%	-4%	0%	0%	-1%	-1%	0%	2%	0%	0%	0%	0%	0%	7%	0%	0%	0%	1%	1%	3%	1%	0%	2%	0%	0%	2%	
TF6 Wood prod	0%	0%	3%	1%	0%	-5%	-1%	0%	1%	0%	-10%	0%	1%	-1%	9%	0%	-1%	0%	0%	-1%	-2%	1%	1%	-2%	4%	0%	0%	
TF7 Paper	0%	-2%	7%	0%	0%	4%	0%	0%	-1%	2%	1%	0%	0%	0%	3%	0%	0%	0%	0%	3%	-1%	1%	0%	0%	1%	0%	0%	-6%
TF9 Petrol prod nucl fuel	-3%	4%	-2%	0%	0%	-3%	0%	0%	1%	0%	-2%	0%	0%	-1%	1%	0%	0%	0%	0%	2%	3%	1%	0%	0%	0%	0%	7%	
TF10 Basic chemical	-1%	2%	-3%	0%	0%	-2%	1%	0%	0%	0%	0%	0%	0%	0%	1%	0%	1%	0%	1%	1%	5%	1%	0%	0%	0%	0%	0%	
TF11 Pesticide agrochem prod	-1%	-1%	-3%	0%	0%	8%	-1%	0%	0%	-1%	0%	0%	0%	0%	-1%	0%	1%	0%	0%	4%	0%	2%	0%	0%	0%	0%	0%	
TF12 Paints varnishes	6%	3%	2%	0%	0%	-1%	3%	1%	0%	1%	0%	1%	0%	0%	-1%	0%	1%	0%	0%	-2%	1%	0%	4%	0%	0%	0%	-5%	
TF13 Pharmaceuticals	1%	-1%	1%	0%	0%	-1%	-1%	0%	1%	0%	-4%	0%	0%	0%	-1%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	-13%	
TF14 Soaps detergents	1%	-1%	4%	0%	0%	3%	-2%	0%	0%	0%	-4%	0%	0%	0%	4%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
TF15 Other chemicals	1%	-1%	-1%	0%	0%	2%	0%	0%	0%	1%	1%	0%	0%	-1%	1%	0%	0%	0%	0%	4%	1%	0%	0%	0%	0%	0%	-7%	
TF16 Man made fibre	-3%	7%	-2%	1%	0%	-7%	1%	0%	2%	-2%	3%	0%	0%	0%	1%	0%	0%	0%	0%	2%	3%	2%	0%	0%	0%	0%	0%	
TF17 Rubber plastic prod	-3%	2%	-2%	0%	0%	-1%	1%	0%	0%	1%	1%	0%	0%	0%	5%	0%	0%	0%	0%	-1%	0%	0%	0%	-1%	0%	0%	-2%	
TF18 Non-metal mineral prod	3%	3%	-1%	0%	0%	-1%	1%	0%	1%	0%	-4%	0%	0%	0%	5%	0%	0%	0%	0%	1%	0%	0%	0%	-1%	1%	0%	0%	
TF19 Basic metals	2%	2%	-1%	0%	0%	2%	-2%	0%	2%	0%	-8%	0%	0%	0%	3%	0%	0%	0%	0%	0%	3%	0%	0%	0%	0%	0%	0%	
TF20 Fabric metal prod	0%	2%	-2%	0%	0%	0%	-3%	0%	0%	1%	-2%	0%	0%	0%	5%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	-6%	
TF21 Energy machinery	4%	0%	-4%	0%	0%	8%	1%	0%	0%	-1%	-5%	0%	-1%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
TF22 Nonspec machinery	2%	-1%	1%	0%	0%	3%	1%	0%	0%	-2%	0%	0%	0%	0%	8%	0%	0%	0%	0%	-1%	2%	0%	0%	0%	0%	0%	0%	
TF23 Agricul forestry machinery	1%	1%	-2%	0%	0%	-6%	-1%	0%	0%	0%	-3%	0%	0%	-1%	2%	0%	0%	0%	0%	-3%	2%	0%	0%	0%	0%	0%	7%	
TF24 Machine tools	1%	0%	2%	0%	0%	7%	0%	0%	1%	-1%	-3%	0%	0%	0%	1%	0%	0%	0%	0%	-1%	0%	0%	0%	0%	0%	0%	-6%	
TF25 Spec purp machinery	2%	0%	-2%	0%	0%	1%	2%	0%	0%	0%	-1%	0%	0%	0%	3%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	
TF26 Weapons ammunition	2%	1%	-1%	0%	0%	2%	9%	3%	0%	-1%	-7%	0%	0%	-1%	7%	0%	0%	0%	1%	-1%	0%	0%	0%	0%	0%	0%	-8%	
TF27 Domestic appliances	-3%	1%	-8%	0%	0%	-5%	0%	0%	4%	0%	3%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-2%	0%	0%	1%	
TF28 Office mach computers	2%	0%	3%	0%	0%	-3%	2%	0%	2%	2%	2%	0%	0%	0%	-2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%	
TF29 Electric motors generators	-1%	0%	-1%	0%	0%	4%	1%	0%	-1%	2%	0%	0%	0%	0%	-2%	0%	0%	0%	0%	-1%	0%	0%	0%	-1%	0%	0%	-7%	
TF30 Elec distr contr wire cable	2%	-3%	-2%	0%	0%	4%	3%	0%	1%	1%	1%	0%	0%	-1%	0%	0%	1%	0%	0%	1%	0%	0%	0%	0%	0%	0%	-5%	
TF31 Accumulators battery	-3%	-1%	0%	0%	0%	14%	-1%	0%	3%	0%	-2%	-1%	0%	0%	-4%	0%	0%	0%	0%	-1%	0%	0%	0%	-1%	0%	0%	-8%	
TF32 Lighting equipment	3%	0%	0%	0%	0%	6%	1%	0%	0%	2%	-4%	1%	-1%	0%	1%	0%	0%	0%	0%	-2%	0%	0%	0%	-2%	0%	0%	-11%	
TF33 Other electr equip	1%	1%	-1%	0%	0%	3%	2%	0%	0%	4%	-3%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-1%	0%	0%	0%	0%	-3%	
TF34 Electr components	2%	2%	0%	0%	0%	-3%	1%	0%	0%	0%	-1%	0%	-1%	0%	-3%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	
TF35 Signal transm telecom	0%	1%	-3%	0%	0%	-6%	4%	0%	0%	1%	0%	0%	0%	1%	4%	0%	0%	0%	0%	-1%	1%	0%	0%	4%	0%	0%	-10%	
TF36 TV radio recelv audio	-2%	0%	10%	0%	0%	-5%	4%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-1%	3%	0%	0%	0%	0%	0%	0%	
TF37 Med equipment	1%	2%	4%	0%	0%	-1%	1%	0%	0%	-1%	-3%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-4%	
TF38 Measuring instruments	-1%	0%	1%	0%	0%	7%	3%	0%	0%	1%	-4%	0%	0%	0%	2%	0%	0%	0%	0%	1%	0%	0%	0%	-1%	0%	0%	0%	
TF39 Ind proc contr equip	2%	0%	3%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	-6%	
TF40 Opti instruments	-1%	1%	-2%	0%	0%	6%	0%	0%	1%	1%	-1%	0%	0%	0%	-2%	0%	0%	0%	-1%	2%	0%	0%	0%	0%	0%	0%	-11%	
TF41 Watches clocks	-8%	0%	6%	0%	0%	9%	2%	0%	4%	0%	1%	0%	0%	0%	-7%	0%	0%	0%	2%	2%	0%	0%	0%	0%	0%	0%	-5%	
TF42 Motor vehicles	1%	1%	-7%	0%	0%	0%	-1%	0%	0%	-1%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%	
TF43 Other transp equip	1%	1%	3%	0%	0%	-2%	0%	0%	1%	0%	-1%	0%	0%	0%	3%	0%	0%	0%	0%	2%	-3%	0%	0%	0%	2%	0%	-5%	
TF44 Furniture_consum_good	5%	1%	-5%	0%	0%	-3%	-1%	0%	1%	-2%	-5%	0%	0%	0%	9%	0%	0%	0%	0%	2%	0%	0%	0%	0%	1%	0%	-4%	
SUM_hightech	1%	1%	2%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	1%	-2%	0%	0%	0%	0%	-1%	1%	0%	0%	0%	0%	0%	-2%	
HT2 Computer_office_mach	1%	1%	8%	0%	0%	1%	2%	0%	2%	2%	-1%	0%	0%	0%	-2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
HT1 Aviation	0%	2%	-1%	0%	0%	5%	0%	0%	4%	0%	-2%	0%	0%	0%	-3%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-4%	
HT3 Laser	2%	0%	-3%	0%	0%	4%	3%	0%	1%	1%	-6%	0%	0%	1%	-4%	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	
HT4 Semiconductors	2%	2%	3%	0%	0%	-1%	0%	0%	0%	0%	-3%	0%	0%	0%	-4%	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%	-4%	
HT5 Communication	0%	0%	-3%	0%	0%	-4%	6%	0%	0%	2%	2%	0%	0%	0%	2%	0%	0%	0%	0%	-3%	1%	0%	0%	4%	0%	0%	0%	
HT6 Microorgan_Genetics	1%	1%	2%	0%	0%	7%	1%	0%	0%	0%	0%	0%	-1%	0%	1%	0%	0%	0%	0%	0%	0%	-1%	0%	0%	0%	0%	-8%	

Source: own calculations and illustration. Notes: change share (percentage points) of regions with $RCI > 16$, 2000-2004 vs. 1990-1994.

Table 3.8. Changing share of research clusters by TF and country with $RCI > 81$, 2000-2004 vs. 1990-1994

Technology Field	AT	BE	CH	CY	CZ	DE	DK	EE	ES	FI	FR	GR	HU	IE	IT	LT	LU	LV	MT	NL	NO	PL	PT	SE	SI	SK	UK
TF1 Food beverages	0%	3%	2%	0%	0%	10%	2%	0%	0%	0%	0%	0%	0%	0%	3%	0%	0%	0%	0%	4%	-2%	0%	0%	1%	0%	0%	-15%
TF2 Tobacco prod	0%	-1%	-2%	0%	0%	3%	-1%	0%	0%	0%	0%	0%	4%	-1%	2%	0%	0%	0%	0%	-3%	0%	2%	0%	0%	1%	0%	-5%
TF3 Textiles	3%	2%	7%	0%	1%	-2%	0%	1%	-2%	0%	0%	0%	0%	0%	-1%	0%	-2%	0%	0%	0%	0%	0%	1%	3%	0%	-11%	
TF4 Wearing apparel	-1%	0%	1%	0%	0%	0%	-4%	0%	1%	-1%	2%	0%	0%	-1%	-1%	0%	0%	0%	0%	-2%	-1%	0%	0%	-4%	0%	10%	
TF5 Leather articles	-8%	0%	-10%	0%	0%	0%	3%	0%	1%	0%	-8%	0%	0%	0%	14%	0%	0%	0%	1%	0%	1%	0%	0%	1%	0%	3%	
TF6 Wood prod	6%	0%	4%	0%	0%	-10%	0%	2%	0%	0%	-8%	0%	0%	-1%	11%	0%	-1%	0%	0%	-1%	-2%	1%	2%	-7%	5%	0%	
TF7 Paper	6%	-2%	17%	0%	0%	0%	-5%	0%	0%	-1%	-3%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	-3%	0%	0%	
TF9 Petrol prod_nucl fuel	-3%	3%	-2%	0%	0%	-5%	3%	0%	2%	2%	-1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
TF10 Basic chemical	4%	1%	-1%	0%	0%	-3%	-1%	0%	0%	0%	-1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	12%	
TF11 Pesticide agrochem prod	0%	0%	-5%	0%	0%	11%	-1%	0%	0%	-2%	-3%	0%	0%	0%	-2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
TF12 Paints varnishes	7%	3%	1%	0%	0%	1%	0%	0%	0%	0%	-5%	1%	0%	0%	-1%	0%	1%	0%	0%	2%	1%	0%	5%	0%	0%	-15%	
TF13 Pharmaceuticals	0%	1%	-1%	0%	0%	3%	1%	0%	0%	0%	-7%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	
TF14 Soaps detergents	0%	-1%	2%	0%	0%	5%	0%	0%	2%	0%	-7%	0%	0%	0%	4%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
TF15 Other chemicals	2%	-2%	7%	0%	0%	-5%	0%	0%	0%	0%	5%	0%	0%	0%	-3%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	
TF16 Man made fibre	-1%	7%	3%	0%	0%	-12%	0%	0%	1%	1%	2%	0%	0%	0%	9%	0%	1%	0%	0%	0%	1%	3%	0%	0%	0%	0%	
TF17 Rubber plastic prod	-3%	0%	-5%	0%	0%	-5%	0%	0%	0%	0%	-3%	0%	0%	0%	4%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
TF18 Non-metal mineral prod	5%	6%	-7%	0%	0%	-2%	-1%	0%	0%	0%	-11%	0%	0%	0%	4%	0%	1%	0%	0%	1%	0%	0%	0%	1%	0%	0%	
TF19 Basic metals	5%	0%	0%	0%	0%	5%	0%	0%	3%	0%	-4%	0%	0%	0%	4%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
TF20 Fabric metal prod	-1%	0%	-6%	0%	0%	6%	0%	0%	0%	0%	-4%	0%	0%	0%	4%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-5%	
TF21 Energy machinery	3%	0%	-9%	0%	0%	6%	0%	0%	0%	0%	-3%	0%	0%	0%	3%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
TF22 Nonspec machinery	-3%	0%	-4%	0%	0%	5%	2%	0%	0%	-2%	-1%	0%	0%	0%	7%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%	-1%	
TF23 Agricul forestry_machinery	-2%	-1%	-1%	0%	0%	-4%	-6%	0%	2%	0%	4%	0%	0%	-2%	4%	0%	0%	0%	0%	-4%	0%	0%	0%	0%	0%	7%	
TF24 Machine tools	4%	0%	3%	0%	0%	1%	0%	0%	1%	-1%	-3%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
TF25 Spec_purp_machinery	6%	0%	-6%	0%	0%	1%	-2%	0%	0%	0%	0%	0%	0%	0%	5%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-5%	
TF26 Weapons ammunition	0%	0%	3%	0%	1%	9%	1%	0%	0%	1%	-10%	0%	0%	-1%	1%	0%	0%	0%	0%	0%	1%	0%	0%	0%	0%	-3%	
TF27 Domestic appliances	0%	2%	-16%	0%	0%	-1%	0%	0%	2%	0%	-1%	0%	0%	0%	6%	0%	0%	0%	0%	-2%	0%	0%	0%	0%	0%	-8%	
TF28 Office mach computers	2%	0%	7%	0%	0%	-4%	2%	0%	4%	2%	2%	0%	0%	0%	-3%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	7%	
TF29 Electric motors_generators	-2%	0%	-4%	0%	0%	0%	3%	0%	0%	3%	1%	0%	0%	0%	2%	0%	0%	0%	0%	-1%	0%	0%	0%	2%	-2%	0%	
TF30 Elec distr contr_wire cable	4%	-1%	-2%	0%	0%	0%	0%	0%	1%	1%	0%	0%	0%	-1%	4%	0%	0%	0%	-3%	0%	0%	0%	0%	0%	0%	-5%	
TF31 Accumulators_battery	-3%	-1%	4%	0%	0%	10%	2%	0%	1%	0%	-1%	0%	0%	0%	-5%	0%	0%	0%	0%	-1%	0%	0%	0%	0%	0%	-6%	
TF32 Lighting equipment	6%	-1%	0%	0%	0%	8%	-1%	0%	-1%	0%	-6%	0%	-3%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%	-1%	0%	-12%	
TF33 Other electr equip	1%	0%	3%	0%	0%	-1%	0%	0%	0%	4%	-2%	0%	0%	0%	2%	0%	0%	0%	0%	-1%	0%	0%	0%	-4%	0%	-1%	
TF34 Electr components	5%	4%	5%	0%	0%	-4%	0%	0%	0%	0%	0%	0%	0%	0%	5%	0%	0%	0%	0%	-1%	0%	0%	0%	0%	0%	0%	
TF35 Signal transm telecom	2%	0%	-3%	0%	0%	-3%	5%	0%	0%	3%	-1%	0%	0%	0%	-4%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-2%	
TF36 TV radio_recv audio	0%	0%	11%	0%	0%	-7%	3%	0%	0%	3%	1%	0%	0%	0%	-2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-12%	
TF37 Med equipment	1%	1%	14%	0%	0%	-4%	0%	0%	-1%	0%	-2%	0%	0%	1%	0%	0%	0%	0%	0%	-3%	1%	0%	0%	0%	0%	0%	
TF38 Measuring instruments	0%	-1%	7%	0%	0%	-1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
TF39 Ind proc contr equip	-2%	0%	-2%	0%	0%	16%	2%	0%	0%	-2%	-5%	0%	0%	0%	2%	0%	0%	0%	0%	-3%	0%	0%	0%	0%	0%	-3%	
TF40 Opti instruments	0%	2%	0%	0%	0%	-1%	-1%	0%	0%	0%	-1%	0%	0%	0%	2%	0%	0%	0%	-2%	2%	0%	0%	0%	0%	0%	-2%	
TF41 Watches clocks	-8%	-2%	16%	0%	0%	-3%	0%	0%	0%	3%	-2%	0%	0%	0%	-5%	0%	0%	0%	3%	0%	0%	0%	0%	0%	0%	1%	
TF42 Motor vehicles	0%	0%	-8%	0%	0%	15%	0%	0%	0%	0%	-5%	0%	0%	0%	-2%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
TF43 Other transp equip	-1%	0%	2%	0%	0%	3%	-1%	0%	2%	2%	-3%	0%	0%	0%	3%	0%	0%	0%	0%	2%	-7%	0%	0%	0%	0%	-5%	
TF44 Furniture_consum_good	4%	2%	-12%	0%	0%	-3%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
SUM_hightech	0%	-2%	3%	0%	0%	1%	0%	0%	0%	2%	1%	0%	0%	0%	-2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	5%	
HT2 Computer_office_mach	4%	0%	5%	0%	0%	1%	4%	0%	4%	2%	2%	0%	0%	-2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
HT1 Aviation	0%	2%	1%	0%	0%	11%	2%	0%	3%	0%	-3%	0%	0%	0%	-2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-10%	
HT3 Laser	2%	0%	-9%	0%	0%	7%	4%	0%	0%	0%	-4%	0%	0%	1%	0%	0%	0%	0%	0%	0%	-2%	0%	0%	0%	0%	0%	
HT4 Semiconductors	8%	4%	4%	0%	0%	-9%	0%	0%	0%	0%	0%	0%	0%	0%	-2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-2%	
HT5 Communication	0%	0%	-3%	0%	0%	0%	6%	0%	0%	1%	-2%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	
HT6 Microorgan_Genetics	-1%	2%	2%	0%	0%	12%	0%	0%	0%	-1%	-3%	0%	0%	0%	-1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	-9%	

Source: own calculations and illustration. Notes: change share (percentage points) of regions with $RCI > 81$, 2000-2004 vs. 1990-1994.

It can be concluded from the results illustrated in table 3.6 (and table B.8, appendix) and figure 3.34 that the EU-15 group of regions (and countries) shows differing structural dynamics compared to the NMS group. Figure 3.34 shows the changes in the absolute numbers of research cluster regions by technology field from 1990-1994 to 2000-2004 for three country groups; the EU-15, the NMS and Switzerland and Norway. The EU-15 countries experienced a significant increase in the absolute number of cluster regions. However, at the same time, the group was characterized by relative losses (i.e., decreasing shares) (see tables 3.6 - 3.8 and figure A.30, appendix). It can be concluded that the largest absolute gains and losses have happened within the EU-15 group. In comparison, the NMS group has increased the absolute number of research clusters in almost every technology field between the 1990s and the 2000s, even in high-technology (i.e., *HT1 Aviation*, *HT5 Communication*, *HT6 Microorg. genetics*). Regarding $RCI > 16$ and $RCI > 81$, the calculations show stronger relative losses in the UK and France. Finally, figure A.30 (appendix) highlights the change of research clustering by technology fields (percentage points). The figure especially differentiates between RCI classes, i.e., $1 < RCI \leq 16$, $16 < RCI \leq 81$ and $RCI > 81$. It can be argued from the previous graphs and tables that the NMS show gains in research clusters across a large fraction of technology fields (and RCI classes), even in high-technology, although absolute growth (numbers) is remarkably smaller compared to EU-15 countries, Switzerland and Norway.

To conclude, the presented “global” European cluster study also indicates noticeable issues and shortcomings: (i) the calculations and presented results are highly dependent on the applied spatial classification system; (ii) the calculations completely ignore region-specific aspects (e.g., institutional differences, culture, policy, firm entry and exit - as this was not the scope of the study); (iii) employment data have not been incorporated into the cluster analysis due to insuperable data constraints; (iv) cluster boundaries are represented by administrative boundaries. Despite these issues and shortcomings, the study is unique because it allows a structural perspective on innovation/ research clustering across 819 European regions. Moreover, all (existing) “top-down” studies suffer from these limitations and shortcomings, especially when they have to address several countries and technology fields.

3.5.4.2. Local Statistics: Innovative Places and Leading Regions

Besides the presentation and discussion of global clustering statistics (previous section), the RCI additionally offers the possibility to identify leading individual regions. However, a comprehensive presentation and discussion of local clustering statistics for all 819 European regions is beyond the scope of this study as the research questions are solely related to global distributional characteristics and clustering dynamics. Accordingly, it is beyond the purpose of this study to highlight and discuss all TOP10 or TOP20 regions for each of the 51 technology field aggregates in Europe.³⁷⁷ Therefore, the subsequent identification and

³⁷⁷ A presentation and discussion of 1000+ regions is clearly beyond the scope of this thesis. A complete ranking of all 819 regions for each of the 50 technology field aggregates, which includes sorted RCI values for 1990-1994 and 2000-2004, is available upon request.

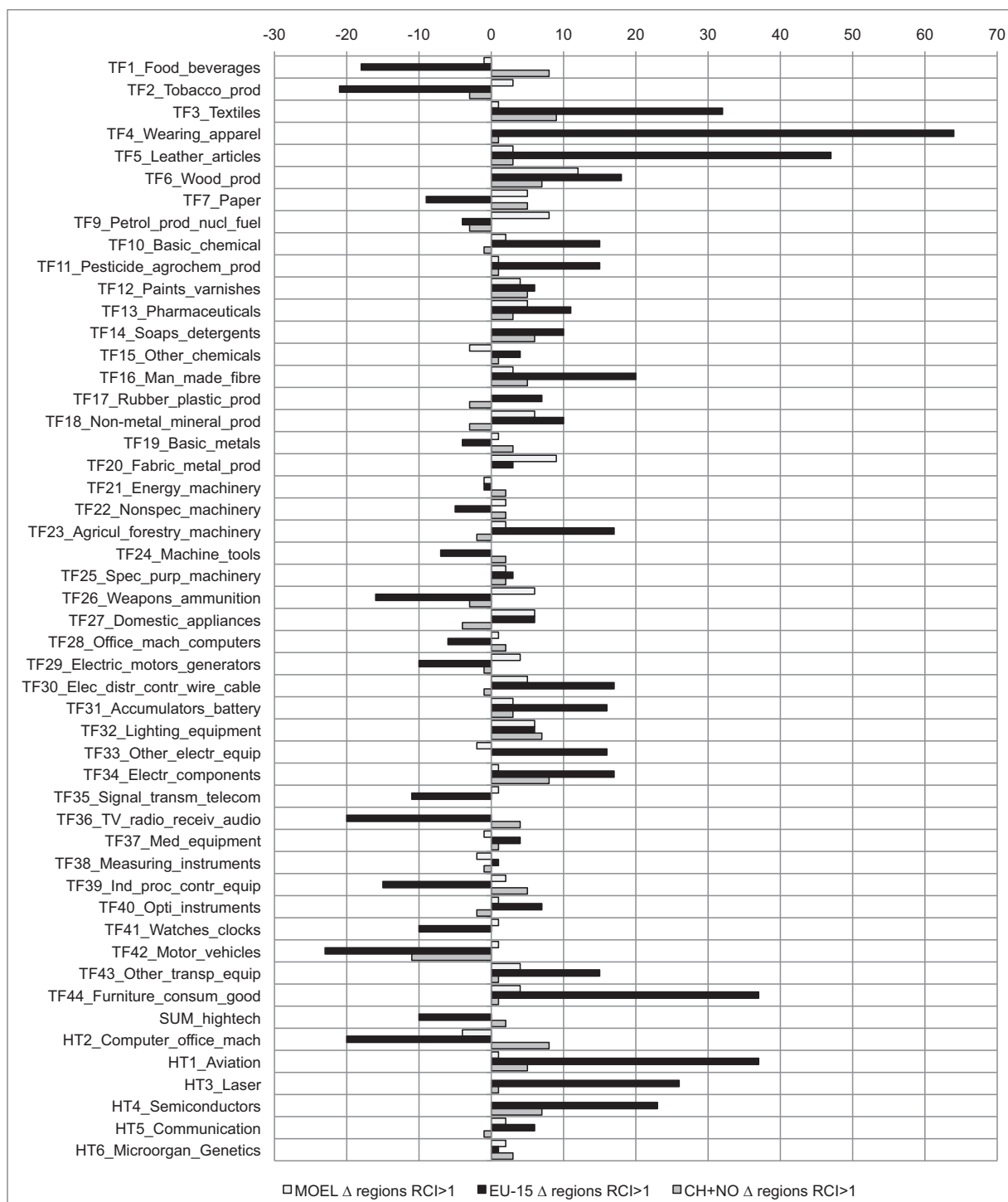


Fig. 3.34. Change of research clusters ($RCI > 1$) by TF and country, 2000-2004 vs. 1990-1994
 Source: own calculations and illustration. Notes: change of number of research clusters by technology field, 2000-2004 vs. 1990-1994; regions by RCI; calculations based upon OECD RegPAT (2009) database extractions and application of the ISI-SPRU-OST concordance.

presentation of research clusters is limited to a few selected technology fields, although the following tables contain the TOP20 European regions (of all 819 TL3 regions).³⁷⁸

Ranking the 819 European regions according to their RCI values generates a list of leading research cluster regions within the ERA as provided in the following five tables. For a detailed descriptive overview, the subsequent tables 3.9, 3.10, 3.11, 3.12 and 3.13 summarize the leading 20 European regions (TOP20) for the period 2000-2004, sorted by RCI_{ij} . It is obvious that the ranked TOP20 European regions are mainly urban areas and metropolitan and capital regions (see also table 3.14).

With respect to more classical industries and technology fields, a significant and strong research clustering of the paper industry and the related technology field (*TF7 Paper*) can be identified in, e.g., Nidwalden (CH005) in Switzerland. Similarly, Fribourg (CH022) shows a high RCI in paper technology (see table 3.9).

Another classical technology field is *TF5 Leather articles* (see table 3.9). Clusters can be identified in several Italian regions, e.g., Treviso (ITD34), Macerata (ITE33), Ascoli Piceno (ITE34), Padova (ITD36), Venezia (ITD35), Prato (ITE15), Verona (ITD31) and Lecco (ITC43). Accordingly, there is a clear dominance by Italian regions with respect to the computed RCI values in *TF5 Leather articles*.

The technology field *TF10 Basic chemicals* (see table 3.9) is highly dominated by German regions, e.g., Rheinpfalz (DE66), Unterer Neckar (DE68), Starkenburg (DE52), Köln (DE44), Rhein-Main (DE51), Bayerischer Untermain (DE80), Rheinhessen-Nahe (DE64), Hochrhein-Bodensee (DE78) and Südostoberbayern (DE97). Besides the German regions, strong research clustering is observed in Graubünden, Switzerland (CH056), and the Belgian region Brabant Wallon (BE31) and its capital region Brussels (BE10). Additionally, the French region Rhone (FR716) and the capital region Paris (FR101) show high RCI values. Finally basic chemicals research is present in the region of Copenhagen (DK001), in the Finish region Ita-Uusimaa (FI162) and the UK region Southampton (UKJ32). According to table 3.9, the majority of the TOP20 regions are located in Germany.

The technology field *TF41 Watches & clocks* (see table 3.12) shows a clear dominance of Swiss regions what people generally expect. In the 2000s, 14 regions of the leading TOP20 regions are located in Switzerland; e.g., Neuchatel (CH024), Valais (CH012), Basel-Landschaft (CH032), Solothurn (CH023), Basel-Stadt (CH031), Bern (CH021), Geneve (CH013). Besides Swiss regions, France shows a very high RCI for the region Doubs (FR431), i.e., in the city of Besancon, where a large fraction of French watch makers is located. Moreover, the Jura region (FR432) and Haute-Savoie (FR718) show high values.

Concerning the technology field *TF42 Motor vehicles* (see table 3.13), a clear majority of the TOP20 regions is located in Germany. Leading regions are, e.g., Stuttgart (DE72), Bayerischer Untermain (DE80), Nordschwarzwald (DE71), Ingolstadt (DE89), Regensburg (DE90), Mittlerer Oberrhein (DE70), Munich (DE93), Braunschweig (DE22), Ost-Württemberg (DE73), Franken (DE69), Neckar-Alb (DE75). It is obvious that most of the listed regions are located in Southern Germany, especially in Baden-Württemberg and Bavaria.

³⁷⁸ For a complete overview and list of abbreviations of all 51 technology field aggregates used in the following graphs and tables see table B.4 (appendix).

Other leading European regions are the French regions Haute-de-Seine (FR105), Yvelines (FR103), the capital region Paris (FR101), Deux-Sevres (FR533) and Val-de-Marne (FR107). Italy is also included in the TOP20 with the region of Torino (ITC11).

A well known example of high-tech research clustering is the Cambridge cluster in the region Cambridgeshire CC (UKH12) in the United Kingdom, 85 kilometers away from London. Cambridgeshire CC shows a strong research clustering in *HT2 Computer & office machines*, *HT3 Laser technology*, *HT4 Semiconductors*, *HT5 Communication technology* and *HT6 Microorgan. & genetics*. Thus, Cambridge is one of the leading research locations within the ERA followed by regions such as Swindon (UKK14) and Bristol (UKK11) (see table 3.13).

The high-technology field aggregate *SUM hightech* (see table 3.13) shows that especially capital and metropolitan regions are among the leading units within the European research landscape, e.g., Paris (FR101), Noord-Brabant (NL41) in the Netherlands, Uusima (FI181) and Pirkanmaa (FI192) in Finland, Frederiksborg (DK003), Copenhagen (DK002), and Copenhagen og Frederiksberg (DK001) in Denmark, and the German regions Munich (DE93), Mittelfranken (DE86) and Aachen (DE45).

In the technology field *HT1 Aviation* (see table 3.13), multinational companies and highly localized regional industries are present; e.g., Airbus, European Aeronautic Defense and Space Company in Hamburg and Munich (Germany), in Ile-de-France, Haute Garonne, Procence-Cote-d'Azur and Midi-Pyrénées (France).³⁷⁹ Accordingly, patenting activity in aviation is highly visible in the French region Haute-Garonne (FR623) around Toulouse, in Val-de-Marne (FR107) and Haute-de-Seine (FR105) around Paris. The German regions Hamburg (DE06), Hamburg-Umland (DE14), Bremen (DE11), Bremen-Umland (DE15) and Bodensee-Oberschwaben (DE79) show strong RCI values. The ranking of the TOP20 regions additionally contains several regions of the UK, e.g., the city of Bristol (UKK11) and the neighboring region of North and North East Somerset and South Gloucestershire (UKK12), Coventry (UKG33), Somerset (UKK23), Blackpool (UKD42) and Buckinghamshire CC (UKJ13) (see also Scherngell, 2007).

The TOP20 regions in the technology field *HT3 Laser* (see table 3.13) are dominated by 8 UK regions. Moreover, French clusters are located in the Greater Paris region and the neighboring spatial areas, i.e., Essonne (FR104), Haute-de-Seine (FR105), Val-de-Marne (FR107), and the capital region Paris (FR101). Berlin (DE30), Regensburg (DE90), Schwarzwald-Baar-Heuberg (DE76), Ostthüringen (DE56) and Dortmund (DE39) are the leading German regions in laser technology that hold a position in the TOP20 ranking.

Finally, strong cluster in *HT5 Communication* (see table 3.13) are mainly present in capital regions and metropolitan areas, e.g., Paris (FR105), Munich (DE93), Stockholm (SE010), Inner London (UKI11), Copenhagen (DK002) and Stuttgart (DE72).

To sum up, the reported rankings of the RCI values seem to correspond to reported results of existing qualitative case studies and quantitative cluster studies for selected technology fields and/or countries (see also Litzenberger and Sternberg, 2006; Fornahl and Brenner,

³⁷⁹ See also Scherngell (2007) and Fischer *et al.* (2009) for empirical results related to the geographic concentration of EPO patent citations in the technology field aviation.

2009). The TOP20 rankings in the tables especially highlight a clear dominance of European research activity by German, French, Swiss and UK regions.³⁸⁰ The conducted RCI analysis is regarded to complement existing studies as it allows to identify and compare patenting activity at a very disaggregated level.³⁸¹ Finally, for a comprehensive and complete overview of all 51 technology-specific research clusters across the 819 European regions refer to tables 3.9, 3.10, 3.11, 3.12 and 3.13.³⁸²

³⁸⁰ RCI ranking are computed for the period 1990-1994; the ranking shows a very similar structure to the one presented above. The results are available upon request.

³⁸¹ Regional variation is by definition completely lost in national studies and cross-country studies.

³⁸² Further details are available from the author upon request.

Table 3.9. Ranking of RCI: TOP20 cluster regions by technology field

TF1_Food_beverages	TF2_Tobacco_prod	TF3_Textiles	TF4_Wearing_apparel	TF5_Leather_articles
UK_UKH22	UK_UKJ32	CH_CH066	IT_ITD34	IT_ITD34
DK_DK001	DE_DE6	UK_UKD54	CH_CH053	FR_FR718
DK_DK003	DE_DE5	IT_ITE15	FR_FR718	IT_ITE33
DK_DK002	UK_UKF11	DE_DE66	IT_ITE15	AT_AT331
AT_AT321	CH_CH066	CH_CH056	UK_UKF16	UK_UKG35
UK_UKE21	DE_DE21	DE_DE88	DE_DE87	IT_ITE34
CH_CH022	IT_ITD55	DE_DE84	IT_ITF13	IT_ITE36
CH_CH011	DE_DE84	DE_DE42	CH_CH062	ES_ES230
NL_NL33	UK_UKD52	IT_ITC13	UK_UKC13	LA_LaRoja
NL_NL31	DE_DE15	FR_FR717	UK_UKE41	DE_DE65
IT_ITD52	DE_DE14	FR_FR101	UK_UMK23	DE_DE86
NL_NL221	CH_CH021	DE_DE46	UK_UMG21	IT_ITD35
DK_DK00D	IT_ITD34	DE_DE78	FR_FR263	IT_ITE15
DK_DK00B	FR_FR815	FR_FR422	AT_AT321	IT_ITD32
DE_DE66	AT_AT312	UK_UKD31	FR_FR101	IT_ITD31
DK_DK004	CH_CH022	IT_ITE22	DK_DK003	UK_UKJ21
CH_CH024	HU_HU312	CH_CH052	AT_AT312	FR_FR714
BE_BE23	UK_UKC21	CH_CH061	DE_DE75	FR_FR624
CH_CH057	AT_AT315	CH_CH062	IT_ITC47	FR_FR624
DE_DE24	UK_UKN02	FR_FR105	IT_ITC42	AT_AT335
TF6_Wood_prod	TF7_Paper	TF9_Petrol_prod_nucl_fuel	TF10_Basic_chemical	TF11_Pesticide_agrochem_prod
DE_DE94	CH_CH065	FR_FR105	DE_DE86	CH_CH056
IT_ITD59	DE_DE73	UK_UKJ11	Rheinpfalz	DE_DE66
AT_AT342	CH_CH022	FL_F182	Graubünden	DE_DE44
UK_UK621	SE_SE061	FR_FR716	Unterer Neckar	UK_UKJ11
UK_UKJ21	BE_BE21	UK_UKJ14	Starkenbug	DE_DE42
PT_PT163	CH_CH023	NL_NL32	Köln	CH_CH013
ES_ES212	CH_CH057	UK_UKD22	Rhein-Main	FR_FR716
CH_CH051	CH_CH013	UK_UKJ23	PROV. BRABANT WALLON	DE_DE51
CH_CH066	UK_UK123	NO_NO011	Düsseldorf	DE_DE68
AT_AT112	AT_AT123	DK_DK003	Emscher-Lippe	DE_DE70
DE_DE71	DE_DE96	NO_NO061	Rhône	UK_UKE11
DE_DE92	CH_CH011	UK_UKF13	RÉGION DE BRUXELLES-CAPITALE	DE_DE65
DE_DE36	FI_F181	FR_FR232	Paris	UK_UKJ32
AT_AT335	CH_CH066	IT_ITA05	Paris	DE_DE64
CH_CH057	CH_CH061	FR_FR101	København og Frederiksberg	DE_DE78
SE_SE071	DE_DE66	UK_UKJ21	kommuner	DE_DE46
CH_CH040	FI_F186	DE_DE66	Bayerischer Untermain	DE_DE6
DE_DE96	FI_F187	DE_DE77	LIMBURG (NL)	DE_DE71
SI_S1002	OBerland	UK_UKJ22	Rheinessen-Nahe	UK_UKL22
CH_CH065	Thurgau	UK_UKM25	Hochrhein-Bodensee	DE_DE53
	Nidwalden	UK_UKJ13	Südostoberbayern	
		UK_UKJ13	Southampton	
		UK_UKJ13	Southampton	

Source: own calculations and illustration. Notes: TL3 regions are ranked according to computed RCI-values in descending order; the table reports the European TOP20 regions for the period 2000-2004; additional information on RCI are available upon request from the author; calculations based upon OECD RegPAT (2009) database extractions and application of the ISI-SPRU-OST concordance.

Table 3.10. Ranking of RCI: TOP20 cluster regions by technology field (cont'd)

TF12_Paints_varnishes		TF13_Pharmaceuticals		TF14_Soaps_detergents		TF15_Other_chemicals		TF16_Man_made_fibre				
SI	SI00A	Notranjsko-kraska	Köbenhavn og Frederiksberg	UK	UKD54	Wirral	DE	DE6	Hamburg	AT	AT315	Traunviertel
PT	PT116	Entre Douro e Vouga	Graubünden	UK	UKF11	Kingston upon Hull, City of	DE	DE66	Rheinpfalz	BE	BE31	PROV. BRABANT WALLON
DE	DE66	Rheinpfalz	Köbenhavns amt	UK	UKC22	Tyneside	FR	FR241	Cher	DE	DE56	Ostthüringen
PT	PT115	Tamega	Paris	DE	DE42	Düsseldorf	UK	UKJ14	Oxfordshire	UK	UKC12	South Teesside
SI	SI00B	Goriska	Inner London - West	BE	BE10	CAPITALE	CH	CH062	Uri	PL	PL113	Miasto Lodz
SI	SI00D	Jugovzhodna Slovenija	Hauts-de-Seine	DE	DE66	Rheinpfalz	DE	DE20	Südheide	UK	UKF11	Derby
DE	DE4	Schleswig-Holstein Ost	Frederiksberg amt	NL	NL33	ZUID-HOLLAND	DE	DE42	Düsseldorf	IT	ITD56	Ferrara
BE	BE31	PROV. BRABANT WALLON	Hertfordshire	DK	DK001	Köbenhavn og Frederiksberg kommuner	BE	BE31	PROV. BRABANT WALLON	NL	NL42	LIMBURG (NL)
SI	SI00E	Osrednjeslovenska	Wirral	IT	ITD35	Venezia	UK	UKI23	Outer London - West and North West	UK	UKE42	Leeds
SI	SI009	Gorenjska	Val-de-Marne	BE	BE33	PROV. LIÈGE	DE	DE24	Göttingen	IT	ITC13	Biella
CH	CH013	Genève	Cambridgeshire CC	DK	DK002	Köbenhavns amt	CH	CH066	Zug	DE	DE80	Bayerischer Untermain
AT	AT323	Salzburg und Umgebung	Cheshire CC	UK	UKC21	Northumberland	SE	SE024	Örebro län	DE	DE88	Augsburg
DK	DK008	Fyns amt	Starkenburg	BE	BE24	PROV. VLAAMS-BRABANT	CH	CH040	Zürich	FR	FR716	Rhône
AT	AT313	Mühlviertel	Nottingham	DK	DK003	Frederiksberg amt	CH	CH025	Jura	CH	CH063	Schwyz
DE	DE28	Lausitz-Spreewald	Oxfordshire	IT	ITC49	Lodi	BE	BE21	PROV. ANTWERPEN	UK	UKK13	Gloucestershire
DE	DE5	Schleswig-Holstein Süd	Hochrhein-Bodensee	CH	CH031	Basel-Stadt	DE	DE97	Südostoberbayern	DE	DE66	Rheinpfalz
DK	DK001	Köbenhavn og Frederiksberg kommuner	Unterer Neckar	UK	UKC11	Hartlepool and Stockton-on-Tees	IT	ITC32	Savona	IT	ITE22	Terni
BE	BE21	PROV. ANTWERPEN	Rheinpfalz	DE	DE68	Unterer Neckar	UK	UKE11	Kingston upon Hull, City of	NO	NO043	Rogaland
DE	DE7	Westmecklenburg	Donau-Ilser (BW)	CH	CH056	Graubünden	DE	DE5	Schleswig-Holstein Süd	CH	CH056	Graubünden
AT	AT312	Linz-Wels	Oberland	BE	BE31	PROV. BRABANT WALLON	UK	UKL21	Monmouthshire and Newport	BE	BE22	PROV. LIMBURG (B)
TF17_Rubber_plastic_prod	TF18_Non-metal_mineral_prod	TF19_Basic_metals	TF19_Basic_metals	TF19_Basic_metals	TF19_Basic_metals	TF19_Basic_metals	TF19_Basic_metals	TF19_Basic_metals	TF19_Basic_metals	TF19_Basic_metals	TF19_Basic_metals	TF19_Basic_metals
FR	FR724	Puy-de-Dôme	Rheinhessen-Nahe	AT	AT331	Außerfern	AT	AT342	Rheinthal-Bodenseegebiet	UK	UKF11	Derby
CH	CH031	Basel-Stadt	Zug	AT	AT341	Bludenz-Bregenzener Wald	DE	DE72	Stuttgart	DE	DE82	Main-Rhön
CH	CH065	Nidwalden	Außerfern	CH	CH057	Thurgau	DE	DE42	Düsseldorf	CH	CH057	Thurgau
CH	CH022	Freiburg	Thurgau	AT	AT223	Östliche Obersteiermark	SI	SI00A	Notranjsko-kraska	DE	DE79	Bodensee-Oberschwaben
CH	CH066	Zug	Bludenz-Bregenzener Wald	AT	AT312	Linz-Wels	DE	DE71	Nordschwarzwald	DE	DE70	Mittlerer Oberrhein
LU	LU000	Luxembourg (Grand-Duché)	Nidwalden	DE	DE41	Duisburg/Essen	CH	CH022	Freiburg	DE	DE72	Stuttgart
CH	CH064	Obwalden	Emscher-Lippe	SE	SE025	Västmanlands län	AT	AT331	Außerfern	DE	DE73	Ostwürttemberg
CH	CH025	Jura	Glarus	CH	CH054	Appenzell Innerrhoden	UK	UKG32	Solihull	DE	DE81	Würtzburg
FR	FR231	Eure	Freiburg	IT	ITD43	Gonzia	DE	DE47	Siegen	DE	DE86	Industrieregion Mittelfranken
FR	FR101	Paris	Southampton	DE	DE42	Düsseldorf	CH	CH057	Thurgau	FR	FR102	Seine-et-Marne
IT	ITC41	Varese	Rhein-Main	DE	DE47	Siegen	DE	DE43	Bochum/Hagen	DE	DE93	München
FR	FR105	Hauts-de-Seine	Basel-Stadt	FI	FI191	Satakunta	CH	CH055	St. Gallen	DE	DE69	Franken
CH	CH057	Thurgau	Starkenburg	CH	CH053	Appenzell Ausserrhoden	DE	DE36	Bielefeld	DE	DE43	Bochum/Hagen
FR	FR243	Indre	Modena	FI	FI1A1	Keski-Pohjanmaa	CH	CH066	Zug	DE	DE89	Appenzell Aarg. A. O.
UK	UKF11	Kingston upon Hull, City of	Vauchuse	LU	LU000	Luxembourg (Grand-Duché)	UK	UKG34	Dudley and Sandwell	CH	CH054	Appenzell Innerrhoden
CH	CH055	St. Gallen	Paris	CH	CH052	Schaffhausen	CH	CH053	Appenzell Ausserrhoden	DE	DE18	Osnabrück
CH	CH051	Glarus	PROV. BRABANT WALLON	FR	FR714	Isère	CH	CH053	Appenzell Ausserrhoden	FR	FR105	Hauts-de-Seine
DE	DE46	Bonn	Schaffhausen	IT	ITD42	Udine	CH	CH054	Appenzell Innerrhoden	DE	DE41	Duisburg/Essen
IT	ITD53	Reggio nell'Emilia	Donau-Ilser (BY)	DE	DE86	Industrieregion Mittelfranken	DE	DE76	Schwarzwald-Baar-Heuberg	CH	CH053	Appenzell Ausserrhoden
DE	DE19	Hannover	Roskilde amt	UK	UKF11	Derby	AT	AT332	Innsbruck	DE	DE71	Nordschwarzwald

Source: own calculations and illustration. Notes: TL3 regions are ranked according to computed RCI-values in descending order; the table reports the European TOP20 regions for the period 2000-2004; additional information on RCI are available upon request from the author; calculations based upon OECD RegPAT (2009) database extractions and application of the ISI-SPRU-OST concordance.

Table 3.12. Ranking of RCI: TOP20 cluster regions by technology field (cont'd)

TF32_Lighting_equipment		TF33_Other_equip		TF34_Electr_components		TF35_Signal_transm_telecom		TF36_TV_radio_receiv_audio			
FR	FR106	Seine-Saint-Denis	CH	CH054	Appenzell Innerrhoden	NL	NL41	NOORD-BRABANT	NL	NL41	NOORD-BRABANT
AT	AT342	Rheinthal-Bodenseegebiet	CH	CH053	Appenzell Ausserrhoden	FR	FR174	Isère	FR	FR101	Paris
DE	DE38	Arnsberg	DE	DE23	Hildesheim	DE	DE58	Oberes Elbtal/Osterzgebirge	FR	FR523	Ille-et-Vilaine
FR	FR101	Paris	DE	DE86	Industrieregion Mittelfranken	DE	DE90	Regensburg	DK	DK001	København og Frederiksberg kommuner
NL	NL41	NOORD-BRABANT	DE	DE22	Braunschweig	DE	DE93	München	FR	FR105	Hauts-de-Seine
DE	DE73	Ostwestfalen-Lippe	DE	DE72	Stuttgart	DE	DE73	Ostwestfalen-Lippe	FR	FR105	Hauts-de-Seine
SI	SI005	Zasavska	FR	FR626	Hauts-Pyrénées	DE	DE45	Aachen	DK	DK002	København amt
DE	DE45	Aachen	CH	CH057	Thurgau	UK	UKH12	Cambridgeshire CC	DK	DK003	Frederiksberg amt
IT	ITE33	Macerata	SE	SE025	Västmanlands län	CH	CH066	Zug	DE	DE86	Industrieregion Mittelfranken
DE	DE89	Ingolstadt	NL	NL41	NOORD-BRABANT	AT	AT211	Klagenfurt-Vilach	UK	UKJ23	Surrey
CH	CH031	Basel-Stadt	FR	FR107	Val-de-Marne	DE	DE86	Industrieregion Mittelfranken	UK	UKM25	Edinburgh, City of
CH	CH051	Glarus	CH	CH040	Zürich	AT	AT225	West- und Südsteiermark	DE	DE19	Hannover
DE	DE97	Südostoberbayern	CH	CH022	Freiburg	UK	UKJ32	Southampton	FR	FR523	Freiburg
AT	AT332	Innsbruck	CH	CH055	St. Gallen	DE	DE72	Stuttgart	CH	CH022	Freiburg
UK	UKC13	Darlington	AT	AT130	Wien	FR	FR107	Neckar-Alb	UK	UKK11	Bristol, City of
DE	DE55	Sudthüringen	DE	DE90	Regensburg	AT	AT331	Außerfern	UK	UKH12	Cambridgeshire CC
DE	DE90	Regensburg	DE	DE93	München	UK	UKM25	Edinburgh, City of	FI	FI192	Pirkanmaa
FI	FI200	Åland	AT	AT226	Westliche Obersteiermark	AT	AT221	Graz	DE	DE93	München
DE	DE43	Bochum/Hagen	DE	DE70	Mittlerer Oberrhein	BE	BE24	PROV. VLAAMS-BRABANT	CH	CH040	Zürich
DE	DE23	Hildesheim	UK	UKF11	Derby	UK	UKJ23	Surrey	UK	UKJ33	Hampshire CC
UK	UKF11	Hildesheim	UK	UKF11	Derby	UK	UKJ23	Surrey	DE	DE23	Hildesheim
TF37_Med_equipment		TF38_Measuring_instruments		TF39_Ind_proc_contr_equip		TF40_Opti_instruments		TF41_Watches_clocks			
CH	CH066	Zug	FR	FR107	Val-de-Marne	DE	DE86	Industrieregion Mittelfranken	CH	CH024	Neuchâtel
UK	UKH06	Nidwalden	UK	UKH12	Cambridgeshire CC	DE	DE72	Stuttgart	NL	NL41	NOORD-BRABANT
DK	DK003	Frederiksberg amt	FR	FR101	Paris	DE	DE70	Mittlerer Oberrhein	CH	CH032	Basel-Landschaft
DK	DK001	København og Frederiksberg kommuner	CH	CH066	Zug	CH	CH057	Thurgau	DE	DE56	Ostthüringen
CH	CH032	Basel-Landschaft	DE	DE72	Stuttgart	DE	DE78	Hochrhein-Bodensee	CH	CH031	Basel-Stadt
DE	DE76	Schwarzwaldbaar-Heuberg	DK	DK001	København og Frederiksberg kommuner	FR	FR178	Hauts-Savoie	CH	CH021	Bern
CH	CH022	Freiburg	UK	UKI11	Inner London - West	DE	DE75	Neckar-Alb	CH	CH013	Genève
DK	DK002	København amt	DE	DE93	München	CH	CH066	Zug	FR	FR432	Jura
FR	FR101	Paris	CH	CH056	Graubünden	DE	DE81	Würzburg	CH	CH011	Vaud
UK	UKI11	Inner London - West	CH	CH054	Appenzell Innerrhoden	DE	DE96	Oberland	CH	CH033	Aargau
CH	CH064	Obwalden	CH	CH022	Freiburg	SE	SE025	Västmanlands län	CH	CH025	Jura
CH	CH031	Basel-Stadt	CH	CH057	Thurgau	DE	DE90	Regensburg	FR	FR431	Doubs
IT	ITF13	Pescara	DE	DE75	Neckar-Alb	DE	DE77	Südlicher Oberrhein	CH	CH052	Schaffhausen
DE	DE45	Aachen	DE	DE68	Unterer Neckar	DE	DE85	Oberpfalz-Nord	CH	CH022	Freiburg
CH	CH057	Thurgau	CH	CH055	St. Gallen	CH	CH032	Basel-Landschaft	DE	DE58	Oberes Elbtal/Osterzgebirge
CH	CH033	Aargau	UK	UKJ14	Oxfordshire	CH	CH040	Zürich	CH	CH040	Zürich
CH	CH040	Zürich	DE	DE23	Hildesheim	DE	DE83	Oberfranken-West	FR	FR178	Hauts-Savoie
CH	CH023	Solothurn	UK	UKM25	Edinburgh, City of	DE	DE87	Südostoberbayern	CH	CH063	Schwyz
SE	SE021	Uppsala län	CH	CH053	Appenzell Ausserrhoden	DE	DE87	Westmittelfranken	CH	CH057	Thurgau
UK	UKF14	Nottingham	UK	UKL22	Cardiff and Vale of Glamorgan	DE	DE93	München	FR	FR104	Essonne
UK	UKF14	Nottingham	UK	UKL22	Cardiff and Vale of Glamorgan	DE	DE93	München	FR	FR104	Essonne

Source: own calculations and illustration. Notes: TL3 regions are ranked according to computed RCI-values in descending order; the table reports the European TOP20 regions for the period 2000-2004; additional information on RCI are available upon request from the author; calculations based upon OECD RegPAT (2009) database extractions and application of the ISI-SPRU-OST concordance.

Table 3.13. Ranking of RCI: TOP20 cluster regions by technology field (cont'd)

TF42_Motor_vehicles		TF43_Other_transp equip		TF44_Furniture consum good		SUM_hightech		HT2_Computer_office_mach	
DE DE72	Stuttgart	UK UKF11	Derby	AT AT342	Rheinthal-Bodenseegebiet	FR FR101	Paris	FR FR101	Paris
FR FR105	Hauts-de-Seine	CH CH057	Thurgau	CH CH051	Glarus	NL NL41	NOORD-BRABANT	NL NL41	NOORD-BRABANT
DE DE80	Bayerischer Untermain	FR FR623	Haute-Garonne	UK UKI11	Inner London - West	FR FR105	Hauts-de-Seine	UK UKK11	Bristol, City of
DE DE71	Nordschwarzwald	DE DE14	Hamburg-Umland-Süd	FR FR718	Haute-Savoie	DE DE83	München	FR FR105	Hauts-de-Seine
DE DE89	Ingolstadt	DE DE11	Bremen	CH CH022	Freiburg	DK DK001	Kobenhavn og Frederiksberg kommuner	DE DE93	München
FR FR103	Yvelines	IT ITC33	Genova	CH CH057	Thurgau	UK UKK11	Bristol, City of	UK UKH12	Cambridgeshire CC
DE DE90	Regensburg	AT AT226	Westliche Obersteiermark	FR FR101	Paris	UK UKH12	Cambridgeshire CC	UK UKJ33	Hampshire CC
DE DE70	Mittlerer Oberrhein	FR FR102	Seine-et-Marne	DE DE94	Donau-Iller (BY)	FI FI181	Uusimaa	UK UKI11	Inner London - West
DE DE93	München	DE DE6	Hamburg	DE DE36	Bielefeld	UK UKI11	Inner London - West	DE DE68	Unterer Neckar
DE DE22	Braunschweig	CH CH064	Obwalden	CH CH070	Ticino	UK UKK14	Swindon	UK UKI12	North and North East Somerset, South Gloucestershire
DE DE73	Ostwürttemberg	FR FR107	Val-de-Marne	IT ITD32	Vicenza	DK DK002	Kobenhavn amt	FR FR107	Val-de-Marne
DE DE69	Franken	AT AT130	Wien	CH CH031	Basel-Stadt	FR FR107	Val-de-Marne	FI FI192	Pirkanmaa
DE DE75	Neckar-Alb	FR FR105	Hauts-de-Seine	CH CH012	Valais	UK UKJ32	Southampton	DE DE86	Industrieregion Mittelfranken
FR FR101	Paris	IT ITD32	Vicenza	IT ITD34	Treviso	FI FI192	Pirkanmaa	FR FR823	Alpes-Maritimes
FR FR633	Deux-Sèvres	CH CH031	Basel-Stadt	DE DE78	Hochrhein-Bodensee	DE DE86	Industrieregion Mittelfranken	DE DE45	Aachen
DE DE51	Rhein-Main	UK UKK11	Bristol, City of	CH CH033	Aargau	FR FR714	Isère	FR FR714	Isère
DE DE18	Osnabrück	CH CH055	St. Gallen	AT AT130	Wien	UK UKJ23	Surrey	UK UKJ23	Surrey
FR FR107	Val-de-Marne	DE DE86	Industrieregion Mittelfranken	DE DE96	Oberland	FR FR523	Ille-et-Vilaine	UK UKM25	Edinburgh, City of
DE DE44	Köln	DE DE93	München	DK DK009	Sønderjyllands amt	DK DK003	Frederiksberg amt	FI FI181	Uusimaa
IT ITC11	Torino	CH CH065	Nidwalden	DK DK001	Kobenhavn og Frederiksberg kommuner	DE DE45	Aachen	UK UKJ11	Berkshire
HT1_Aviation		HT3_Laser		HT4_Semiconductors		HT5_Communication		HT6_Microorgan_Genetics	
FR FR623	Haute-Garonne	UK UKJ32	Southampton	DE DE58	Oberes Elbtal/Osterzgebirge	FR FR101	Paris	DK DK001	Kobenhavn og Frederiksberg kommuner
DE DE14	Hamburg-Umland-Süd	UK UKK42	Torbay	DE DE90	Regensburg	UK UKK14	Swindon	DK DK002	Kobenhavn amt
DE DE11	Bremen	UK UKM34	Glazow City	FR FR714	Isère	FI FI181	Uusimaa	DK DK003	Frederiksberg amt
DE DE6	Hamburg	UK UKH14	Suffolk	NL NL41	NOORD-BRABANT	FR FR105	Hauts-de-Seine	FR FR101	Paris
UK UKK11	Bristol, City of	DE DE90	Regensburg	DE DE93	München	NL NL41	Zuidoost-Noord-Brabant	UK UKI11	Inner London - West
UK UKK12	North and North East Somerset, South Gloucestershire	FR FR104	Essonne	UK UKH12	Cambridgeshire CC	UK UKK11	Bristol, City of	DE DE96	Oberland
FR FR107	Val-de-Marne	FR FR105	Hauts-de-Seine	CH CH066	Zug	DE DE93	München	UK UKH12	Cambridgeshire CC
UK UKG33	Coventry	UK UKC13	Darlington	DE DE73	Ostwürttemberg	FI FI192	Pirkanmaa	DE DE30	Berlin
DE DE79	Bodensee-Oberschwaben	FR FR107	Val-de-Marne	UK UKJ32	Southampton	FR FR523	Ille-et-Vilaine	UK UKJ14	Oxfordshire
UK UKK23	Somerset	UK UKM35	Inverclyde, East Renfrewshire and Renfrewshire	AT AT211	Klagenfurt-Villach	DK DK001	Kobenhavn og Frederiksberg kommuner	UK UKL22	Cardiff and Vale of Glamorgan
DE DE15	Bremen-Umland	AT AT342	Rheinthal-Bodenseegebiet	DE DE86	Industrieregion Mittelfranken	SE SE010	Stockholms län	DE DE68	Unterer Neckar
FR FR105	Hauts-de-Seine	FR FR101	Paris	BE BE24	PROV. VLAAMS-BRABANT	FR FR107	Val-de-Marne	UK UKE21	York
UK UKD42	Blackpool	DE DE76	Schwarzwald-Baar-Heuberg	UK UKJ23	Surrey	UK UKJ32	Southampton	CH CH056	Graubünden
IT ITC41	Varese	UK UKH12	Cambridgeshire CC	DE DE45	Aachen	UK UKJ23	Surrey	NL NL310	Utrecht
DE DE95	Allgäu	DE DE30	Berlin	FR FR107	Val-de-Marne	UK UKH12	Cambridgeshire CC	BE BE31	PROV. BRABANT WALLON
SE SE023	Östergötlands län	UK UKF23	Northamptonshire	DE DE75	Neckar-Alb	DE DE86	Industrieregion Mittelfranken	DE DE93	München
FR FR824	Bouches-du-Rhône kommuner	DK DK001	Kobenhavn og Frederiksberg kommuner	UK UKM25	Edinburgh, City of	UK UKH14	Suffolk	AT AT130	Wien
UK UKJ13	Buckinghamshire CC	DE DE56	Ostthüringen	DE DE54	Mittelthüringen	UK UKI11	Inner London - West	CH CH022	Freiburg
CH CH065	Nidwalden	DE DE39	Dortmund	CH CH057	Thurgau	DK DK002	Kobenhavn amt	UK UKE32	Sheffield
UK UKF11	Derby	IE IE021	Dublin	DE DE72	Stuttgart	DE DE72	Stuttgart	FR FR105	Hauts-de-Seine

Source: own calculations and illustration. Notes: TL3 regions are ranked according to computed RCI-values in descending order; the table reports the European TOP20 regions for the period 2000-2004; additional information on RCI are available upon request from the author; calculations based upon OECD RegPAT (2009) database extractions and application of the ISI-SPRU-OST concordance.

3.5.5. Co-Agglomeration of Research Clusters in Europe

Co-location and co-agglomeration of technology-specific clusters is another serious issue in a European context because such studies do, to the author's knowledge, not exist for the entire population of 819 European regions.

The number of spatially co-located technology-specific research clusters can be interpreted as a possible measure for the strength of co-agglomeration of regional research activity, for diversity of region-specific knowledge pools and thus the existence of multi-technology regions. The idea is to explore potential similarities and regularities of technology field-specific clustering by contrasting regions' ranking positions in all 50 technology field aggregates, i.e., the geographic coincidence of the distributions. Therefore, the empirical analysis uses the computed RCI indices of the 819 European regions (see section 3.5.2). Spearman rank correlation coefficients are calculated for RCI by technology field. A high Spearman correlation coefficient ($\rho \leq 1$) is obtained if the two distributions are quite similar. Thus, the ranking position of each observation within two or more different technology field-specific distributions has to be compared.³⁸³ After having studied 5 EU countries, Maggioni *et al.* (2007) concluded that co-patenting activity, and patenting activity in general, are similarly distributed across European regions. Similar conclusions are reported by Scherngell (2007). Nevertheless, a detailed descriptive analysis of co-agglomeration has not been incorporated in the mentioned studies.

The following analysis is focusing on technology field-specific research clustering indices (RCI) at the level of European TL3 regions within a total population of 819 TL3 regions. If a region has a low RCI value compared to other regions, it obtains a low ranking position. The computation of Spearman rank correlation coefficients was executed for all RCIs across all 50 technology fields for 1990-1994 and 2000-2004.³⁸⁴ The obtained correlation coefficients illustrate the degree of similarity (overlap) of the respective RCI distributions in two technology fields.³⁸⁵ It gives information, which technology fields reflect a similar distribution/RCI ranking of the 819 European regions. For a better visualization, the color intensity of the cells increases with the obtained Spearman correlation coefficient values between two technology fields.

With regard to the main hypothesis, even a brief look at the correlograms illustrates that there exists indeed a diversified clustering and thus co-agglomeration (co-location) of several technology fields in the same regions, meaning that technology-specific RCI distributions geographically overlap. Figure 3.35 highlights the Spearman rank correlation coefficients for all 50 technology field aggregates (see figure A.31, appendix, for the same

³⁸³ Spearman's rank correlation coefficient is a non-parametric measure. It measures statistical dependence between two variables. It tests how well a relationship between two variables can be described using a monotonic function. In case of not identical values, a (perfect) Spearman correlation coefficient occurs (with +1, -1); then every variable is a perfect monotone function of the other. The n raw scores X_i, Y_i are converted to ranks x_i, y_i , and the differences $d_i = x_i - y_i$ between the ranks of each observation on the two variables are calculated. In the case of tied observations, i.e., observations with identical parameter values (which happened frequently), the arithmetic average of the rank numbers has to be taken.

³⁸⁴ For a complete overview and list of abbreviations of all 51 technology field aggregates used in the following graphs and tables see table B.4 (appendix).

³⁸⁵ Spearman rank correlation analysis has been done with STATA 11.

correlogram for the period 1990-1994). It can be concluded that regional centers and “hot spots” of innovative activity seem to co-agglomerate with some regularity in similar regions within the landscape of the European Union and the ERA. Several co-agglomerated technology fields are identified: *TF10 Basic chemicals*, *TF13 Pharmaceuticals*, *TF15 Other chemicals*, *TF37 Medical equipment* and *TF38 Measuring instruments* show high Spearman correlation coefficients. High parameter values can also be observed for *TF42 Motor vehicles* and *TF21 Energy machinery*, which may be a result of technological relatedness of these research activities. Another strong co-agglomeration seems to exist between *TF28 Office machinery & computers* and *TF38 Measuring instruments*. Moreover, the results point to high Spearman correlation coefficients in the following technology fields: *TF35 Signal transmission & telecommunication* and *TF28 Office machinery & computers*. Finally several machinery-related technology fields seem to co-agglomerate in similar regions, e.g., *TF21 Energy machinery*, *TF22 Non-special purpose machinery*, *TF24 Machine tools* and *TF25 Special purpose machinery*.³⁸⁶ It can be concluded from the results presented in this section that technology fields indeed co-agglomerate with a kind of regularity in European regions. Thus, based upon RCI, some kind of geographic coincidence and regularity with regard to the distribution of research clusters across the regions of the European Union can be observed.

³⁸⁶ Positive Spearman correlation coefficients (co-location) are not only a statistical artefact due to similar IPC fields. However, it has to be noted that the strong correlation coefficients between several technology fields essentially depend on the IPC-technology field concordance and the similarity of the built technology fields, which represents technological relatedness (Boschma and Frenken, 2009; Frenken et al., 2009).

3.5.6. Research Clustering in Urban Areas and Capital Regions

The empirical results presented in the previous sections (e.g., the TOP20 regions) suggest that mainly capital regions and urban and metropolitan areas represent leading European research clusters. It has been argued by theoretical contributions, as presented and discussed in the theoretical literature review, that knowledge-intensive industries and research clusters in large urban areas and agglomerations possess an ideal combination of connectivity within global networks. Urban areas facilitate the exchange of codified knowledge via research collaboration networks and increase the advantages of spatial proximity in agglomerations due to an improvement of tacit knowledge exchange via localized networks and social relationships (Ter Wal and Boschma, 2008). Moreover, dense regions offer several crucial inputs and requirements, e.g., skilled labor, capital inputs, financial capital, home market (Frenken and Hoekman, 2006; Neffke et al., 2009; Malecki, 2010).

Moreover, metropolises and urban areas seem to benefit from diversified industry structures. This hypothesis is of great interest with respect to the 819 European TL3 regions. Accordingly, besides the global co-location analysis (see the former section), it has to be analyzed if there is higher co-agglomeration of technology field-specific research clustering in highly populated areas; i.e., in capital regions, metropolises and urban areas. Furthermore, it has to be analyzed whether the structures have changed considerably since the 1990s. Therefore, an analysis that explicitly controls for the regional typology may enrich our understanding of co-agglomeration of industries/ technology fields. With respect to the regional typology, 231 observations out of the entire population of 819 European regions are classified as urban regions, 289 observations as rural regions and 299 observations as intermediate regions. Moreover, an additional capital-metro-region concordance table is used. According to this methodology, 63 capital regions and 330 metropolitan regions within the entire population of 819 European TL3 regions can be extracted.³⁸⁷ Accordingly, each of the 819 European regions is classified into the above presented five (partially overlapping) categories. Besides an overall presentation, each settlement type is highlighted in a separate figure which includes the following RCI intensity classes/ subgroups (see section 3.5.2): $RCI > 1$, $1 < RCI \leq 16$, $16 < RCI \leq 81$ and $RCI > 81$. For completeness, figures A.32-A.36 (appendix) visualize the number of research clusters by regional settlement structure and RCI class for the periods 1990-1994 and 2000-2004. Table 3.14 offers a summary statistic.

According to the calculations, urban regions, and especially capital regions and metropolises, show a much higher technological diversity/variety in terms of technology field-specific clustering, which can be interpreted as evidence for strong co-agglomeration. Table 3.14 highlights the number of research clusters by RCI class for the periods 1990-1994 and 2000-2004.

The 63 identified European “capital regions,” which host the capital cities of the member states (or are at least located at a proximate distance), are showing diversified structures of co-agglomerated research clusters (see table 3.14 and figure A.32, appendix). The table and figure demonstrate that the structure and distribution within the group of capital regions has not changed significantly since the 1990s compared to the 2000s. Between 1990-1994, 7

³⁸⁷ The 63 capital regions include regions that do not explicitly host the capital city, but functionally belong to a larger capital region.

Table 3.14. Co-agglomeration of research clusters and regional typology

region type	RCI>1	1<RCI≤16	16<RCI≤81	RCI≥81
1990-1994				
average number of technol. spec. clusters by region and RCI				
rural	5,9	3,0	1,1	1,7
intermediate	10,3	5,1	2,2	3,0
urban	20,3	8,2	4,5	7,6
metro	17,0	7,5	3,7	5,8
capital	21,7	8,3	4,8	8,6
% regions with n≥1 cluster (by RCI)				
rural	69,2%	64,7%	42,2%	44,6%
intermediate	75,3%	71,6%	53,8%	58,9%
urban	92,2%	88,3%	79,2%	81,8%
metro	85,2%	83,0%	69,4%	72,4%
capital	88,9%	84,1%	73,0%	74,6%
2000-2004				
average number of technol. spec. clusters by region and RCI				
rural	6,5	3,5	1,3	1,7
intermediate	11,2	5,7	2,2	3,2
urban	20,5	8,9	4,4	7,2
metro	17,8	8,3	3,8	5,8
capital	22,3	9,6	5,0	7,7
% regions with n≥1 cluster (by RCI)				
rural	71,6%	67,8%	46,0%	48,1%
intermediate	84,3%	78,3%	61,2%	61,9%
urban	95,2%	92,2%	86,1%	82,7%
metro	90,3%	86,1%	79,1%	74,5%
capital	92,1%	88,9%	77,8%	76,2%

Source: own calculations and illustration. Notes: calculations based upon OECD RegPAT (2009) database extractions and application of the ISI-SPRU-OST concordance.

capital regions (11,1% of all 63 capital regions) host not any single research cluster; between 2000-2004, only 5 regions (7,9%) are without any significant research activity ($RCI > 1$). When classifying all 63 capital regions into different classes of RCI, it can additionally be shown that the class $RCI > 81$ is not fulfilled by 15 capital regions (23,8%) between 2000-2004 compared to 16 regions (25,4%) between 1990-1994. Nevertheless, capital regions generally fulfill the lower threshold level ($RCI > 16$) but also host strong research clusters ($RCI > 81$).

Concerning “metropolitan regions,” 330 regions (out of 819) can be identified in total, which fit into the classification of EUROSTAT (European Union, 2009) (see figure A.33, appendix). Between 2000-2004, 32 metro regions (9,7%) do not host a single technology field-specific research cluster ($RCI > 1$), compared to 49 regions (14,8%) in 1990-1994. The highest threshold level ($RCI > 81$) of research clustering is not fulfilled by 91 regions (27,6%) in the 1990s, whereas 84 regions (25,5%) remain without significant research clustering ($RCI > 81$) in the 2000s.

In the following, for comparison purpose, the results with respect to the “urban-intermediate-rural” classification are presented and discussed. In the case of “urban regions,” only 18

European regions (7,8%) of all 231 urban European regions remain without research clustering above the lower threshold level ($RCI > 1$) between 1990-1994 (see figure A.34, appendix); between 2000-2004 the value decreased to 11 regions (4,7%). Even higher threshold levels of the cluster index, i.e., $RCI > 81$, are fulfilled by a meaningful number of regions; only 42 regions (18,2%) between 1990-1994 and 40 regions (17,3%) between 2000-2004 do not fulfill $RCI > 81$. Again, the results indicate that urban regions are, on average, characterized by a large and increasing number of research clusters and thus co-agglomeration.

The computational results for the group of “intermediate regions” in Europe are, however, hard to interpret (see figure A.35, appendix). 74 regions (24,7%) of all 299 intermediate regions show no research clustering in 1990-1994 with $RCI > 1$. In comparison, 47 intermediate regions (15,7%) remain without any research clustering activity ($RCI > 1$) between 2000-2004. Accordingly, a significant increase in the number and share of research clusters in the population of intermediate European regions can be observed. However, with respect to higher RCI classes, i.e., $RCI > 81$, 123 regions (41,1%) of all intermediate regions remain without a single technology field-specific research cluster between 1990-1994. Between 2000-2004, 114 intermediate regions (38,1%) remain without strong clustering ($RCI > 81$).

Finally, the majority of European “rural regions” host only, if at all, very small numbers of research clusters. This tendency is, on average, accompanied by stronger absolute and relative specialization of rural areas into a few technology fields, i.e., higher RTA (and employment-based location quotients) (see figure A.36, appendix).³⁸⁸ 89 rural areas (30,8%) are characterized by a lack of weak clustering tendencies ($RCI > 1$) in all 50 technology fields between 1990-1994, which supports the commonly known picture of backwardness and lock-in of peripheral areas. Similarly, between 2000-2004, the number of such backward regions has decreased to 82 (28,4%). In addition, 160 rural regions (55,4%) between 1990-1994 and 150 regions (51,9%) between 2000-2004 do not fulfill $RCI > 81$. These results are in line with the well known picture of spatial hierarchy (see, e.g., Fujita and Ishii, 1999; Duranton and Puga, 2001; Trippl, 2009; Henderson, 2010).

Finally, figures 3.36 and 3.37 highlight the density functions of $RCI > 81$ for the 819 European regions for the periods 1990-1994 and 2000-2004, according to the regional typology. Comparing the density functions leads to the aforementioned conclusions. Capital and urban regions de facto show a much more diversified clustering structure compared to rural and intermediate areas, meaning that rural regions are, on average, more specialized into a few technology fields.³⁸⁹

It can be concluded from the presented results that there exists considerable research clustering and visible co-agglomeration of technology fields in the same regional units. Technological diversity, however, is mainly present in capital regions and urban and metropolitan areas. It can be argued that concentration and co-agglomeration of research activities is

³⁸⁸ This is one reason, why sole relative specialization measures are left out of this study, as rural and peripheral regions are, on average, more specialized but in absolute terms significantly below the output and productivity levels of urban or metropolitan regions.

³⁸⁹ Density graphs have been generated with STATA 11.

more likely to occur in highly populated areas, but is less likely to happen in rural European regions, which gives some support to Jacobs' approach (see chapter 2, section 2.1.6.3). Unfortunately, the study cannot offer statistical results related to the origins, causes and effects of the observed distributions and the reasons for obvious co-agglomeration and clustering in urban regions. One may interpret these results as (preliminary) descriptive evidence that European cities and agglomerations generally offer a higher absolute and relative number of highly skilled employees, researchers and networks, among other factors that are crucial for regions' research performance and development (see chapter 2.1).

Furthermore, the calculations show that technological diversity in research clustering is especially present in the majority of European capital regions, e.g., Paris, London, Vienna, Berlin, Copenhagen, Stockholm, Nord-Holland, Bern, Oslo, Dublin and close neighborhoods. Exceptions are a few capital regions in the NMS (i.e., Budapest, Warsaw, Bratislava, Vilnius) and Southern Europe (i.e., Athens), which still show only small values of research clustering in both periods of analysis. In Southern Europe and the NMS, only Madrid, Rome, Lisbon and Riga are characterized by research clustering in several technology fields. Moreover, the dynamic analysis indicates that especially urban and metropolitan regions have experienced high growth rates of research clustering between the 1990s and 2000s. Another result of this comparative analysis is that rural regions in general do not show a diversified technology and research base and that a large fraction of rural European regions remains without research clustering in the 1990s and 2000s.

To conclude, research clustering, according to the former results, seems to exist predominantly in the capital regions, metropolises and urban regions of the EU-15, but it can also be increasingly observed in capital regions, metropolises, and secondary (urban) growth poles in the NMS, which is in line with the concept of regional development and convergence (see also Williamson, 1965; Henderson, 2010).³⁹⁰

³⁹⁰ For more details on regional development and inequality refer to the empirical analysis in chapter 5. For a review and alternative analysis refer to, e.g., Szörfi (2007).

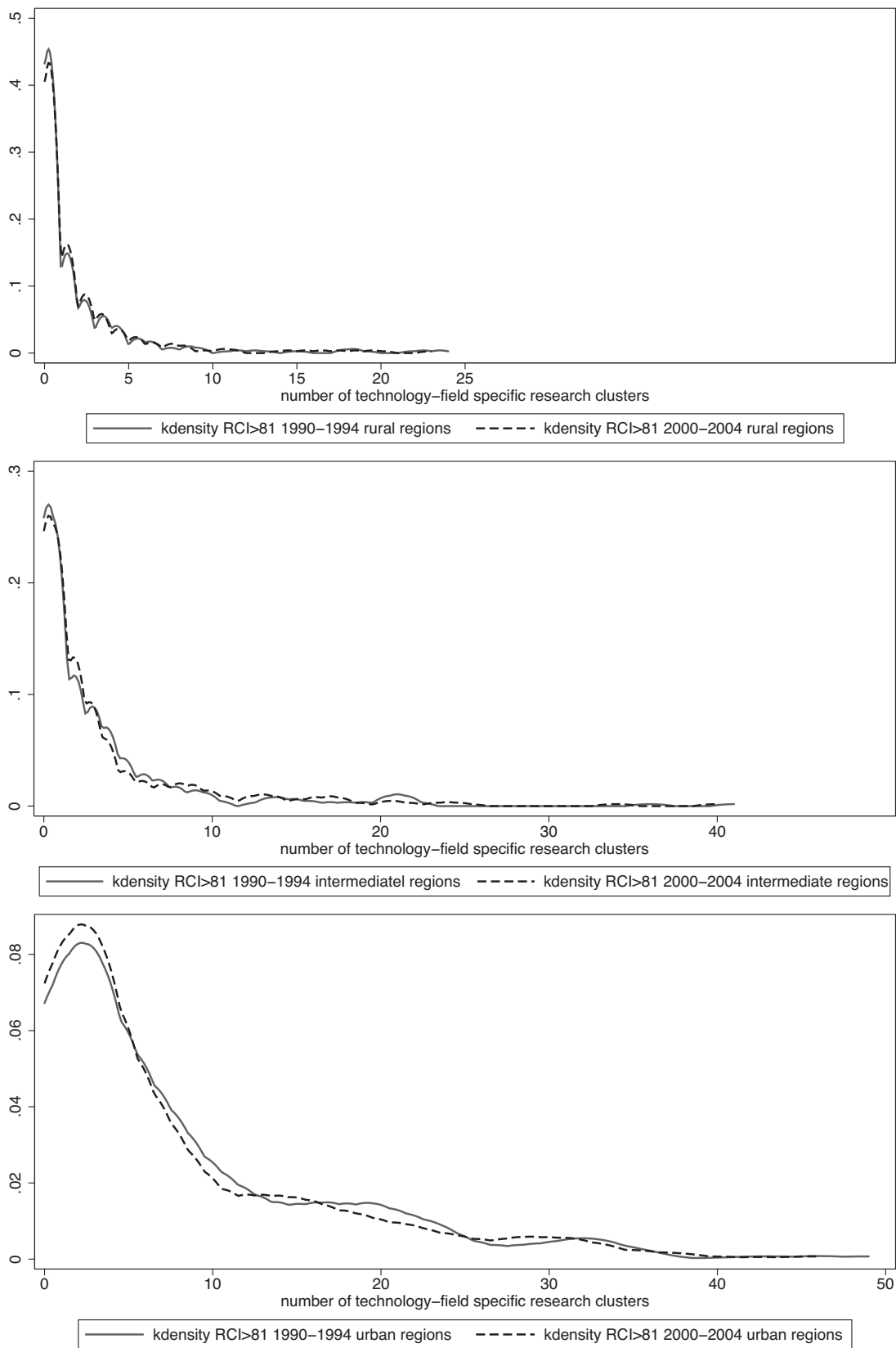


Fig. 3.36. Density function of clusters with $RCI > 81$, 1990-1994 and 2000-2004

Source: own calculations and illustration. *Notes:* Each of the 819 European regions can host up to 50 research clusters with $RCI > 81$.

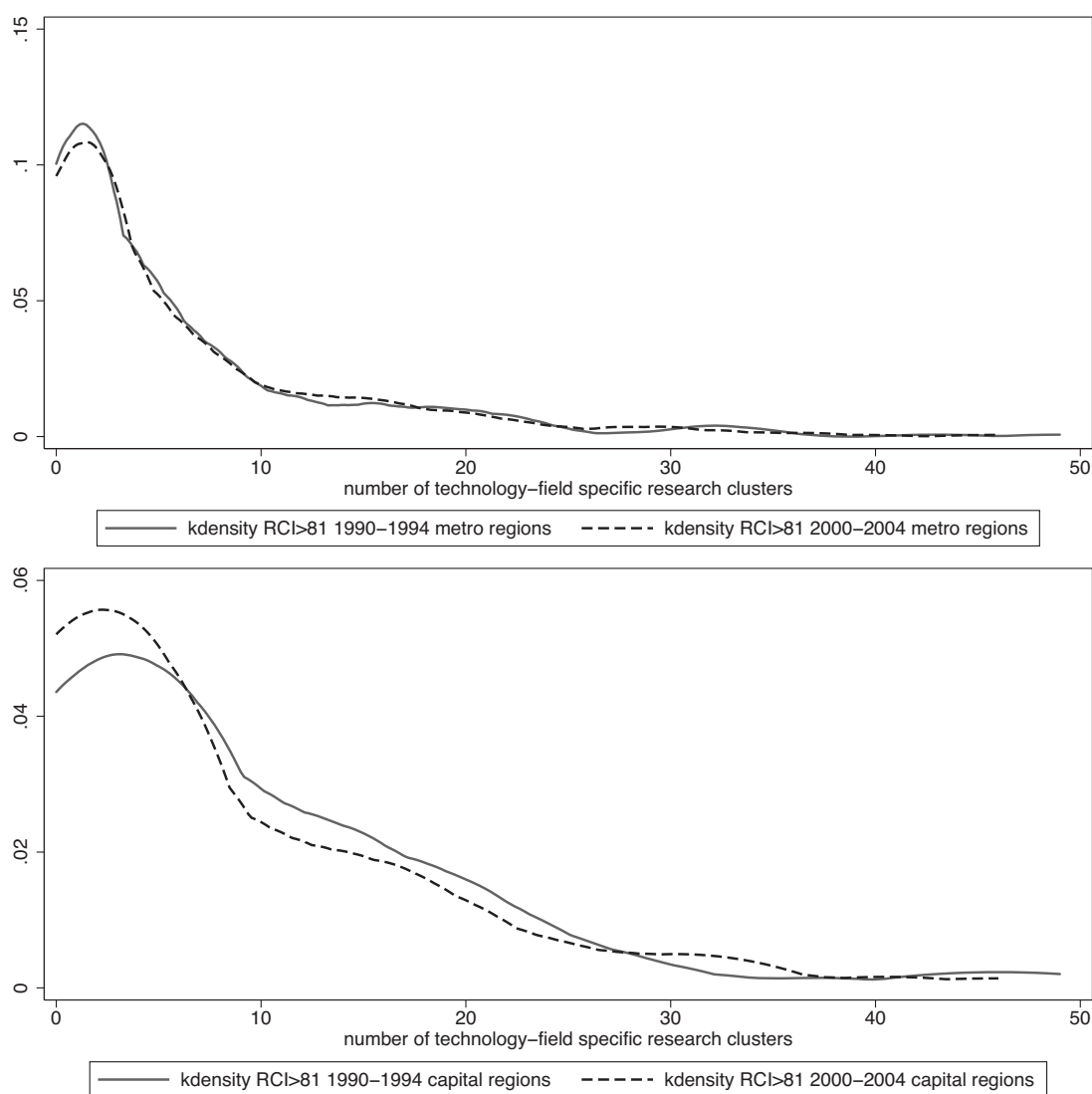


Fig. 3.37. Density function of clusters with $RCI > 81$, 1990-1994 and 2000-2004

Source: own calculations and illustration. *Notes:* Each of the 819 European regions can host up to 50 research clusters with $RCI > 81$.

4. European Co-Patenting Networks and Inter-Regional Linkages

4.1. Analyzing European Research Collaborations

It has been evidenced by several studies that human activities cluster in space. Applied research and scientific tasks are no exception to these tendencies (Frenken et al., 2009; Maggioni and Uberti, 2009; Hoekman et al., 2010). In light of the empirical results presented in chapter 3 and the identified research gaps, the spatial patterns of research collaboration and inter-regional co-patenting networks within Europe are of central interest. However, Harris (2008, 22) recently argued that

“[r]esearch on agglomerations/clusters has focused on the internal characteristics and mechanisms in those places and diverted attention from the necessary distinct, even global, linkages that competitive places require.”

From a statistical point of view, the subsequent study analyzes whether patenting activity is characterized by significant positive spatial dependence, meaning not only that the distribution of research activity in geographic space is highly skewed (chapter 3, sections 3.4 and 3.5), but also that innovative places and research clusters are neighbored by centers of research excellence, which may result in significant positive spatial autocorrelation. Therefore, the exploration of the relational aspect of patent data in the context of European regional neighborhood structures is a topic of central interest.

The development of geographic information systems (GIS) has had a central influence on spatial data analysis, especially in regional studies. The existing technical abilities to capture and explore geo-spatial data are co-evolving and advancing with databases and data-intensive studies. GIS environments support the computation of spatial relationships, e.g., distance decay effects, travel times and connectivity matrices. Accordingly, GIS helps to visualize and explore spatial data. Spatial statistics can be applied in order to analyze EPO patenting activity at the regional level. Accordingly, this section is considered to enrich our understanding of research clustering and regional spillovers and to complement the results from the previous chapter (sections 3.4 and 3.5).

Furthermore, a closer look at spatial interdependence of patenting activity, i.e., spatial relationships, is of central interest (section 4.2). It is argued that not only is technological knowledge created within randomly distributed European research locations and isolated clusters but also that it emerges from research collaborations between leading innovative places, which means that research locations are increasingly interconnected. The study of European co-patenting activities analyzes an important relational aspect of patent statistics with regard to the co-invention process. Co-inventorship, i.e., co-patenting activity, is a process that involves the exchange of both codified and tacit knowledge (chapter 2, section 2.1.7). Thus, it implies a series of both long-distance relationships (transaction

linkages) between inventors and face-to-face knowledge transmissions at a proximate distance (chapter 2, section 2.1.7.3) (see also Maggioni *et al.*, 2007; Hoekman *et al.*, 2009). According to the classification in chapter 2, transaction externalities and proximity externalities are more likely to occur in both cases besides the formal R&D co-operation. In view of this, a closer look at research collaboration activities between European countries and regions seems to be fruitful, as theoretically discussed in chapter 2 (see sections 2.1.7.4 and 2.1.7.5). Therefore, the structures and dynamics of co-patenting activities with foreign co-inventors in the ERA are analyzed at the national and regional level. The analysis also incorporates the inter-regional research collaborations of multinational corporations (section 4.3). If, e.g., European researchers from different national research locations collaborate as co-inventors within the same company, then the co-patent is also included in this study.³⁹¹ A significant absolute and relative increase in foreign co-inventor activity can be interpreted as a sign for increasing effectiveness and efficiency and a way towards the ERA. For this reason, co-patenting activities with foreign researchers are analyzed in section 4.3.4. Moreover, the analysis identifies the numbers and shares of research linkages (and knowledge flows) within the ERA (which may induce spatial autocorrelation).

In light of the above presented issues and the presented theoretical arguments (chapter 2, sections 2.1.7.4 and 2.1.7.5), section 4.3.4 tries to find empirical evidence for the following research questions: (i) Which countries show the highest absolute number and share of co-patenting linkages? (ii) Have European member states increased their co-patenting (research) activity with foreign countries in absolute and/or relative terms? The explanatory spatial data analysis is related to the different theories on core-periphery structures reviewed in chapter 2, section 2.1, and contributes to the empirical studies presented in sections 2.2.2, 2.2.3 and 2.2.7.

Besides co-patenting activities and research collaborations between European countries, the analysis also gives priority to the identification of inter-regional research collaborations across the European area in section 4.3.5.

The major contribution of the empirical analyses in chapter 3 (sections 3.4 and 3.5) was to demonstrate that research activity is mostly a regional phenomenon. In this regard, national innovation indicators (e.g., patent densities and patent intensities) are only reflections of research activity that varies extraordinarily at the regional level. Aggregated data at the national level can be regarded as a severe loss in variation due to aggregation from the regional to the national level. This issue is also relevant to relational data analysis, i.e., co-patenting analysis. Further to this, the reviews in chapter 2 indicated that collaborative activities (i.e., scientific co-publications and EPO patent citations) are highly sensitive to physical distance. In view of these results, the review of the empirical literature on European co-patenting activity (chapter 2, section 2.2.7) has unfolded the need for additional research.

From a co-patenting perspective, especially with regard to research clustering, the analysis of European research network structures and the identification of potential core-periphery structures in Europe is of pivotal interest. The existence of core-periphery structures may be reflected by so-called “scale-free networks” that exhibit power-law distributions (skewed degree distribution) but not the desired bell-shaped distributions (Poisson law) (Bergman,

³⁹¹ See Frietsch and Schmoch (2006) for methodological issues.

2009). In this respect, the analysis places special emphasis on the calculation of global network statistics for each technology field and the identification of important regional knowledge hubs and central inter-regional co-inventor linkages in technology-specific co-patenting networks. As such, the results of the national co-patenting analysis in section 4.3.4 will be enriched by a detailed analysis of research collaboration linkages, i.e., co-patenting networks, at the regional level. It is assumed that not all European regions are identically integrated into inter-regional research networks in the ERA. As has been shown by many case studies and regional studies, regional networks (and especially localized networks) have their particular characteristics and thus differ tremendously in their functioning and set-up (Ejeremo and Karlsson, 2004; Frietsch and Schmoch, 2006; Saxenian, 2007).³⁹² However, a comprehensive analysis of co-patenting linkages between (and within) European regions improves the understanding of regional interdependence in the research and patenting processes. In light of this, the regional co-patenting study aims to identify and analyze the spatial structures and dynamics of inter-regional co-patenting activities. In the following, several motivations related to an analysis of knowledge flows via research collaborations at the level of European TL2 and TL3 regions are exposed (OECD, 2003, 2006).

A strong motivation for exploring European research collaborations in terms of networks (i.e., co-patenting networks) is based upon the fact that spatial data in general show strong spatial autocorrelation (see section 4.2) (Fotheringham *et al.*, 2002; Anselin, 2007; Hauser *et al.*, 2008). However, a significant fraction of spatial dependence of EPO patenting activity is mainly a statistical artifact that emerges from the localization and fractional counting method of patent data. Spatial dependence increases with the fraction of patents that are characterized by co-inventors from neighboring regions. In this respect, the usage of relational (network) data has the advantage that it builds upon a direct relation with the theoretical conceptualization of the structure of spatial dependence (Anselin, 1988b; Ponds *et al.*, 2010). Section 4.3.4 will show that the share of national EPO patents with foreign co-inventors is today, on average, still below 30-40%. However, the share of EPO patents with co-inventors from more than one region within the same country may be beyond this threshold. Accordingly, if co-inventors are located in a proximate neighborhood, then spatial dependence may be significant and positive. In light of this, the analysis of network structures, opposed to spatial econometrics, has the advantage that it addresses the origin, i.e., the real structure, of spatial dependence of patenting (and research) activities. Thus, co-inventor network analysis does not simply assume an “ad hoc” spatial structure (Anselin, 1988b; Ponds *et al.*, 2010). As empirical research on the geographical dimension of these networks also stresses the importance of inter-regional and border-crossing collaboration linkages, technology-specific co-inventor networks are assumed to differ in their structure and dynamics (see Bergman, 2009; Ponds *et al.*, 2009; Hoekman *et al.*, 2009, 2010). In view of this, such an analysis has to be accomplished for each technology field separately. Accordingly, the following analysis offers a clear hypothesis and potential explanation, for why patent statistics and regional knowledge production functions are in most cases characterized by significant positive global and local spatial autocorrelation. The existence of significant spatial interdependence needs an economic explanation that goes beyond the common knowledge spillover story (see chapter 2) that solely incorporates an additional

³⁹² See also Saxenian (1990) and Hotz-Hart (2000).

spatially weighted control, i.e., “black boxes,” for economic treatment. On account of that, the co-inventor network analysis and the global and local network statistics in this study challenge spatial interdependence in terms of co-patenting network structures within and between European regions (counties and districts) and their respective larger aggregates. It will be shown that the analysis of technology-specific EPO co-patenting networks is a key approach to understanding the spatial peculiarities of research collaboration, co-inventorship and spatial dependence at the level of European regions.

Furthermore, inter-regional co-inventorship networks and collaboration linkages represent the counterpart of industry agglomerations and innovation clusters, as theoretically discussed in chapter 2 (section 2.1.7.5). Research clustering and inter-regional knowledge pipelines seem to represent two sides of the same coin (Maggioni et al., 2007; Maggioni and Uberti, 2009). The network analysis is fruitful, as it sheds light on the inter- and intra-regional connectedness of regions in terms of research linkages and the centrality of regions in the European co-patenting network. Significant research clusters, the so-called core units of the networks, as well as peripheral regions, can be identified and analyzed. From a core-periphery perspective, it is then a central issue to depict the hub-and-spoke structure of technology fields and their development in the course of time. Today, some European regions represent weak and decentralized network nodes, whereas other spatial units are obtaining a “gatekeeping” position in certain technology fields. Additionally, some smaller and/or larger regions could represent “multi-technology hubs” due to their diversified research structure and strength in several technology fields. It is argued that the co-location/co-agglomeration of technology-specific research network nodes in specific places determines the birth, growth and decline of research clusters (Maggioni et al., 2007). In view of this, there exists anecdotal evidence from case studies and other empirical contributions, which argue that technology-specific research structures in the ERA have been undergoing significant structural changes since the mid 1990s. In this respect, the restructuring and integration of regions from the NMS and other formerly poor(er) European regions into European technology-specific co-inventor and research networks seem to be crucial. The study addresses these points and contributes with findings on European technology-field-specific research networks. Figure 4.1 shows the conceptual base of the aforementioned aspects and the following empirical analysis.

Moreover, it seems to be difficult, perhaps impossible, to separate (pure) knowledge spillovers from agglomeration and network economies, although several authors have discussed, criticized and finally contributed to the “black box” issue of knowledge transmission (see, e.g., Jaffe et al., 1993; Breschi and Lissoni, 2003, 2006, 2009). The separation between pure knowledge spillovers and semi-compensated knowledge flows that originate from a research collaboration is conceptually impossible, because knowledge sourcing via formal research collaboration linkages may enable both transmission channels (see chapter 2, section 2.1.7).

The European Union’s member states make use of significant public expenditures to support inter-regional long-distance research collaborations in order to push the ERA (see Box 1.1) and to induce coherence of European research activities in a geographic context by coordinating local, inter-regional, national and European research activities. Moreover, policy programs with the aim of strengthening local and regional innovation potentialities have become very popular during recent years. This circumstance is based on the idea that

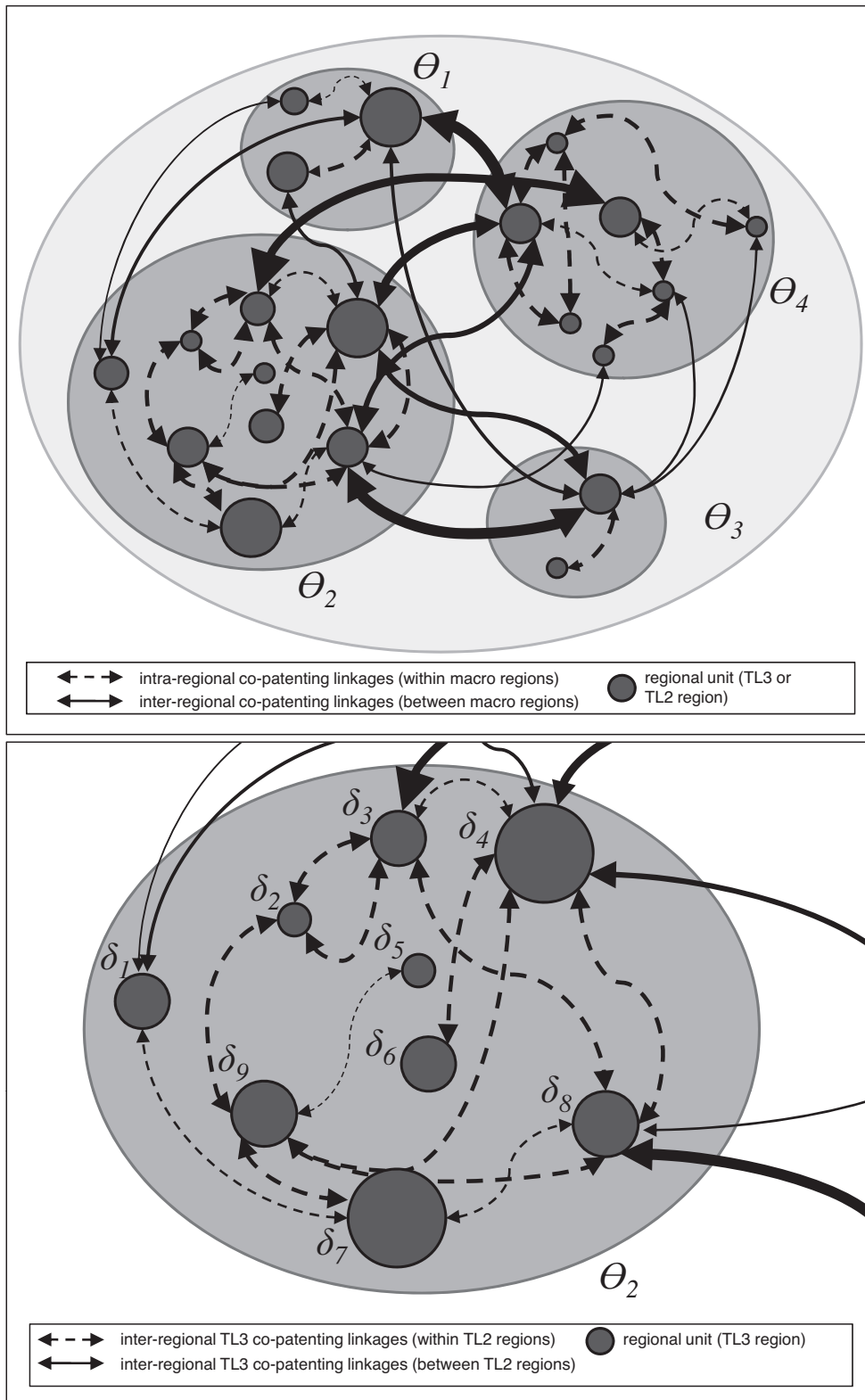


Fig. 4.1. Inter-regional knowledge pipelines and co-patenting network linkages
Source: own illustration.

localized research activities and collaborations induce positive externalities of information and knowledge which are conducive to innovative capacities and regional growth. Additionally, regional programs on spatial clustering and regional networking could strengthen pecuniary externalities and thus improve the attractiveness of research locations. However, there is a significant gap in research on core-periphery structures of patenting networks and the changes in European inter-regional research collaborations in a technological and spatial context.

According to the above-presented issues, section 4.3 tries to find empirical evidence for the following research questions: (i) Is Europe characterized by a significant increase in co-patenting activities and research collaborations between European regions since the 1990s? (ii) Do technology fields differ in their overall network size? (iii) Which regions represent the most essential leaders in technology-specific inter-regional co-patenting activity? (iv) Which regions represent crucial within- and between-network bridges (hubs)? (v) Are European regions “multi-technology network hubs” that are characterized by a diversified technology base? The co-patenting study is related to the theoretical concepts reviewed in chapter 2, section 2.1.7, and contributes to the empirical studies presented in section 2.2.7 (and section 2.2.2).

The chapter is organized as follows. In a first step, the study offers an empirical analysis of spatial interdependence of European patenting activity at the regional level (section 4.2). In a second step, the study proceeds with an in-depth analysis of EPO co-patenting activity (section 4.3). Therefore, the study highlights the development of co-patenting activity with foreign co-inventors since the 1980s at the national level for the EU-25 countries, Switzerland and Norway (section 4.3.4). Moreover, at a more disaggregated level, the study offers a detailed analysis of the structures and dynamics of inter-regional co-patenting networks by technology field (section 4.3.5). Finally, local network statistics are discussed 4.3.6.³⁹³

4.2. Spatial Interdependence of European Patenting Activity

4.2.1. Measuring Spatial Interdependence

4.2.1.1. Explanatory Spatial Data Analysis

Regarding the observed global disparities of European regional patenting activity (chapter 3, section 3.4) and the spatial distribution and strength of identified research clusters (section 3.5), it can be argued that strong research clustering is solely present in a few European regions. Moreover, it seems that these leading innovative places are defined by strong spatial proximity to each other and maybe interdependence. Therefore, it is necessary to determine the strength of spatial interdependence, i.e., the strength and significance of spatial autocorrelation of regional EPO patenting activity by technology field at the TL3 level.

³⁹³ Network analysis has been performed with the Codeplex NodeXL software.

From a methodological point of view, spatial analysis and spatial econometric tools distinguish between the presence of spatial dependence and spatial heterogeneity (Anselin and Florax, 1995; Keilbach, 2000; Andersson and Gråsjö, 2009).³⁹⁴ Spatial dependence is an econometric issue that can be found in almost every data set that contains spatial information. The value of an attribute in one location depends on the value of the attribute in neighboring locations (regions). Measures of spatial dependence challenge this issue by applying global instruments, which means that the presence of (global) spatial dependence is tested for the entire population of observations (Anselin and Florax, 1995; Brunson *et al.*, 1998; Fotheringham *et al.*, 2002). Spatial (inter-)dependence is said to partially depend on measurement problems of regional activity and is in most cases statistically relaxed in regional production functions by allowing for spatial externalities (e.g., spillovers between regions). The following sections especially account for this problem by addressing the treatment, implementation or alternative explanation of spatial dependence regarding research/ patenting activity (Anselin, 1988a; Anselin and Florax, 1995; Andersson and Gråsjö, 2009). A common but serious issue with regional data stems from the fact that economic activities are generally not bounded by administrative borders (the aggregation level may represent the origin of spatial dependence). That being the case, economic activities show inter-regional functional relationships (Anselin, 1988a; Anselin and Florax, 1995). Box 4.1 presents a short definition of spatial interdependence.

The measure of spatial relationships depends crucially on the aggregation level. Thus, social and economic processes are assumed to vary across geographic space, which underlines the idea of changing tastes in preferences, incentives, different administrative characteristics, varying institutions, among other factors. As such, the lack of spatial (global) stability can lead to problems in regressions. In light of this, ESDA and spatial econometric methods have to bridge significant global spatial mechanisms (global interdependence) and local spatial peculiarities (spatial heterogeneity) (Brunson *et al.*, 1998; Fotheringham *et al.*, 2002; Zimmerman, 2003). Moreover, the statistical results are endogenous to aggregation and zoning of spatial units (see section 4.2.1.2) (Keilbach, 2000; Arbia, 2001; ESRI, 2010).³⁹⁵

³⁹⁴ See also Cliff and Ord (1973), Anselin (1988a), de Smith *et al.* (2007) and ESRI (2010).

³⁹⁵ Spatial heterogeneity exists if spatial processes are not uniform and thus not global (Anselin and Florax, 1995; Fingleton *et al.*, 2007).

Box 4.1: Spatial Interdependence and Autocorrelation

Consider three neighboring regions Y_1 , Y_2 and Y_3 that can be aggregated. The regions' economic activities are interrelated by the following spatial mechanisms/process:

$$\begin{aligned} Y_A &= Y_1 + \phi Y_2 \\ Y_B &= Y_3 + (1 - \phi) Y_2 \end{aligned} \quad (4.2.1)$$

The equations demonstrate that the output Y_A and Y_B of the statistical units are interrelated via the spillover parameter ϕ , which influences neighboring regions' output. Accordingly, researchers directly link the presence of spatial dependence (autocorrelation) to regional unit size (aggregation and zonation). Moreover, it is assumed that small spatial units can also crucially influence the output of neighboring regions, although their absolute size seems negligible. Opposed to autocorrelation in common time-series analysis, the highlighted spatial processes are two-dimensional, which means that processes are bi-directional and influence spatial units via spillovers. Recent debates center econometric tools that implement "black boxes" of spatial mechanisms (Keilbach, 2000; Arbia, 2001; Andersson and Gräsjö, 2009).

4.2.1.2. Spatial Analysis and the Modifiable Areal Unit Problem

The "modifiable areal unit problem" (MAUP) is a central issue in the analysis of spatial data (e.g., patent statistics), which are arranged in geographic zones, and where the conclusion depends on the size of the units (Puga, 2010; Arbia and Petrarca, 2010; ESRI, 2010).³⁹⁶ As a consequence, MAUP has to be recognized as a serious problem in geographical economics. Spatial data analyses often involve the usage of aggregated spatial units (i.e., regions). Consequently, the usage of administrative units may represent generally accepted modeling convenience or statistical data collection issues rather than homogeneous regions. On account of that, the spatial units are modifiable or arbitrary and represent artifacts related to the degree of spatial aggregation or the (policy driven) (re-)modification of boundaries. In this respect, administrative regions are inferior in dealing with spatial mechanisms opposed to functional units. The empirical and theoretical problem arises because the statistical results directly depend on the classification of zones. The aggregation of point data into (larger) zones of different size and shape may lead to opposite conclusions. In empirical studies, the MAUP is then a serious source of statistical bias which can radically determine the statistical inference. Consequently, MAUP can induce and change spatial association between two variables (Keilbach, 2000; Arbia, 2001; Arbia and Petrarca, 2010). Although the MAUP has been discussed since the 1950s, it was preliminarily challenged by Openshaw and Taylor (1979) and Openshaw (1984), among others, and is today increasingly applied in regional studies.³⁹⁷ The problem is especially crucial when aggregated data are used for spatial statistics or mapping, in which false interpre-

³⁹⁶ For further discussions and applications related to MAUP see Anselin and Florax (1995), Anselin *et al.* (1996), Keilbach (2000), Arbia *et al.* (2005), Dewhurst and McCann (2007), Puga (2010), Arbia and Petrarca (2010) and Guillain and Le Gallo (2010).

³⁹⁷ Openshaw (1984, 3) concluded that "[...] the areal units (zonal objects) used in many geographical studies are arbitrary, modifiable, and subject to the whims and fancies of whoever is doing, or did, the aggregating."

tations are possible.³⁹⁸ MAUP is directly related to the issue of ecological fallacy/bias. MAUP-based ecological bias enters the analysis (and data) as two separate effects that occur simultaneously. First and foremost, the “scale effect” by MAUP leads to variation in statistical results between different levels of spatial aggregation (NUTS1 vs. NUTS2 vs. NUTS3). Accordingly, statistical association between variables essentially depends on the size of regions. In general, the correlations between observations are assumed to increase with the size of regions (i.e., a loss in variation due to aggregation and averaging). Second, the “zonation effect” represents variation in spatial correlation statistics due to the (re-)grouping of regions into different zones (spatial boundaries) at the same scale of analysis (Arbia *et al.*, 2005; Dewhurst and McCann, 2007). For the European case, this issue is a serious one when applying the standard NUTS classification. The effects from agglomeration economies and the existence of spatial interdependence between regions is endogenous to the size of sub-national administrative areas. To challenge this issue, the analysis has explicitly abandoned the NUTS classification. In this study, all regional data have been recalculated according to the OECD TL3 classification which has several advantages compared to the standard NUTS classification system (see chapter 3, section 3.3). Figure 4.2 illustrates the origin of the MAUP.³⁹⁹

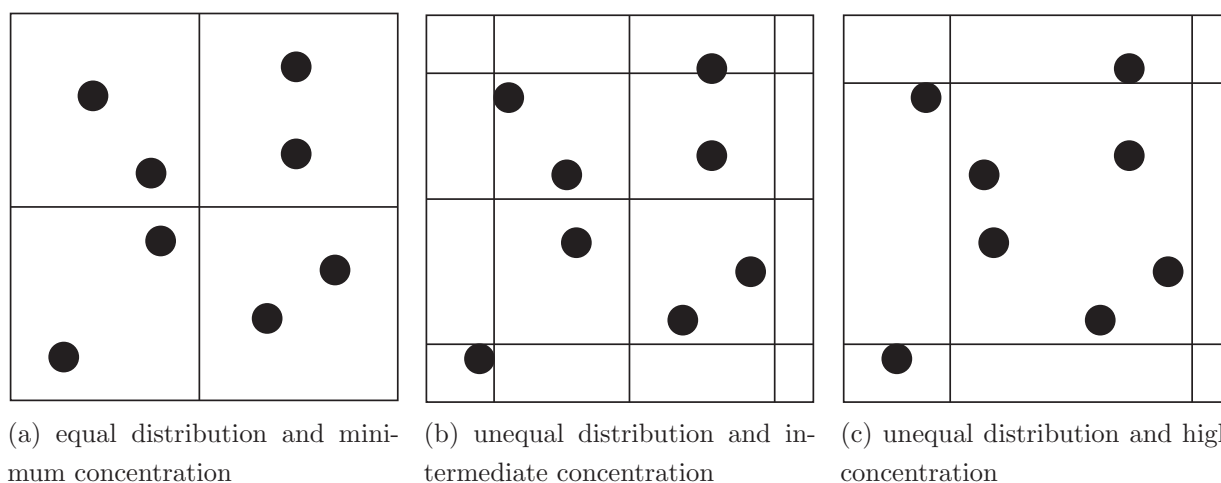


Fig. 4.2. Aggregation, zones and concentration measures
Source: own illustration.

4.2.1.3. Neighborhood Effects, Distances and Weight Matrices

For identifying and analyzing potential spatial interdependence, spatial statistics generally use different ways of implementing spatial proximity and neighboring structures. The main idea of “spatial weights” is to incorporate potential influences from neighboring regions (Arbia, 2001; Scherngell, 2007; Breschi, 2008).⁴⁰⁰ However, the computation and modeling

³⁹⁸ Several fields of science (especially human geography) try to disregard the MAUP when drawing inferences from statistics based on aggregated data.

³⁹⁹ For illustrative examples refer also to Keilbach (2000), Arbia (2001), Dewhurst and McCann (2007) and ESRI (2010).

⁴⁰⁰ For an overview of distance concepts refer to Keilbach (2000), de Smith *et al.* (2007), OECD (2009a) and ESRI (2010).

of spatial weights can be accomplished by using several alternative distance concepts.⁴⁰¹ As such, the assumptions about the underlying “spatial interactions” and “spatial processes” determine the choice of the distance concept.⁴⁰²

Different neighborhood concepts assume different spatial processes of economic activity.⁴⁰³ In general, all listed concepts are tested in order to find the most significant weight/distance concept. The subsequent empirical analysis follows this approach and applies the mentioned distance concepts to the applied spatial EPO patent application database for all 819 European regions (see section 4.2.2). Selected statistical tools from explanatory spatial data analysis (ESDA) are discussed in section 4.2.1.4.

Contiguity based matrices or “polygon contiguity” are a central instrument for modeling spatial interdependence of observations (e.g., regions) (Anselin, 2006; Scherngell, 2007). Polygon contiguity represents the neighboring relationship between two or more regions that either share an administrative boundary (edge) or a common corner (node). In comparison, second- (third-) order contiguity takes into account second- (third-) order neighborhood. The applied contiguity matrices are binary (see 4.2.2).

$$w_{ij} = \begin{cases} 1, & \text{if } i \text{ and } j \text{ share a common border with } (i \neq j) \\ 0, & \text{otherwise.} \end{cases} \quad (4.2.2)$$

W denotes a spatial weighting matrix and element $w_{ij} = 1$ if two spatial units i and j share the same border; $w_{ij} = 0$ if not. W is an $n \times n$ weight matrix, where n represents the overall number of regions. The diagonal elements of W are zero; moreover, region i will never be its own neighbor. Additionally, the weight matrix is symmetric (i.e., i is a neighbor of j , and vice versa).⁴⁰⁴

Interdependence between regions can also be implemented by assuming that regions are surrounded by an identical number of influencing units k (see 4.2.3).

$$w_{ij} = \begin{cases} 1, & \text{if } d_{ij} \leq d_{im_i} \\ 0, & \text{otherwise.} \end{cases} \quad (4.2.3)$$

If k is set to m , then each region has exactly m neighboring regions; these m neighbors are selected in terms of geographical distance, e.g., polygon contiguity distance. For simplification purpose, the m neighbors are assumed to perform an identical influence on region i (row standardized). However, if k is defined exogenously, dense and central units that have many neighbors, e.g., the European core regions, will show only k neighboring regions. Peripheral units, in opposition, will show relatively higher spatial dependence due to the

⁴⁰¹ It is important to note that the choice of the distance concept is highly related to the economic question under analysis.

⁴⁰² Consequently, the measured spatial interaction is endogenous to the ex ante defined weight concept, which means that different weights have to be tested. Finally, the most significant weight should be chosen based upon objective selection criteria, e.g., spatial LM statistics, among others.

⁴⁰³ Table B.5 (appendix) summarizes different ways of dealing with spatial distances and neighboring relations between observations.

⁴⁰⁴ See also Keilbach (2000), de Smith *et al.* (2007), Freund (2008), OECD (2009a) and ESRI (2010) for more details.

ex ante assumption of m neighboring regions, irrespective of their real spatial distance. Accordingly, k -nearest neighbor distance computation produces a weight matrix that artificially increases spatial influence of peripheral regions, which is in opposition to simple first- or second-order contiguity due to ignored variation in feature density (Anselin, 2006; Scherngell, 2007). With regard to this shortcoming, k -density will not be applied in the subsequent analyses.⁴⁰⁵

Furthermore, “distance bands” are common alternatives to contiguity distance (Anselin, 2006; Scherngell, 2007). In implementing distance bands, spatial processes have an ex ante geographically limited range of influence in terms of a cut-off threshold ϑ . Only those regions are incorporated that are located within a predefined spatial distance band ϑ , e.g., kilometers, miles, travel time (see 4.2.4).⁴⁰⁶

$$w_{ij} = \begin{cases} 1, & \text{if } d_{ij} \leq \vartheta \\ 0, & \text{otherwise.} \end{cases} \quad (4.2.4)$$

As most data show distance decay effects of spatial autocorrelation, a common application is to compute and test n th-order distance bands with varying cut-off threshold levels ϑ . Distance decay effects then solely depend on the predefined distance bands’ range ϑ (e.g., 100km, 200km, 300km).

4.2.1.4. Spatial Dependence and Regional Spillovers

Spatial autocorrelation statistics measure the degree of dependency between spatial units. These statistics primarily assume a spatially random distribution of the values under analysis. Then, structures and patterns of spatial dependence are typically depicted from the underlying data. The presence of spatial (auto-)correlation can be addressed by spatial summary statistics that are incorporated in ESDA software environment (ESRI, 2010).

The most popular and widely used measures of spatial interdependence are the Moran’s I and Geary’s C statistic (Arbia, 2001; Anselin, 2007; Guillain and Le Gallo, 2010).⁴⁰⁷ Spatial autocorrelation statistics, such as Moran’s I and Geary’s C , are global indices. They estimate the overall degree of spatial autocorrelation for a population of regions (Anselin, 2007; Guillain and Le Gallo, 2010). Spatial autocorrelation means that neighboring observations of the same phenomenon are correlated. In opposition to time-series autocorrelation, spatial autocorrelation is about proximity (and similarity) in two-dimensional space (latitude, longitude). That being the case, spatial autocorrelation is more complex. The correlation is two-dimensional and bi-directional as observations influence each other. However, the origins and working channels of spatial dependence (and bi-directional spatial processes) in models are not easy to define, as they can originate from, e.g., knowledge spillovers,

⁴⁰⁵ See also de Smith *et al.* (2007), Freund (2008), OECD (2009a) and ESRI (2010) for more details.

⁴⁰⁶ See also Freund (2008), OECD (2009a) and ESRI (2010) for more details.

⁴⁰⁷ Moran’s I is a measure of spatial autocorrelation introduced by Patrick A.P. Moran (1950). It represents a viable alternative to the Theil index, known from concentration studies, although it lacks the decomposability (Brakman *et al.*, 2005). Refer also to Moran (1950), Cliff and Ord (1973), Arbia (1989) and Getis and Ord (1992). For an overview see Keilbach (2000), OECD (2009a) and ESRI (2010).

co-patenting linkages between two regions, or regional labor market effects within large functional areas. Spatial statistics solely take into account the neighboring characteristics of regions (Anselin, 1995; Rey and Montouri, 1999; Fingleton, 2000). Nevertheless, these statistics provide evidence on “global” spatial correlation for a predefined population of regional units, but also for other forms of functional misspecification, e.g., heteroscedasticity (Arbia, 2001; Fingleton *et al.*, 2007). The calculation of spatial dependence depends on information regarding the functional relationship between locations. It requires the definition of a spatial weight matrix that reflects the intensity of regional interdependence in an *ex ante* defined spatial neighborhood; e.g., the distances between neighbors, the lengths of shared regional borders, or whether the regions fall into a predefined directional class such as “north,” “east,” “south” or “west.” Orthodox spatial autocorrelation statistics compare the spatial weights to the covariance relationship at pairs of locations. Spatial autocorrelation that is more positive than expected from random distribution indicates the existence of clustering.⁴⁰⁸ More generally, the presence of such spatial interdependence induces spatial autocorrelation problems in regional statistics and econometric applications. Regression analysis that does not compensate for spatial interdependence maybe suffers from unstable point estimates and unreliable inference (Arbia, 2001). As a consequence, spatial regression models are applied to capture spatial relationships and to avoid such issues. Accordingly, it is appropriate to define spatial dependence as a pivotal source of information rather than something to be simply corrected by spatial tools (Arbia and Petrarca, 2010).⁴⁰⁹ In this respect, spatial statistics help to identify, quantify and understand the spatial nature of economic processes (e.g., patenting activity, regional growth processes) (Anselin, 1995; Rey and Montouri, 1999; Arbia, 2001).

Equation 4.2.5 shows the standard Moran’s I statistic for spatial autocorrelation with $(x_i - \bar{x})$ being the deviation of an attribute for the feature i from its mean value; w_{ij} is the spatial weight between feature i and j with $i \neq j$ and n equals the total number of units (Cliff and Ord, 1973; Anselin, 1995). The coefficient can be standardized (see equation 4.2.7).⁴¹⁰

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^n \sum_{j=1}^n w_{i,j} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (4.2.5)$$

S_0 is the aggregate of the spatial weights (row-standardized) with

$$S_0 = \sum_{i=1}^n \sum_{j=1}^n w_{ij} \quad (4.2.6)$$

⁴⁰⁸ Negative spatial autocorrelation indicates that values of neighboring units are more dissimilar than expected by chance. For an application see, e.g., Caniels (1997) and Guillain and Le Gallo (2010).

⁴⁰⁹ For further details on autocorrelation from co-patenting activity between neighboring regions refer to section 4.3.5.

⁴¹⁰ See also Freund (2008), OECD (2009a) and ESRI (2010).

The z-score for the Moran's I statistic is then

$$z_I = (I - E[I]) / \sqrt{V[I]} \quad (4.2.7)$$

and

$$E[I] = -1/(n - 1); V[I] = E[I^2] - E[I]^2 \quad (4.2.8)$$

Moran's I is determined by each region's value x_i , neighboring units' value x_j , average value \bar{x} of n locations, and the spatial distance between i and j with w_{ij} .⁴¹¹ "Neighboring" is implemented by assuming that spatial units have a non-zero spatial relationship; thus the population interacts by means of W , w_{ij} respectively. For the case of contiguity based distance, w_{ij} represents the spatial weight of contiguity, with $w_{ij} = 0$, if the units are non-contiguous (no common border), and $w_{ij} = 1$ if region i is contiguous to region j . The results of the Moran's I test are essentially based upon the ex ante implemented spatial neighborhood structure. It is argued in spatial statistics that the elements of the underlying spatial weight matrices W are exogenous, non-stochastic and (in most cases) "row-standardized." $S_0 = \sum_i \sum_j w_{i,j}$ is then a standardized weight matrix.⁴¹² However, the obtained Moran's I values have to be interpreted with caution as the implemented (ex ante defined) neighborhood structure determines the measure. A significant and positive Moran's I coefficient indicates that there exists spatial dependence between observations, given the ex ante implemented neighborhood structure. Furthermore, spatial interdependence could originate from spatial pattern and relationships in the data which are not specified in the model (Keilbach, 2000; Freund, 2008; ESRI, 2010).

Box 4.2 summarizes inference issues and additional information regarding Moran's I . The next section presents first statistical results of Moran's I calculations with regard to EPO patent applications at the regional level.

⁴¹¹ $I = z'Wz/z'z$ is a regression coefficient of Wz on z . Note that z denotes the a vector of difference between the variable under analysis and its mean. Wz contains the weighted averages of observed neighborhood values of z for each location (Anselin, 1995, 1999; Fingleton *et al.*, 2007; OECD, 2009a; ESRI, 2010).

⁴¹² In case of n observations by means of row-standardized weights we obtain $\frac{n}{S_0} = 1$.

Box 4.2: Interpreting Moran's I

In order to test for the existence of spatial autocorrelation in regional data the computed Moran's I measure is compared with its theoretical mean (i.e., expected value), which is approximately 0 (no spatial autocorrelation). Generally, negative (positive) values indicate negative (positive) spatial autocorrelation. Moran's I values range between -1 (perfect dispersion/negative spatial autocorrelation) and $+1$ (perfect correlation/positive spatial autocorrelation). A value of 0 indicates a random spatial pattern without statistical dependence. Under the null hypothesis of no global spatial autocorrelation, the expected value of Moran's I is given by $E(I) = -1/(n - 1)$. If Moran's I is larger than its expected value, then the overall distribution of the variable under analysis is characterized by positive spatial autocorrelation. This means that the value of each region i tends to be similar to the values of neighboring regions. If, however, Moran's I is smaller than its expected value, then the distribution exhibits negative spatial autocorrelation. Then, the value of each region i differs significantly from the values of neighboring regions. Finally, Moran's I values can be transformed to z -scores with $z_{I,i} = (I_i - E(I_i))/sd(I_i)$; (standardized) values greater than 1.96 or smaller than -1.96 indicate spatial autocorrelation (e.g., significant at the 5% level) (Anselin, 1995, 2002; Fotheringham *et al.*, 2002; ESRI, 2010).

4.2.2. Spatial Interdependence of Patenting Activity in Europe

The previous analyses in chapter 3 have already illustrated the existence of strong spatial disparities and clustering of patenting activity across the 819 European regions. Based upon the previous theoretical discussion on co-patenting activity (see chapter 2, section 2.1.7), the analysis of inter-regional R&D linkages and research collaborations within co-inventor networks is of central interest. Tests for spatial autocorrelation of EPO patent applications are inevitable as considerable spatial interdependence between European regions seems to exist. Further to this, a serious question centers the origins of potential spatial dependence by means of (pure) knowledge spillovers, knowledge flows via linkages or randomly distributed and unconnected regions with similar technological specialization characteristics.

Table 4.1 highlights the presence and significance of spatial dependence in terms of z -transformed Moran's I values for 51 technology fields.⁴¹³ Regionalized EPO patent data (patent applications by inventor location and priority date) at the level of OECD TL3 regions are used (OECD, 2003, 2006).⁴¹⁴ The patent data are extracted from OECD RegPAT (January 2009) (Maraut *et al.*, 2008; OECD, 2009e). The full description of the underlying database, the raw data and the data extraction processes have been presented in detail in chapter 3, section 3.3.⁴¹⁵

Using ESDA tools, Moran's I values for all technology fields (Schmoch *et al.*, 2003; EUROSTAT, 2009) are calculated for distance bands (kilometers) with varying cut-off distance,

⁴¹³ For a complete overview of abbreviations of all 51 technology field aggregates used in table 4.1 see table B.4 (appendix).

⁴¹⁴ The empirical analysis centers 819 TL3 units (EU-25+CH+NO) as highlighted in table B.3 (appendix).

⁴¹⁵ Spatial autocorrelation analysis has been performed with OpenGeoDA, GeoDA and ArcGIS 9.3.1. environment.

i.e., $d_{ij} \leq \vartheta$. On account of that, table 4.1 presents spatial autocorrelation measures for EPO patent application densities by technology field for the period 2003-2004. Different distance bands (100 to 600 kilometers) are applied.⁴¹⁶

Table 4.1 shows that the technology field aggregates differ by means of standardized z-values of the Moran's I coefficients (see Box 4.2 for an overview), which can be interpreted as evidence for varying global spatial processes. Consequently, it seems that several technology fields exhibit low spatial autocorrelation values and thus weak spatial interdependence; e.g., *TF6 Wood prod.*, *TF2 Tobacco prod.*, *TF12 Paints & varnishes*, *TF41 Watches & clocks*, *TF37 Med. equipment*. Further to this, the high-technology fields *HT1 Aviation* and *HT3 Laser* are characterized by a spatial autocorrelation at a proximate distance, which is related to the fact that these technology fields are highly concentrated in space and generally not surrounded by regions with a similar research activity and intensity.⁴¹⁷

In opposition, several technology fields show strong spatial dependence within the European landscape, which is empirically identified by large distance bands of significant Moran's I values, e.g., *HT6 Microorgan. & Genetics*, *HT4 Semiconductors*, *HT2 Computer & office mach.*, *SUM hightech*, *TF35 Signal transm. & telecom.*, *TF23 Agricul. & forestry machinery*, *TF10 Basic chemicals* or even *TF3 Textiles*. However, it has to be noted that these technology fields are generally characterized by a larger number of patent applications; moreover, most regions are surrounded by other regions with similar patent densities. As the Moran's I calculations are related to fractionally collected patent data (patent densities), the findings presented in table 4.1 point to the same direction as the results of the patent citation studies of, e.g., Scherngell (2007) and Paci and Usai (2009). These studies showed that Europe features inter-regional knowledge exchange, i.e., patent citations, with an average distance band of around 500-600 kilometers, e.g., in the high-technology field *Computing*. Their results, although based upon citation data, are very similar to the ones presented in this study, as spatial autocorrelation shows up to 600-700 kilometers.

Accordingly, spatial interdependence is present in fractionally counted EPO patent applications at the regional TL3 level, although Moran's I values vary remarkably across technology fields. However, the observed spatial interdependence of EPO patenting activity could originate from several factors that are simply absent in fractionally counted patent data. First of all, European regions could be considered to be isolated research units, which by chance exhibit similar patenting structures and patent intensities due to similar specialization, which would be measured by spatial autocorrelation tests. However, European regions could also be considered being part of larger functional areas, interconnected via co-patenting linkages (i.e., co-patenting linkages in inter-regional research networks), which would show up in terms of significant and positive Moran's I coefficients. That being the case, spatial interaction between and within regions by means of EPO patent co-applications, i.e., patent statistics as relational data, has to be analyzed and explained. In light of this, the following analyses particularly place emphasis on inter-regional co-patenting activities by technology field. The hypothesis is that co-patenting

⁴¹⁶ Contiguity distance was additionally computed; however, the study only presents results based upon the Euclidean distance concept with varying threshold distance ϑ .

⁴¹⁷ Only the highest z-value is presented in table 4.1 for each technology field. See Scherngell (2007) for a similar approach.

Table 4.1. Moran's I z-scores by technology field and threshold ϑ

Technology field	$\vartheta=200$	$\vartheta=300$	$\vartheta=400$	$\vartheta=500$	$\vartheta=600$
SUM 44TF			49,05***		
TF1 Food, beverages				13,76***	
TF2 Tobacco prod.	4,75***				
TF3 Textiles					14,52***
TF4 Wearing, apparel					7,31***
TF5 Leather articles					7,48***
TF6 Wood prod.		11,73***			
TF7 Paper			16,24***		
TF9 Petrol. prod., nucl. fuel					9,68***
TF10 Basic chemicals					19,19***
TF11 Pesticides, agrochem. prod.			4,24***		
TF12 Paints, varnishes	7,90***				
TF13 Pharmaceuticals			8,99***		
TF14 Soaps, detergents		4,13***			
TF15 Other chemicals					11,87***
TF16 Man-made fibre					3,34***
TF17 Rubber, plastic prod.				31,99***	
TF18 Non-metal mineral prod.				34,20***	
TF19 Basic metals					20,41***
TF20 Fabric. metal prod.					38,54***
TF21 Energy machinery			30,65***		
TF22 Nonspec. machinery				42,17***	
TF23 Agricul., forestry machinery					14,01***
TF24 Machine tools			35,68***		
TF25 Spec. purp. machinery				34,42***	
TF26 Weapons, ammunition					5,06***
TF27 Domestic appliances			30,82***		
TF28 Office mach., computers				16,13***	
TF29 Electric , generators		19,61***			
TF30 Elec. distr. contr. wire cable			27,27***		
TF31 Accumulators, battery			12,14***		
TF32 Lighting equipment				11,08***	
TF33 Other electr. equip.					20,41***
TF34 Electr. components				14,68***	
TF35 Signal transm., telecom.					18,66***
TF36 TV, radio receiv., audio			9,31***		
TF37 Med. equipment	26,86***				
TF38 Measuring instruments			28,34***		
TF39 Ind. proc. contr. equip.			27,46***		
TF40 Optical instruments			16,01***		
TF41 Watches, clocks	17,44***				
TF42 Motor vehicles			30,98***		
TF43 Other transp. equip.					16,46***
TF44 Furniture consum. good			27,51***		
SUM Hightech					18,52***
HT2 Computer, office mach.			16,44***		
HT1 Aviation	9,12***				
HT3 Laser		5,54***			
HT4 Semiconductors				9,96***	
HT5 Communication					15,95***
HT6 Microorgan., genetics					10,55***

Source: own estimations. Notes: Moran's I z-scores for EPO patent applications by technology field (year 2000-2004) and varying threshold distance, ϑ , in kilometers; significance level: ***significant at 0.01 level.

networks are highly concentrated in the European landscape of regions. Nevertheless, it is also said that there is a general tendency towards long-distance research collaboration linkages today (Maggioni and Uberti, 2009; Powell and Giannella, 2010). The more these network linkages are crossing regional borders, connecting neighboring regions, the higher is the expected spatial autocorrelation (see section 2.1.7 for a theoretical discussion).

Finally, from a normative and political economy point of view, increasing co-patenting activity could be interpreted as statistical evidence for raising efficiency and effectiveness of the ERA, as research co-operations are increasingly dispersed across the 819 European TL3 regions. Regarding this issue, conventional knowledge production function estimation would identify inter-regional co-patenting linkages in terms of positive spatial autocorrelation. Therefore, the subsequent analysis prefers an explicit analysis of European co-patenting structures at the regional level.

4.3. European Co-Patenting Networks, Inter-Regional Linkages and Foreign Co-Inventors

4.3.1. International versus Inter-Regional Co-Patenting Linkages

As has been reported in the previous section, patenting activity shows significant and positive spatial dependence, meaning that the distribution of research activity is not only highly skewed in geographic space (chapter 3), but also that highly innovative regions are surrounded by neighboring innovative regions as highlighted by spatial autocorrelation statistics (chapter 4, section 4.2). However, it can be argued that the observed spatial interdependence of patenting activity originates, *inter alia*, from border-crossing research activities. That being the case, significant increases of foreign co-inventorship activities, *i.e.*, international co-patenting activities, could be interpreted as a tendency away from sole proximate distance collaborations, meaning that national boundaries in Europe are vanishing. Such a development could indicate an ongoing integration of European countries and their regions into European technology-specific co-inventor networks.

In general, co-inventions across countries, in terms of co-patents with multiple inventors, are today quite frequent as has been addressed in the introductory chapter. Several studies have picked up this development (Balconi *et al.*, 2004; Belitz *et al.*, 2006). Glänzel *et al.* (2003), *e.g.*, found that around 30% of all biotechnology EPO patent applications are co-inventions (see also Frietsch and Schmoch, 2006; Fraunhofer, 2009; Powell and Giannella, 2010).⁴¹⁸ Frietsch and Schmoch (2006) showed that cross-national technology production has increased considerably, although important co-inventors are foremost located in the United States and the European Member States. Similarly, Maggioni and Uberti (2009) argued that co-patenting activity is quite frequent in the group of the five largest European

⁴¹⁸ Glänzel *et al.* (2003) identified 12,412 co-invented patent applications out of approximately 45,000 EPO patent applications in biotechnology for the period 1992 to 2001. However, ownership structures are not that inter-regional (inter-national); *i.e.*, 3,926 applications out of 45,000 between 1992 and 2001.

countries.⁴¹⁹ Although there is an increasing tendency towards joint ownership and joint exploitation of research output in many technology fields, the overall share of co-assigned EPO patents is still relatively small in several technology fields (Glänzel *et al.*, 2003).⁴²⁰ From an industrial organization point of view, increasing foreign co-patenting activity may originate from intensified R&D fragmentation and offshoring of R&D tasks (Verspagen and Schoenmakers, 2004; D'Agostino *et al.*, 2010). The applied data indeed support the hypothesis that industrial R&D activities, i.e., co-patenting activities, are increasingly globalized.

Unfortunately, it seems rather impossible to identify and differentiate between the motives and incentives based upon the available co-patenting data, i.e., (i) cost reduction incentives of agents that lead to increasing shares of patents with foreign co-inventors; (ii) co-patenting that is associated with firms' target to enter markets; (iii) the incentives to access "knowledge hot spots" and forefront knowledge elsewhere (Frietsch and Schmoch, 2006; Maggioni and Uberti, 2009). Accordingly, co-patenting analysis cannot unfold if increasing co-patenting activities with foreign researchers mainly occur due to cost-oriented global sourcing strategies, i.e., cost-based R&D offshoring (and/or offshore outsourcing) or simply due to companies' demand for scarce research excellence that is localized in a few European regions. Moreover, it is impossible in this study to verify the direction of knowledge flows as the millions of existing relations represent undirected linkages.

4.3.2. The Relational Database

4.3.2.1. Regional Classification and Raw Data

The regional network analysis in section 4.3.5 is, again, based upon OECD RegPAT (January 2009) raw data (Maraut *et al.*, 2008; OECD, 2009e). The RegPAT files have been implemented into a workable mySQL database (see appendix) in order to generate "relational" data from EPO patent applications (see section 4.3.3 for methodological issues). The analysis is exclusively related to the geography of European co-inventor networks within and between European regions, which consequentially prefers EPO to PCT and national patent applications due to an explicitly defined macro area. Table B.3 in the appendix summarizes the spatial classification and structure. Patents have been incorporated according to the priority year (also mentioned in the patent document).⁴²¹

For the co-inventorship network analysis of large patent databases, the NUTS3 level generally represents the most detailed and available regionalization level for European member

⁴¹⁹ 30,000 out of 170,900 patents were analyzed in their study. Their sample consists of five countries at the NUTS2 level, in which only those co-patents are analyzed if regions i and j belong to different countries.

⁴²⁰ Co-assignment indicates a joint ownership of an invention, i.e., an EPO patent, and normally represents a joint exploitation by two or more agents/ organizations.

⁴²¹ A serious problem, however, in geographical economics and the geography of innovation literature is the definition and usage of spatial units (see also section 3.3). For modeling inventor networks, two units that are in general called a place, a region or country are needed. However, the difficulties with regional classifications are rather unnoticed. It seems that the "concept of the region" is similarly fuzzy as the "concept of the industry." Both concepts allow some intermediate and flexible levels of aggregation and are thus not easy to define.

states. The classification also simplifies comparison with other studies. However, as the NUTS3 units widely differ in their overall size (areal size), population and number across the European countries, inhomogeneity of regional units and strong commuting between very small NUTS3 units represent central issues (Paas and Schlitte, 2008; Hoekman *et al.*, 2009).⁴²² To challenge this problem, the NUTS classification is abandoned in favor of the OECD TL3 classification as the general territorial concept for counting inter-regional co-inventor linkages. The TL3 classification is considered to be more homogenous and to offer additional advantages for relational data analysis. Moreover, the spatial range of the extracted inter-regional TL3 linkages is analyzed by aggregating from TL3 to TL2 units. Some of the inter-regional TL3 co-patenting linkages disappear due to aggregation as they are transformed from inter- to intra-regional linkages. This happens when connected regions are located within the same larger spatial aggregate. The extracted co-inventor linkages are also aggregated to spatial units larger than TL2, i.e., to the OECD TL1 level (nation state level). Section 4.3.3.1 summarizes the methodology and discusses the aggregation of inter-regional linkages in more detail.⁴²³

As a result of the above mentioned issues, the developed relational database in this study focuses on 819 TL3 regions (846 units including extra territorial areas) within a group of more aggregated 184 TL2 regions (211 units including extra territorial areas) that form the European landscape of the EU-25 and 45 TL3 units in Norway (19 NUTS3) and Switzerland (26 NUTS3) (see appendix, table B.3).⁴²⁴ The TL3 regions represent the population for generating relational data, i.e., co-patenting linkages between regions at different levels of aggregation (i.e., at the TL3, TL2 and TL1 level), which represent the network nodes.⁴²⁵ Every EPO patent application leaves a paper trail in the form of a patent document.⁴²⁶

4.3.2.2. From IPC to Technology Field Aggregates

The analysis of co-patenting activity separates between various technology field aggregates. This technologically disaggregated view offers the possibility to draw unbiased conclusions with respect to major regional differences in technological specialization and the spatial

⁴²² Accordingly, the NUTS3 classification cannot be used to generate relational data. Germany, e.g., consists according to the NUTS3 classification of 439 units, whereas the United Kingdom only contains 133 NUTS3 regions. Thus, the NUTS3 level would essentially overweight the overall and unique number of inter-regional research collaboration linkages of German regions and artificially increase the network size as the size of the network is endogenous to the absolute number of regions.

⁴²³ Furthermore, the aggregation is useful as it addresses (includes) potential labor market effects such as commuting of inventors.

⁴²⁴ Switzerland and Norway are included to avoid “black holes” in the network structure. However, Croatia, Romania and Liechtenstein are excluded due to data constraints and issues relating to the spatial classification system.

⁴²⁵ The empirical results have been illustrated in individual co-inventorship network graphs at the TL3, TL2 and TL1 level and are available upon request.

⁴²⁶ Accordingly, the number of analyzed and cross-checked relationships is massive. The data generation process has taken into account all possible inter-regional (unique) relations for the entire population of 819 European regions in 43 technology fields and 10 years (periods 1990-1994 and 2000-2004). Therefore, the database queries have analyzed potential 153,697,050.00 unique relations at the TL3 level and potential 9,526,650.00 relations at the TL2 level. If intra-regional linkages are included the numbers change to (i) 153,878,940.00 TL3 potential relations and (ii) 9,572,015.00 TL2 relations.

distribution of co-patenting networks. According to this perspective, there exist major differences across technology fields in terms of the level of international collaboration between European regions. Aggregation and matching of the *International Patent Classification* (IPC) and the technology field classification is accomplished in this project by application of the *ISI-SPRU-OST-concordance*.⁴²⁷

4.3.3. The Research Methodology

4.3.3.1. Calculating Co-Patenting Network Linkages

The relational EPO patent database builds upon several interlinked data files, which include 1,829,807 EPO patent applications from 1977 until 2005 (by priority date). Each European inventor and co-inventor (inventor address information) is first assigned to a specific TL3 region and the respective larger aggregate, i.e., TL2 (macro region) and TL1 (country). The central agents are inventors, whose postal address, which is in most cases their work place location, can be used to determine their location in geographic space (TL3 ID) (Hoekman *et al.*, 2009; Paci and Usai, 2009; Fornahl and Brenner, 2009). However, the study does not explicitly consider or visualize co-patenting networks between individuals. It makes use of relational data (between individuals) and transforms this information to the regional level, but maintaining that behind the regional co-patenting network lies the network of individual researchers (Balconi *et al.*, 2004; Paci and Usai, 2009; Hoekman *et al.*, 2010). The inter-regional linkages result from the absolute number of EPO patent applications on which inventors of different regions had worked together (attribute of co-inventorship). Accordingly, inventor linkages can be regarded as some kind of knowledge relation (Balconi *et al.*, 2004). Furthermore, the spatial co-patenting networks are quasi weighted ones, meaning that an inter-regional linkage between two different spatial units has a weight referring to the overall number of co-patenting linkages (Balconi *et al.*, 2004; Maggioni and Uberti, 2009). Consequently, the extraction process has generated networks based on European TL3 regions, larger TL2 regions and countries (TL1), in which the intensity of inter-regional relationships and collaborations is reflected by the number of inter-regional co-patenting linkages that result from co-invented EPO patent applications. Figure A.37 (appendix) illustrates the data extraction process and figure 4.3 below shows two examples. Additionally, the IPC information from patent applications is used for exploring co-patenting networks for different technology field aggregates.⁴²⁸ The patent applications are selected on the basis of “full counting,” meaning that each inter-regional co-inventor pair, i.e., inter-regional TL3 region network linkage, is counted as an inter-regional co-inventor linkage or inter-regional research collaboration that ended with a patent application at the EPO. Patent co-applications which contain multiple inventors from a single TL3 region are excluded as the analysis solely emphasizes inter-regional collaboration activities between European TL3 regions and their larger spatial aggregates (TL2 and TL1). Accordingly, the EPO patent applications (unique ID) have to contain at

⁴²⁷ Fraunhofer ISI, Karlsruhe, Germany, Observatoire des Sciences et des Techniques (OST), Paris, France and SPRU, University of Sussex, Brighton, UK (Schmoch *et al.*, 2003). See chapter 3, section 3.3 for more details.

⁴²⁸ The overall number of EPO patent applications between 1977 and 2005 with more than one inventor is 672,432. However, only the linkages that exist between European regions are incorporated.

least two inventors ($m > 1$) from at least two TL3 regions ($n > 1$). Pairs of inter-regional linkages have been extracted step-by-step for every patent application, taking the spatial ID as main reference.⁴²⁹ Contrary to several existing studies, this study additionally analyzes inter-regional co-patenting linkages that happen within the same country.⁴³⁰ Maggioni and Uberti (2009), in comparison, focused only on inter-regional linkages between European countries as they explicitly examined international knowledge flows, although arguing that co-patenting is mainly a national phenomenon. Hence, research linkages are extracted and classified into three categories in the following analyses: (i) inter-regional TL3 co-patenting linkages within the same TL2 region (and within the same country (TL1)); (ii) inter-regional TL3 co-patenting linkages between two TL2 regions within the same country (TL1); (iii) inter-regional TL3 co-patenting linkages between two TL2 macro regions between two countries (TL1). Accordingly, different types of borders are classified: regional borders within countries and regional borders between countries. A significant change in the structure (share) of these categories may indicate that the European research landscape is characterized by significant changes regarding the integration of regions and the dispersion of co-patenting networks.⁴³¹ The subsequent graphs in figure 4.3 show two examples of research collaborations and the data extraction process applied in this study. The first graph represents an EPO patent co-application from seven inventors (δ_m) who are located in four different regions (θ_n) but within the same country. The overall number of extracted linkages is 21. The second graph in the figure shows the same regional borders; however, the national border-line has changed and four linkages are now of international type. Co-inventor networks can vary in five parameters: (i) the accumulated knowledge and the research competence of each region, (ii) the distance between the network regions, (iii) the general connectivity of regions in the networks, (iv) the structural change of regions in the network, and (v) the trajectory of the network structure (Ejeremo and Karlsson, 2004, 2006; Powell and Giannella, 2010).

Since patent data show annual fluctuations, especially in less populated and backward regions of Europe, the study focuses on co-patenting linkages for longer periods, i.e., 1990-1994 and 2000-2004. The overall number of extracted inter-regional inventor linkages from EPO co-patents is 336,302 (1990-1994) and 755,374 (2000-2004).⁴³² The co-patenting study focuses on technology-specific linkages. It seems senseless to analyze linkages and network structures of the overall aggregate (all IPC codes), because this would connect almost all regions and reduce transparency.

⁴²⁹ As such, linkages that happen between two or more inventors ($m > 1$) within one TL3 region ($n = 1$) are excluded.

⁴³⁰ According to Maggioni and Uberti (2009), 10% of all co-patenting is international and 90% is intra-national. This thesis comes to similar results.

⁴³¹ It is essential to note, that the extraction process solely focused on the number of linkages but not the number of patent IDs. Accordingly, only linkages between European regions are counted. Moreover, linkages have also been counted if the patent applications additionally included an extra-European inventor (e.g., from the US, Japan or somewhere else outside the EU).

⁴³² However, these numbers include multiple counting due to partially overlapping technology fields (Schmoch *et al.*, 2003).

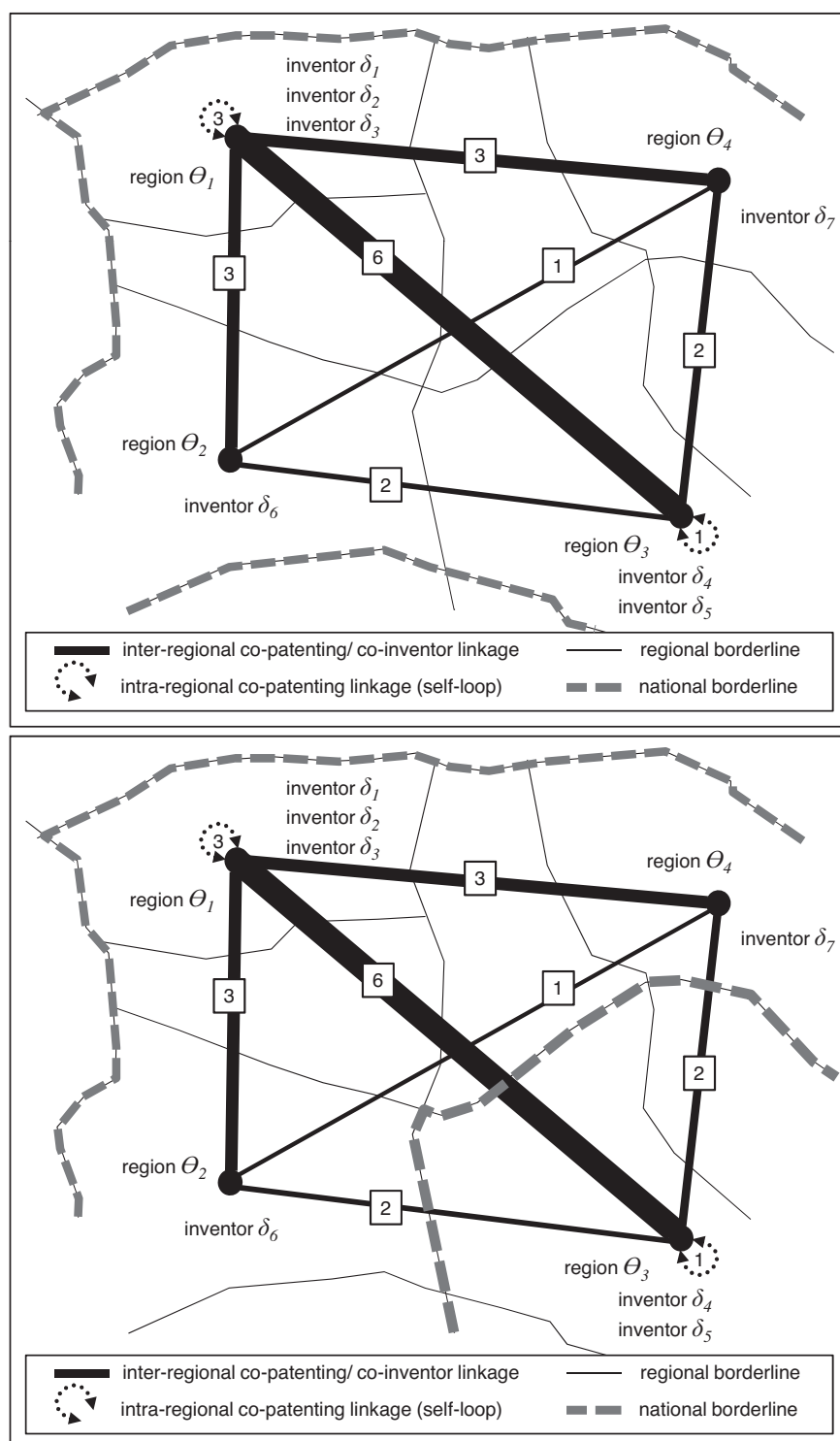


Fig. 4.3. Inter-regional co-patenting network linkages

Source: own illustration. *Notes:* Example shows the construction of undirected co-inventor linkages from an EPO patent application; the patent document contains 7 co-inventors (unique inventor-IDs; inventors δ_1 , δ_2 , δ_3 , δ_4 , δ_5 , δ_6 and δ_7) located in 4 regions θ_1 , θ_2 , θ_3 and θ_4 . A total number of 17 undirected inter-regional and 4 intra-regional linkages (self-loops) between the 7 inventors are extracted; the patent document contains 6 unique inter-regional linkages ($\theta_1\theta_2$, $\theta_1\theta_3$, $\theta_1\theta_4$, $\theta_2\theta_3$, $\theta_2\theta_4$, $\theta_3\theta_4$). Accordingly, the EPO patent application contains 21 linkages; 0 of them are international. In the second figure 10 linkages are international.

4.3.3.2. Measuring Network Centralities of Regions

Besides global network statistics, local statistics are additionally of central interest, i.e., the “network centrality” and “connection” of European regional units by technology field. To understand the complexity and dynamics of industries and their underlying co-inventor networks, the position and centrality of actors, respectively regions, within the networks have to be evaluated. For that reason, local centrality statistics (and rankings) are presented in the following. The agents are EPO inventors and their work place location is used to identify their geographic position within complex inter-regional co-inventor networks (TL3 and TL2 regions). Using this information, networks between European regions are produced. The intensity of inter-regional relationships (research collaborations) is reflected by the number of EPO co-patents (co-applications). Moreover, the TL3 level was chosen to unfold potential spatial heterogeneity for two reasons: (i) some TL3 regions simply do not innovate at all; this leads to a serious bias when aggregating to a larger spatial level (averaging process) as large units contain regions that are not active in inter-regional co-patenting networks; (ii) some regions are not connected to co-inventor networks during the whole period although they exhibit EPO patent applications; however, they represent totally isolated units. Accordingly, the common and well-known national co-patenting studies (Belitz *et al.*, 2006; Frietsch and Schmoch, 2006; Fraunhofer, 2009) are determined by a severe loss of information and, maybe, an *ex ante* bias in the calculation of linkages at the aggregated level (e.g., NUTS1, NUTS2). Nevertheless, a highly skewed distribution of inter-regional inventor linkages within and between countries is generally observed. As a consequence, the sole focus on international (aggregated) co-patenting linkages would cause a severe loss of specificity. Moreover, countries differ tremendously in size compared to the rather homogenous regional TL3 classification. The importance of regions within co-patenting networks is empirically challenged by calculating “co-inventor network centrality indices” (Maggioni and Uberti, 2009). From a conceptual perspective, centrality indices normally measure how central an agent is positioned in a “scale-free network” or “ego network” (Schintler *et al.*, 2006; Blum, 2008; Bergman, 2009). Scale-free networks are networks whose degree distributions follow a power law (at least asymptotically). As it is the case with almost all technological and economic systems that are characterized by such power law distributions, the most essential attribute of scale-free networks is the relative importance of nodes (regions). Especially those regions are of great interest, which exhibit a degree centrality that greatly exceeds the average centrality of regions in the network. The most central regions in terms of degree centrality are often labeled “network hubs” because they are connected to many others. Measuring the “network location” then means to calculate the centrality of the region in relational space. The various centrality measures enable insights into the differing roles and groupings within spatially organized networks. From a “core-periphery” perspective, as has been theoretically discussed in chapter 2 (sections 2.1.6.7 and 2.1.7.5), it is essential to explore the “hub-and-spoke structure” of technology fields. Within graph theory and network analysis, various centrality measures have been proposed to determine the relative importance of a region, which are briefly summarized in the following (Maggioni and Uberti, 2009).⁴³³

⁴³³ Centrality indices and network graphs are computed in this study by application of the software “Codeplex NodeXL (2009-2011).” See Hansen *et al.* (2009) for a technical overview.

“Degree centrality” is a very simple centrality index and it is used as a standard measure in network and graph theory. Network nodes (i.e., regions) which have more ties to other nodes may obtain an advantageous position. Because these regions have many ties, they may have alternative ways to satisfy informational or commodity needs. Hence, such regions are less dependent on a few neighbors. Basically, the degree of a region in a spatial network is then defined as the number of unique linkages to other regions (Maggioni and Uberti, 2009; Hansen *et al.*, 2009). Based on this measure, the activity of a region in an inter-regional research network can be evaluated. In order to calculate a standardized score, each value is divided by $n - 1$ (with n being the overall number of regions in the network). In case of undirected data, regions may differ from one another only in their number of inter-regional linkages. Degree centrality is defined and used in this study for measuring the embeddedness of European regions into inter-regional co-patenting networks by taking the number of linkages (edges) of every spatial unit (TL2 and TL3 region). The degree centrality of a region then represents its popularity within the network with $C_D(\kappa) = degree(\kappa)/(n - 1)$. Accordingly, degree centrality can be interpreted as the likelihood that a region (and its agents) makes contact with what is flowing through the research network by means of the linkages to immediate vicinity (Hansen *et al.*, 2009). Based upon co-patenting information, undirected degree centrality measures are used in this study to explore the structure of the networks.

Besides the importance of regions in a network by means of their number of (unique) linkages to other regions (i.e., degree centrality), “betweenness centrality” represents another network measure that indicates to what extent regions occur on the shortest paths between all other regions (Lobo and Strumsky, 2008; Hansen *et al.*, 2009). Generally, the interaction (i.e., flows and linkages) between two regions, which are not directly connected, might depend on a third region which is on the path between the two. In view of this, it might be possible that co-patenting is controlled by the third one. Betweenness centrality explores the bridge-function of regions in co-patenting networks. Therefore, the mathematical algorithm calculates the position of each region within the inter-regional research network. It then illustrates to what extent informational flows exchanged in the network, i.e., knowledge flows via co-patenting linkages, will likely pass by a certain region or not due to its bridge-function. This centrality is then calculated as the ratio of all geodesics between pairs of regions which run through each region. The betweenness measure $C_B(\kappa) = \sum_{x \neq \kappa \neq y \in \kappa} \phi_{xy}(\kappa)/\phi_{xy}$ reflects how often a region is positioned on the geodesics between the other regions of the network. The geodesic distance is the length of the shortest path between two connected regions (x, y) .⁴³⁴ Accordingly, from an economic point of view, regions that are characterized by a high betweenness centrality have greater influence over what flows in the network or not (Lobo and Strumsky, 2008; Hansen *et al.*, 2009).

Finally, network density $d_{i,t,TF}$ with $d_{i,t,TF} = [l_{i,t,TF}]/[n_{i,t,TF}(n_{i,t,TF} - 1)]$ is defined as the number of existing linkages $l_{i,t,TF}$ with region i in a population of n regions in a technology field (TF) in year t , divided by the maximum $n_{i,t,TF}(n_{i,t,TF} - 1)$ number of linkages between

⁴³⁴ First, all shortest paths ϕ_{xy} between each pair of vertices (x,y) have to be computed. Then, the fraction of the shortest paths ϕ that pass through the region under analysis (here, region κ) has to be calculated. Finally, this fraction has to be summed up over all pairs of vertices (x,y) .

regions. $d_{i,t,TF}$ increases with the density of the inter-regional network (Wilhelmsson, 2009; Hansen *et al.*, 2009).

4.3.4. Foreign Co-Inventors and Cross-Country Research Collaborations in Europe

First and foremost, co-patenting activity can be analyzed in terms of absolute and relative numbers. Therefore, the absolute numbers and shares of EPO patent applications with foreign co-inventors are illustrated in the following.

Figure 4.4 shows that the absolute number of EPO patents by country with foreign co-inventors has increased tremendously for nearly all European countries since the early 1980s (extra European countries are reported in the appendix). With respect to absolute numbers, Germany, France and the UK represent the countries with the largest numbers of EPO patent applications with foreign co-inventors. In 2004, the number is eight times higher compared to the 1980s for Germany and four times higher for France and the UK. Similarly, a tremendous increase can be identified in Switzerland, the Netherlands, Belgium, Italy, Sweden and Austria.⁴³⁵

Figure 4.5 shows the numbers of EPO patent applications with foreign co-inventors for Eastern European countries, especially with focus on the NMS. A strong increase of foreign co-inventor activity is especially identified in the Czech Republic, Hungary, Poland and Slovenia. Interestingly, a similarly strong increase can be identified for the Slovak Republic, Latvia, Romania and Croatia since the 1990s. Malta, Estonia, Bulgaria, Cyprus and Lithuania only show small numbers. However, it is essential to note that these are absolute values which are not corrected for country size.

In addition, the figures A.38 and A.39 (appendix) present relative positions; i.e., EPO patent applications with foreign co-inventors as a share of overall patenting activity by country. Belgium, Luxembourg, Switzerland, Portugal, Norway, Ireland, Greece and Austria are the countries with the highest shares (see also Frietsch and Schmoch, 2006). However, Greece and Portugal show high variance (volatility) due to their rather small absolute numbers of EPO patent applications and backward stage of development in research activities. In sharp contrast, countries such as Italy, Sweden, Germany, Denmark, the Netherlands and the UK are not the leading countries in terms of relative co-patenting activity, although they are leading in absolute numbers. Nevertheless, it can be summarized that all European countries show a significant increase in numbers and shares of foreign co-patenting activity.

The case of the NMS shows some similarity to Portugal and Greece (see figure A.39, appendix). The graphs unveil a strong variance due to the very small but continuously increasing amount of patents with foreign co-inventors. Poland is the only country in the NMS group that shows an increase in foreign co-patenting activity between 1980 and 1995 and, on average, a decline in the share of patents with foreign co-inventors after 1995, which means that national EPO patenting is increasingly dominating overall research activities.

⁴³⁵ A similar development is demonstrated for Northern and Southern European countries in the graphs of figure 4.4.

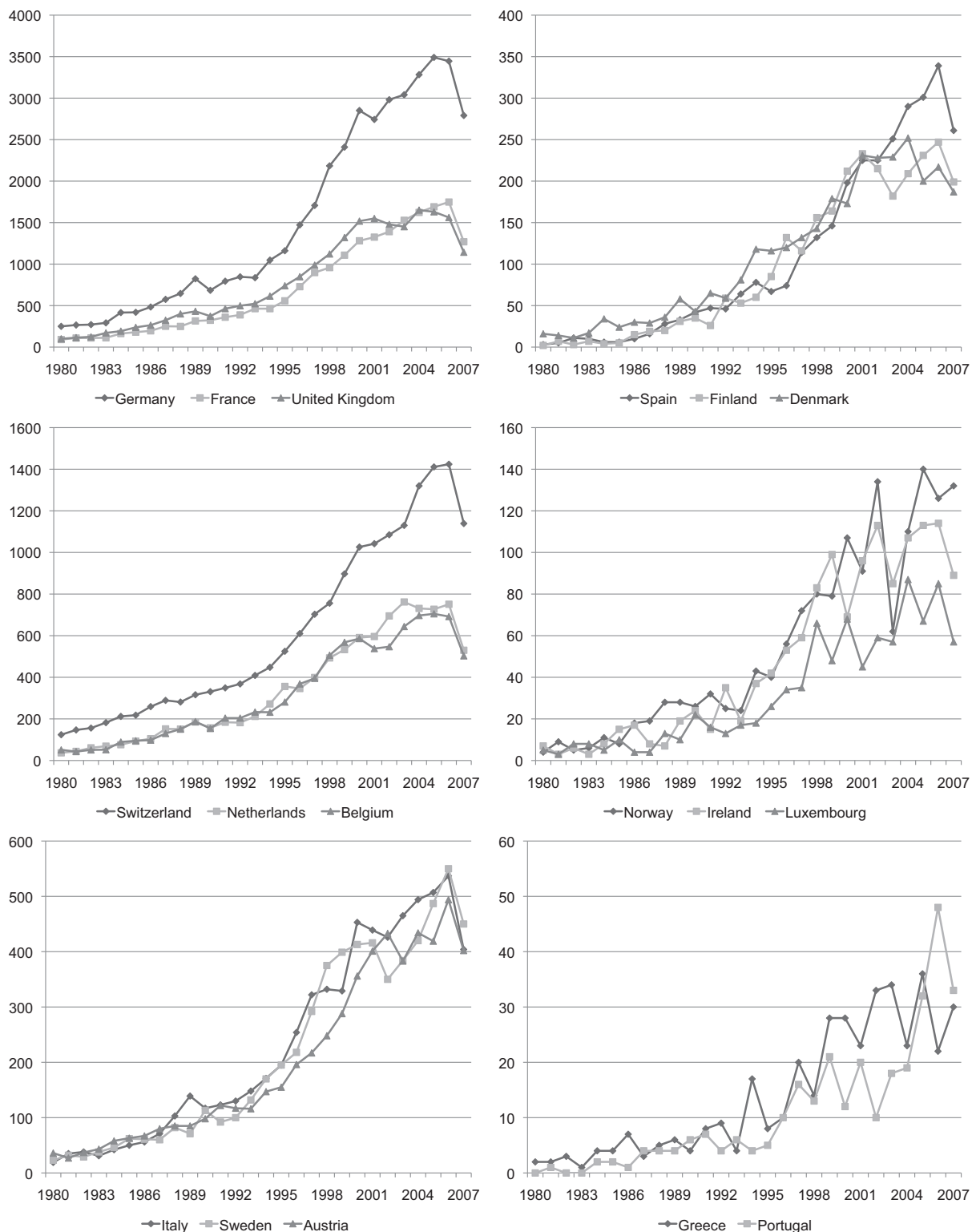


Fig. 4.4. Number of EPO patents with foreign co-inventors by country (1)

Source: own illustration. *Notes:* Number of EPO patents with foreign co-inventors by country since 1980; total co-operation with abroad; EU-15 countries, CH, NO; data extracted from OECD RegPAT (January 2009) and OECD (2009d); fractional counts.

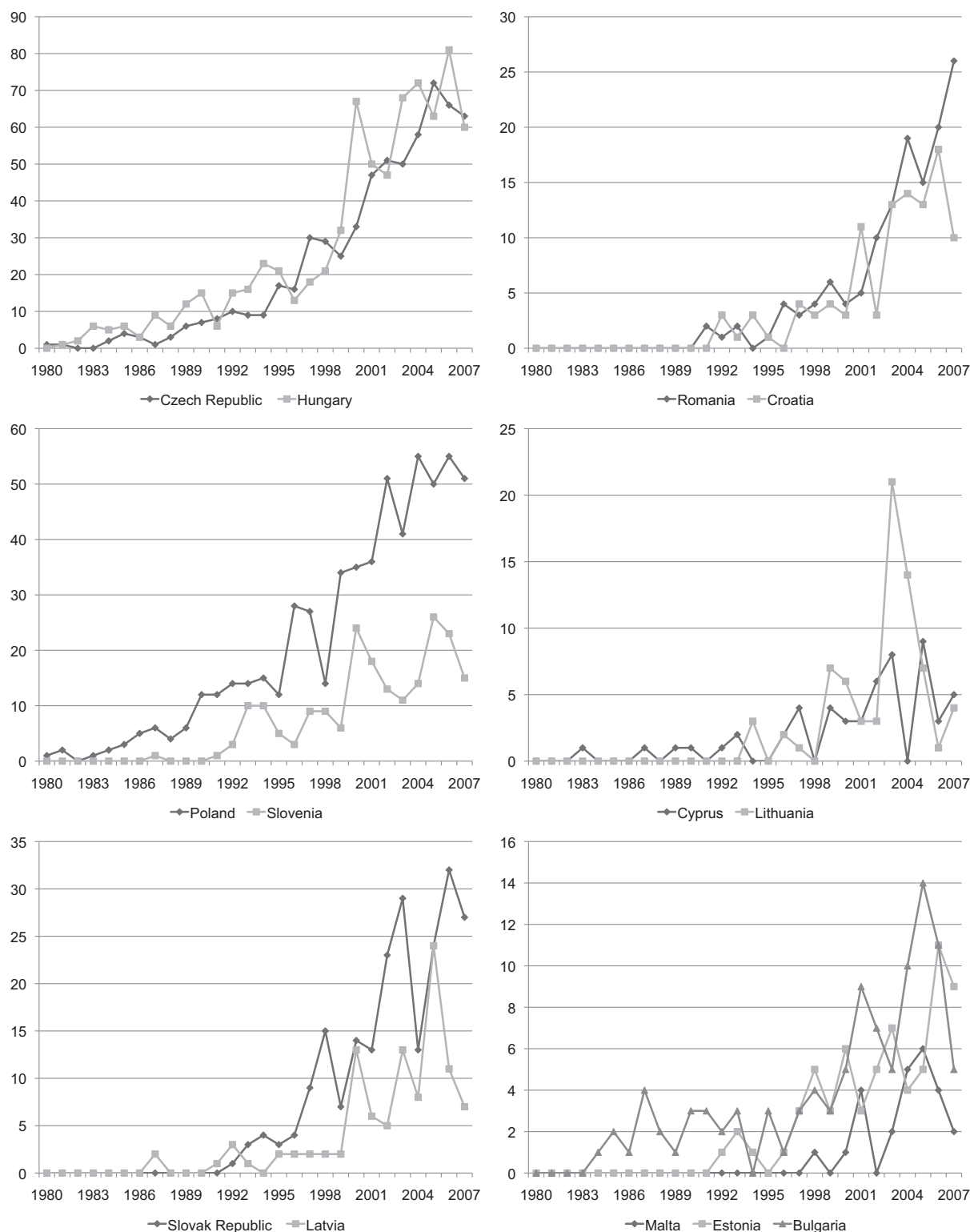


Fig. 4.5. Number of EPO patents with foreign co-inventors by country (2)
 Source: own illustration. Notes: Number of EPO patents with foreign co-inventors by country since 1980; total co-operation with abroad; NMS countries, BG, RO, CR; data extracted from OECD RegPAT (January 2009) and OECD (2009d); fractional counts.

Concerning the numbers and shares of foreign co-inventors, the analysis unveils a similar picture as the one already highlighted in figures 4.4 and 4.5. Austria, Belgium, Denmark, Finland, France, Germany, Italy, Luxembourg, the Netherlands, Norway, Switzerland, the UK, Spain and Sweden are determined by meaningful increases in the share of patent applications with foreign co-inventors (see figure A.38, appendix). The NMS group shows a similar development (see figure A.39, appendix). With respect to the EU-15 countries, figures A.40 and A.41 (appendix) additionally illustrate the changing structure of foreign co-inventors by country. It is clearly visible that the overall share of co-patents with US co-inventors has decreased between 1990/1991 and 2003/2004; especially in the NMS. Finally, it can be concluded from this first descriptive analysis at the national level that co-patenting activity with foreign inventors has grown in all European countries in absolute and relative terms.⁴³⁶ This unambiguous development can be interpreted as a general trend towards a more integrated research area. Accordingly, European countries seem to be increasingly incorporated into cross-national research collaborations. Moreover, these results are complementary to the observed general dispersion tendencies of patenting activity (see chapter 3). However, the origins of the observed developments are rather unknown and not empirically challenged in more detail. Increasing co-patenting activity could be induced by a small number of geographically fragmented multinationals but also by heterogeneous small and medium-sized firms. Furthermore, the presented results do not tell anything about the regional structure of research collaborations, which represents a severe research gap that will be addressed in the following. Therefore, the analysis will place special emphasis on the distribution of these co-inventor linkages in the context of European TL3 and TL2 regions. The analysis sheds light on the spatial nature of European co-patenting networks at the regional level. Moreover, it allows to calculate the centrality of European regions in technology field-specific co-patenting networks.

4.3.5. European Regional Co-Patenting Networks: Global Network Statistics

4.3.5.1. Network Size and Structure by Technology Field

This section offers a detailed overview of technology field-specific inter-regional co-patenting networks at the TL3, TL2 and TL1 level. It provides general network statistics for 43 technology fields. A first question addresses the overall network size of the 43 technology fields under analysis in terms of the number of incorporated regions. In the first section, “global” descriptive network statistics will be presented for each technology field, which cover (i) the overall numbers and shares of regions, (ii) the unique and overall numbers and shares of inter-regional co-patenting linkages, and (iii) the numbers and shares of inter- and intra-national linkages.⁴³⁷

⁴³⁶ Refer also to the study results of Frietsch and Schmoch (2006), Belitz *et al.* (2006) and Maggioni *et al.* (2007).

⁴³⁷ Computations were done with the software “Codeplex NodeXL (2009-2011).”

The overall numbers of regions are presented in table 4.2.⁴³⁸ The largest technology-specific networks in the 1990s (1990-1994), which connect more than 50% of all European TL3 regions, are the following ones: *TF9 Petrol. prod. & nucl. fuel* (437 regions), *TF10 Basic chemicals* (606 regions), *TF13 Pharmaceuticals* (573 regions), *TF17 Rubber & plastic prod.* (519 regions), *TF18 Non-metal mineral. prod.* (482 regions), *TF19 Basic metals* (437 regions), *TF20 Fabricated metal prod.* (442 regions), *TF22. Nonspec. machinery* (508 regions), *TF25 Spec. purp. machinery* (547 regions), *TF28 Office mach. & computers* (457 regions), *TF35 Signal. transm. telecom.* (452 regions), *TF37 Med. equipment* (504 regions), *TF38 Measuring instruments* (515 regions), *TF42 Motor vehicles* (484 regions). 14 technology fields showed a co-patenting network with more than 50% of all European regions. In the 2000s (2000-2004), 23 technology fields showed networks that connect more than 50% of all European TL3 regions. Among the largest technology field-specific networks are the following: *TF10 Basic chemicals* (697 regions), *TF13 Pharmaceuticals* (709 regions), *TF25 Spec. purp. machinery* (631 regions), *TF35 Signal. transm. telecom.* (635 regions), *TF38 Measuring instruments* (632 regions). 9 technology fields consist of more than 70% of all European TL3 regions. It can be concluded from the presented calculations in table 4.2 that European co-patenting networks have on average expanded in their overall size between the 1990s and 2000s. In comparison, the smallest networks in the 1990s, by means of connected European TL3 regions, are the following ones: *TF2 Tobacco prod.* (67 regions), *TF4 Wearing & apparel* (74 regions), *TF5 Leather articles* (74 regions), *TF12 Paints & varnishes* (75 regions), *TF41 Watches & clocks* (70 regions). However, it is essential to note that market structures, organizational structures and competitive forces widely differ between the analyzed technology fields, which may also affect the dispersion of inventors and their co-inventor networks across the 819 European regions. The technology field *TF10 Basic chemicals* is the only one that includes all 25 European countries (and Switzerland and Norway) and exhibits the largest number of European regions.⁴³⁹ It can be concluded that European technology-specific co-patenting networks have generally increased in size.

⁴³⁸ “Count” is the number of counted regions in the network; “share (%)” is the share of possible European regions in the network. Calculations at the TL3, TL2 and TL1 level. For a complete overview and list of abbreviations of all technology field aggregates used in the following graphs and tables see table B.4 (appendix).

⁴³⁹ See also Frietsch and Schmoch (2006) for complementary results at the national level.

Table 4.2. Number of connected regions in technology-specific co-patenting networks, 1990-1994 and 2000-2004

technology field	Structure of inter-regional TL3 co-inventor networks: TL3 and TL2 regions and countries (TL1) in networks (counts and shares)										change (%:points)				
	1990-1994					2000-2004					TL3 regions	TL2 macro regions	TL1 countries	share (%)	
	TL3 regions (count)	share (%)	TL2 macro regions (count)	share (%)	TL1 countries (count)	share (%)	TL3 regions (count)	share (%)	TL2 macro regions (count)	share (%)					TL1 countries (count)
TF1_Food_beverages	379	45%	120	57%	19	70%	465	55%	153	73%	20	74%	10%	16%	4%
TF2_Tobacco_prod	67	8%	36	17%	7	26%	66	8%	37	18%	12	44%	0%	0%	19%
TF3_Textiles	272	32%	94	45%	15	56%	323	38%	112	53%	19	70%	6%	9%	15%
TF4_Wearing_apparel	74	9%	39	18%	10	37%	148	17%	71	34%	15	56%	9%	15%	19%
TF5_Leather_articles	74	9%	43	20%	10	37%	116	14%	50	24%	11	41%	5%	3%	4%
TF6_Wood_prod	130	15%	58	27%	11	41%	182	22%	79	37%	18	67%	6%	10%	28%
TF7_Paper	299	35%	96	45%	16	59%	350	41%	121	57%	19	70%	6%	12%	11%
TF9_Petrol_prod_nucl_fuel	437	52%	134	64%	19	70%	312	37%	117	55%	18	67%	-15%	-8%	-4%
TF10_Basic_chemical	606	72%	169	80%	23	85%	697	82%	198	94%	27	100%	11%	14%	15%
TF11_Pesticide_agrochem_prod	296	35%	105	50%	19	70%	324	38%	121	57%	21	78%	3%	8%	7%
TF12_Paints_varnishes	75	9%	35	17%	10	37%	76	9%	42	20%	12	44%	0%	3%	7%
TF13_Pharmaceuticals	573	68%	174	82%	23	85%	709	84%	207	98%	26	96%	16%	16%	11%
TF14_Soaps_detergents	248	29%	90	43%	14	52%	295	35%	101	48%	17	63%	6%	5%	11%
TF15_Other_chemicals	393	46%	121	57%	18	67%	409	48%	139	66%	21	78%	2%	9%	11%
TF16_Man_made_fibre	138	16%	61	29%	13	48%	159	19%	77	36%	13	48%	2%	8%	0%
TF17_Rubber_plastic_prod	519	61%	144	68%	22	81%	601	71%	165	78%	22	81%	10%	10%	0%
TF18_Non-metal_mineral_prod	482	57%	134	64%	19	70%	549	65%	164	78%	24	89%	8%	14%	19%
TF19_Basic_metals	437	52%	134	64%	19	70%	508	60%	163	77%	24	89%	8%	14%	19%
TF20_Fabric_metal_prod	442	52%	123	58%	18	67%	547	65%	153	73%	23	85%	12%	14%	19%
TF21_Energy_machinery	418	49%	122	58%	18	67%	542	64%	158	75%	21	78%	15%	17%	11%
TF22_Nonspc_machinery	508	60%	146	69%	21	78%	600	71%	171	81%	24	89%	11%	12%	11%
TF23_Agricul_forestry_machinery	319	38%	109	52%	18	67%	396	47%	139	66%	22	81%	9%	14%	15%
TF24_Machine_tools	405	48%	117	55%	19	70%	469	55%	140	66%	22	81%	8%	11%	11%
TF25_Spec_purp_machinery	547	65%	142	67%	22	81%	631	75%	176	83%	24	89%	10%	16%	7%
TF26_Weapons_ammunition	160	19%	64	30%	13	48%	173	20%	73	35%	13	48%	2%	4%	0%
TF27_Domestic_appliances	397	47%	114	54%	18	67%	501	59%	147	70%	23	85%	12%	16%	19%
TF28_Office_mach_computers	457	54%	129	61%	18	67%	627	74%	179	85%	26	96%	20%	24%	30%
TF29_Electric_motors_generators	231	27%	84	40%	14	52%	352	42%	124	59%	20	74%	14%	19%	22%
TF30_Elec_distr_contr_wire_cable	310	37%	110	52%	20	74%	376	44%	123	58%	20	74%	8%	8%	0%
TF31_Accumulators_battery	181	21%	73	35%	13	48%	313	37%	117	55%	21	78%	16%	21%	30%
TF32_Lighting_equipment	160	19%	64	30%	12	44%	225	27%	84	40%	17	63%	8%	9%	19%
TF33_Other_elect equip	340	40%	102	48%	15	56%	451	53%	136	64%	21	78%	13%	16%	22%
TF34_Electr components	371	44%	116	55%	19	70%	538	64%	162	77%	24	89%	20%	22%	19%
TF35_Signal_transm_telecom	452	53%	135	64%	19	70%	635	75%	184	87%	25	93%	22%	23%	22%
TF36_TV_radio_receive_audio	265	31%	91	43%	16	59%	424	50%	144	68%	23	85%	19%	25%	26%
TF37_Med equipment	504	60%	137	65%	22	81%	619	73%	176	83%	24	89%	14%	18%	7%
TF38_Measuring_instruments	515	61%	144	68%	22	81%	632	75%	179	85%	24	89%	14%	17%	7%
TF39_Ind_proc_contr equip	294	35%	97	46%	17	63%	391	46%	127	60%	21	74%	11%	14%	11%
TF40_Opti_instruments	364	43%	112	53%	18	67%	448	53%	135	64%	21	78%	10%	11%	11%
TF41_Watches_clocks	70	8%	36	17%	7	26%	94	11%	41	19%	9	33%	3%	2%	7%
TF42_Motor_vehicles	484	57%	143	68%	20	74%	580	69%	169	80%	24	89%	11%	12%	15%
TF43_Other_transp equip	345	41%	117	55%	18	67%	447	53%	133	63%	20	74%	12%	8%	7%
TF44_Furniture_consum_goods	324	38%	100	47%	16	59%	435	51%	133	63%	20	74%	13%	16%	15%

Source: own calculations and illustration. *Notes:* "Count:" Number of regions in network; "share:" share of possible regions in network.

The highest growth rates between 1990-1994 and 2000-2004, with respect to the number of interconnected European regions, can be observed for the following technology fields (see table 4.2): *TF1 Food & beverages* (10%), *TF10 Basic chemicals* (11%), *TF13 Pharmaceuticals* (16%), *TF20 Fabricated metal prod.* (12%), *TF21 Energy machinery* (15%), *TF22 Nonspec. machinery* (11%), *TF27 Domestic appliances* (12%), *TF28 Office mach. & computers* (20%), *TF29 Electric motors & generators* (14%), *TF31 Accumulators & battery* (16%), *TF33 Other electr. equip.* (13%), *TF34 Electr. components* (20%), *TF35 Signal transm. & telecom.* (22%), *TF36 TV & radio receiv. & audio.* (19%), *TF37 Med. equipment* (14%), *TF38 Measuring instruments* (14%), *TF39 Ind. proc. contr. equip.* (11%), *TF42 Motor vehicles* (11%), *TF43 Other transp. equip.* (12%), *TF44 Furniture & consum. goods* (13%). *TF9 Petrol. prod. & nucl. fuel.* is the only technology field that experienced a decrease in the number of interconnected regions in the European co-patenting network between the 1990s and 2000s.

4.3.5.2. Spatial Proximity versus Inter-Regional Linkages

Chapter 2 reviewed the theoretical and empirical debate regarding proximity vs. long-distance networks. This issue will be addressed in the following. The size of a network can additionally be calculated and expressed in terms of the number of inter-regional linkages. The results presented in table 4.3 contain information with respect to the shares and numbers of “unique” and “overall” inter-regional TL3 linkages (research collaborations), which are used to identify the intensity and frequency of inter-regional research collaborations. Furthermore, the linkage numbers and shares are also calculated at the higher TL2 and TL1 level. For completeness, inter-regional TL3 linkages, which occur within and between the larger European TL2 regions (i.e., at a proximate distance), are listed for comparison purpose. The linkage calculation enables an analysis of potential distance decay and proximity effects of inter-regional co-patenting activity in Europe and the identification of structural changes in research collaboration activity and border-crossing knowledge flows. Table 4.3 summarizes the numbers and shares of extracted linkages for all 43 technology fields (1990-1994 and 2000-2004). In addition, figures A.42 and A.43 (appendix) illustrate the overall numbers of inter-regional TL3 linkages (within and between European countries) for the 1990s (1990-1994) and 2000s (2000-2004). First of all, the following results can be reported with respect to the overall co-patenting network size. The largest technology field-specific co-patenting networks in 1990-1994 represent *TF10 Basic chemicals* (56,363 linkages), *TF13 Pharmaceuticals* (51,194) and *TF25 Spec. purp. machinery* (22,464), *TF38 Measuring instruments* (14,205), *TF42 Motor vehicles* (14,330), among others. In the second period of analysis, 2000-2004, the picture has not changed much. The largest networks are still represented by *TF10 Basic chemicals* (83,218), *TF13 Pharmaceuticals* (147,266), *TF42 Motor vehicles* (47,250), *TF37 Med. equipment* (34,902), *TF35 Signal transm. & telecom.* (36,784), among others. It is important to note that the numbers of linkages are implicitly related to the technology field-specific propensity to file patents.⁴⁴⁰

⁴⁴⁰ For similar conclusions, although at a higher level of aggregation, refer to the cross-country studies (national level) of Frietsch and Schmoch (2006) and Belitz et al. (2006).

Second, the majority of European co-patenting activity happens at a “proximate” distance and have an intra-regional nature - they occur within large TL2 regions, i.e., inter-regional TL3 linkages within TL2 regions. Table 4.3 clearly shows that around 90% of all identified European inter-regional research linkages are inter-regional TL3 linkages within the same countries, i.e., inter-regional TL3 linkages within and between TL2 regions within countries (1+2). Even in the 2000s, a strong concentration of inter-regional research co-operations within the national borders of European member states can be observed. However, the overall share of these linkages has decreased in almost all analyzed technology fields. At the same time, international linkages, i.e., inter-regional TL3 linkages between countries (3), have increased in numbers and shares. That being the case, the technology fields with the highest share of international linkages are the following: *TF1 Food & beverages* (31%), *TF3 Textiles* (16%), *TF4 Wearing & apparel* (11%), *TF9 Petrol. prod. & nucl. fuel.* (14%), *TF10 Basic chemicals* (13%), *TF13 Pharmaceuticals* (13%), *TF14 Soaps & detergents* (25%), *TF16 Man-made fibre* (20%), *TF19 Basic metals* (15%), *TF23 Agricul. & forestry machinery* (37%), *TF35 Signal transm. & telecom.* (12%), *TF37 Med. equipment* (13%), *TF38 Measuring instruments* (12%) and *TF41 Watches & clocks* (12%). The other technology fields remain below the 10% threshold even in the 2000s. These structures (numbers, shares) are additionally illustrated in the subsequent figures 4.6 and 4.7. These figures explicitly differentiate between (i) linkages that happen at a proximate distance within larger TL2 regions (within countries) and (ii) linkages that occur at a distance between TL2 regions (within countries) and (iii) linkages that occur between countries.

Table 4.3. Number of inter-regional technology-specific co-patenting network linkages, 1990-1994 and 2000-2004

technology field	Structure of inter-regional TL3 co-inventor networks: TL3 linkages between European regions and countries (total numbers)											
	1990-1994					2000-2004						
	inter-regional TL3 linkages (count)	inter-regional TL3 linkages within country (count)	inter-regional TL3 linkages within country (%) (1+2)	inter-regional TL3 linkages between TL2 & within country (%) (2)	inter-regional TL3 linkages between TL2 & between country (%) (3)	inter-regional TL3 linkages (count)	inter-regional TL3 linkages within country (count)	inter-regional TL3 linkages within country (%) (1+2)	inter-regional TL3 linkages within country (%) (1)	inter-regional TL3 linkages between TL2 & within country (%) (2)	inter-regional TL3 linkages between TL2 & between country (%) (3)	
TF1_Food_beverages	4,447	3,702	83%	34%	50%	17%	11,205	8,212	73%	30%	43%	27%
TF2_Tobacco_prod	304	292	96%	16%	80%	4%	712	690	97%	7%	90%	3%
TF3_Textiles	2,759	2,426	88%	40%	48%	12%	3,933	3,107	79%	41%	38%	21%
TF4_Wearing_apparel	145	119	82%	26%	56%	18%	480	405	84%	51%	34%	16%
TF5_Leather_articles	148	135	91%	55%	36%	9%	250	223	89%	49%	40%	11%
TF6_Wood_prod	313	289	92%	28%	64%	8%	798	736	92%	45%	47%	8%
TF7_Paper	3,283	2,986	91%	36%	55%	9%	9,283	8,505	92%	29%	62%	8%
TF9_Petrol_prod_nucl_fuel	2,156	2,028	94%	39%	55%	6%	3,165	2,661	84%	38%	46%	16%
TF10_Basic_chemical	56,363	51,166	91%	36%	55%	9%	83,218	70,416	85%	35%	50%	15%
TF11_Pesticide_agrochem_prod	9,921	9,410	95%	43%	52%	5%	24,546	23,066	94%	30%	64%	6%
TF12_Paints_varnishes	386	361	94%	42%	51%	6%	315	297	94%	40%	55%	6%
TF13_Pharmaceuticals	51,194	44,956	88%	40%	48%	12%	147,266	121,256	82%	43%	39%	18%
TF14_Soaps_detergents	6,044	5,521	91%	47%	53%	20%	3,331	3,830	72%	39%	33%	28%
TF15_Other_chemicals	850	800	94%	34%	60%	6%	7,410	6,446	87%	34%	53%	13%
TF16_Man_made_fibre	12,547	11,528	92%	39%	59%	8%	19,388	16,831	87%	36%	50%	13%
TF17_Rubber_plastic_prod	9,967	8,947	90%	34%	55%	10%	16,094	14,192	88%	36%	52%	12%
TF18_Non-metal_mineral_prod	6,399	5,759	90%	34%	56%	10%	9,978	8,413	84%	38%	46%	16%
TF19_Basic_metals	8,224	7,731	94%	38%	56%	6%	14,992	13,691	91%	51%	40%	9%
TF20_Fabric_metal_prod	7,798	7,371	95%	47%	48%	5%	22,287	20,597	92%	52%	41%	8%
TF21_Energy_machinery	13,468	12,577	93%	37%	56%	7%	26,315	23,774	90%	43%	47%	10%
TF22_Nonspec_machinery	2,533	2,383	94%	41%	53%	6%	5,091	3,983	78%	38%	41%	22%
TF23_Agricul_forestry_machinery	5,302	5,039	95%	38%	57%	5%	11,601	10,690	92%	51%	41%	8%
TF24_Machine_tools	22,464	21,088	94%	36%	58%	6%	35,421	31,631	89%	34%	55%	11%
TF25_Spec_purp_machinery	541	518	96%	39%	56%	4%	777	743	96%	35%	61%	4%
TF26_Weapons_ammunition	4,816	4,385	91%	39%	52%	9%	10,773	9,557	89%	44%	45%	11%
TF27_Domestic_appliances	11,007	10,321	94%	42%	51%	6%	33,360	30,042	90%	47%	43%	10%
TF28_Office_mach_computers	1,769	1,693	96%	39%	56%	4%	5,330	4,877	92%	58%	33%	8%
TF29_Electric_motors_generators	4,567	4,340	95%	44%	51%	5%	7,037	6,323	90%	44%	46%	10%
TF30_Elec_distr_contr_wire_cable	978	942	96%	37%	59%	4%	5,037	4,595	91%	37%	54%	9%
TF31_Accumulators_battery	756	710	94%	45%	49%	6%	1,744	1,623	93%	52%	42%	7%
TF32_Lighting_equipment	4,199	4,064	97%	47%	49%	3%	7,473	6,762	90%	46%	44%	10%
TF33_Other_electr equip	7,411	6,974	94%	42%	52%	6%	19,213	17,317	90%	46%	44%	10%
TF34_Electr_components	11,630	10,849	93%	42%	51%	7%	36,784	31,425	85%	43%	42%	15%
TF35_Signal_transm_telecom	2,168	1,977	91%	42%	49%	9%	8,902	8,190	92%	47%	45%	8%
TF36_TV_radio_receiv_audio	11,232	9,976	89%	31%	58%	11%	34,902	29,883	86%	35%	50%	14%
TF38_Measuring_instruments	2,395	2,183	91%	45%	53%	10%	44,710	38,740	87%	51%	36%	13%
TF39_Ind_proc_contr equip	6,159	5,824	95%	38%	57%	5%	6,874	6,397	93%	52%	41%	7%
TF40_Opt_instruments	451	424	94%	19%	75%	6%	13,845	12,529	90%	36%	55%	10%
TF41_Watches_clocks	14,330	13,568	95%	50%	44%	7%	683	581	85%	35%	50%	15%
TF42_Motor_vehicles	3,253	3,050	94%	34%	59%	6%	47,250	43,351	92%	54%	38%	8%
TF43_Other_transp equip	3,026	2,762	91%	28%	64%	9%	6,449	5,873	91%	44%	47%	9%
TF44_Furniture_consum_good							4,358	3,903	90%	44%	45%	10%

Source: own calculations and illustration. Notes: Number of linkages by technology-specific co-patenting networks (1990-1994 and 2000-2004).

Accordingly, in order to explore the spatial technology-specific structures of European co-patenting networks in more detail, the numbers and shares of the inter-regional linkages between European TL3 regions with respect to different regional border characteristics have been calculated for the same two periods: (i) inter-regional TL3 linkages [intra-TL2 within country overall], (ii) inter-regional TL3 linkages [inter-TL2 within country overall]; (iii) inter-regional TL3 linkages [inter-TL1 between country overall]. The three groups accumulate to 100% (to an overall linkage number by technology field respectively, as presented in table 4.3 and figures A.42 and A.43, appendix). It is obvious from table 4.3 that the share of international inter-regional TL3 linkages has increased since the 1990s. Further to this, figures 4.6 and 4.7 present and compare the numbers (and shares) of these different linkage types. By definition, linkage types (i) and (ii) are national co-patenting linkages (within and between macro regions); they represent the largest fraction of inter-regional co-patenting linkages for almost all technology fields. In comparison, linkage type (iii) represents international co-patenting linkages; however, these linkages only represent a small amount of the observed overall inter-regional research collaborations. Nevertheless, it is obvious from these calculations that the overall share of international research collaborations has increased since the 1990s. Regarding the large fraction of linkages within national borders (and within larger TL2 regions), the results are in line with the presented Moran's I measures in section 4.2.2.

Third, with regard to the dynamics of the networks, tables 4.4 and 4.5 highlight the change/growth of the different linkage types between 1990-1994 and 2000-2004 (percent and percentage points). It can be concluded that almost all technology fields show increases in international co-patenting linkages, i.e., inter-regional TL3 linkages [inter-TL1 between country overall]; e.g., *TF13 Pharmaceuticals*, *TF1 Food & beverages*, *TF23 Agricul. & forestry machinery*, *TF28 Office mach. & computers*, *TF31 Accumulators & battery*. These results are also in line with the Gini computations and other global disparity measures in chapter 3.4.

Fourth, with respect to unique co-patenting linkages between European TL3 regions, table 4.6 summarizes the numbers and shares of unique European inter-regional co-patenting linkages by technology field for the periods 1990-1994 and 2000-2004 and gives information about the structure of inter-regional co-inventor network linkages (total number and % of all possible combinations). In light of this analysis, the numbers and shares of (i) unique inter-regional TL3 linkages [within and between country], (ii) unique inter-regional TL2 linkages [within and between country], and (iii) unique inter-regional TL1 linkages [between country] are calculated; the table additionally includes the shares of existing unique linkages of all possible combinations (network density) between the incorporated European regions. It can be concluded from the results presented in table 4.6 that the number of unique linkages has expanded in almost every technology field between the 1990s and 2000s. As expected, the number of heterogenous (unique) linkages (and density) has increased since the 1990s (see table 4.6) as it is the case with the unique number of European regions within the technology-specific networks (see also table 4.2). Nevertheless, the development is technology field-specific.

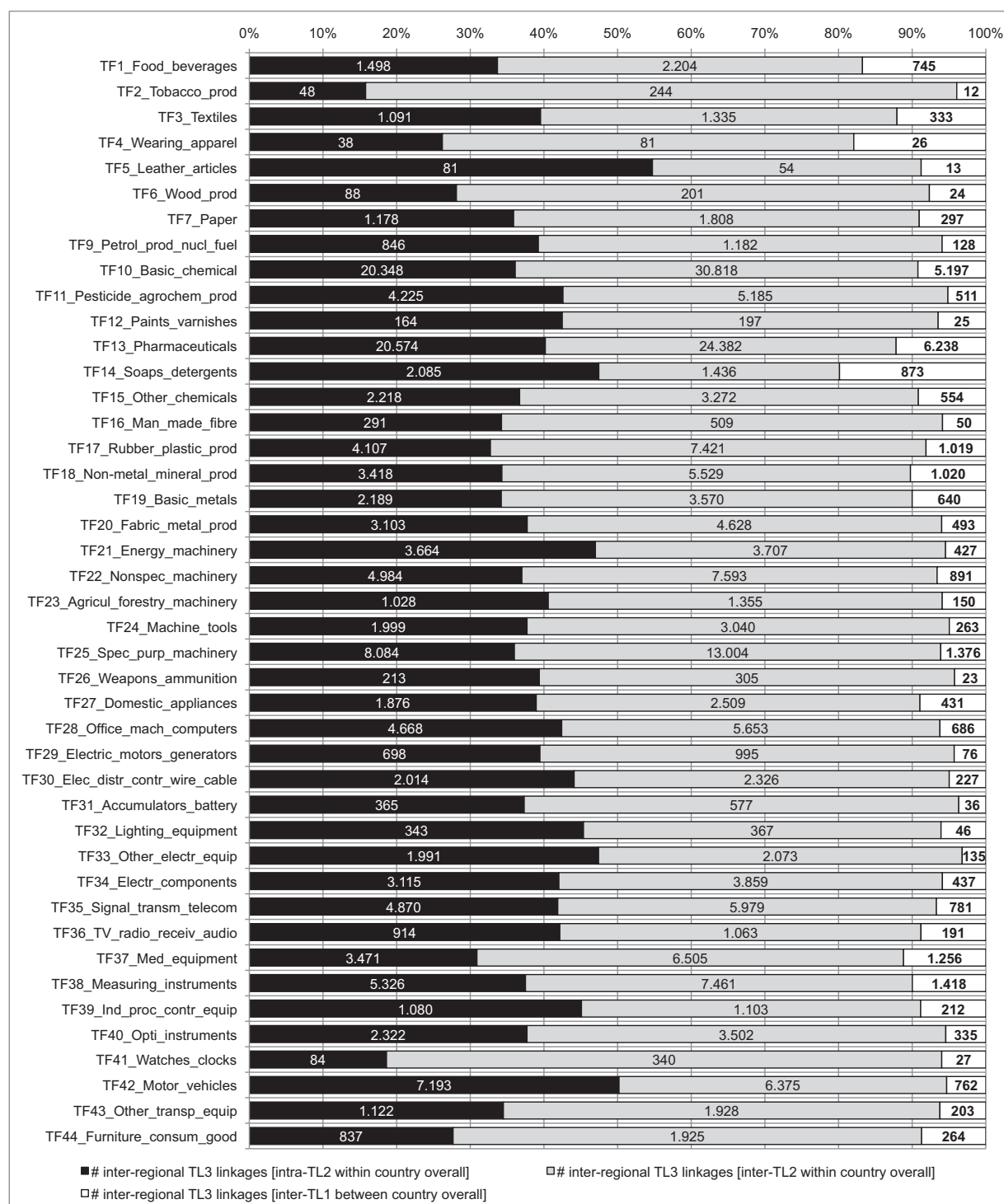


Fig. 4.6. Structure of European co-patenting networks, 1990-1994

Source: own calculations and illustration. Notes: Number of linkages by technology-specific co-patenting network (1990-1994).

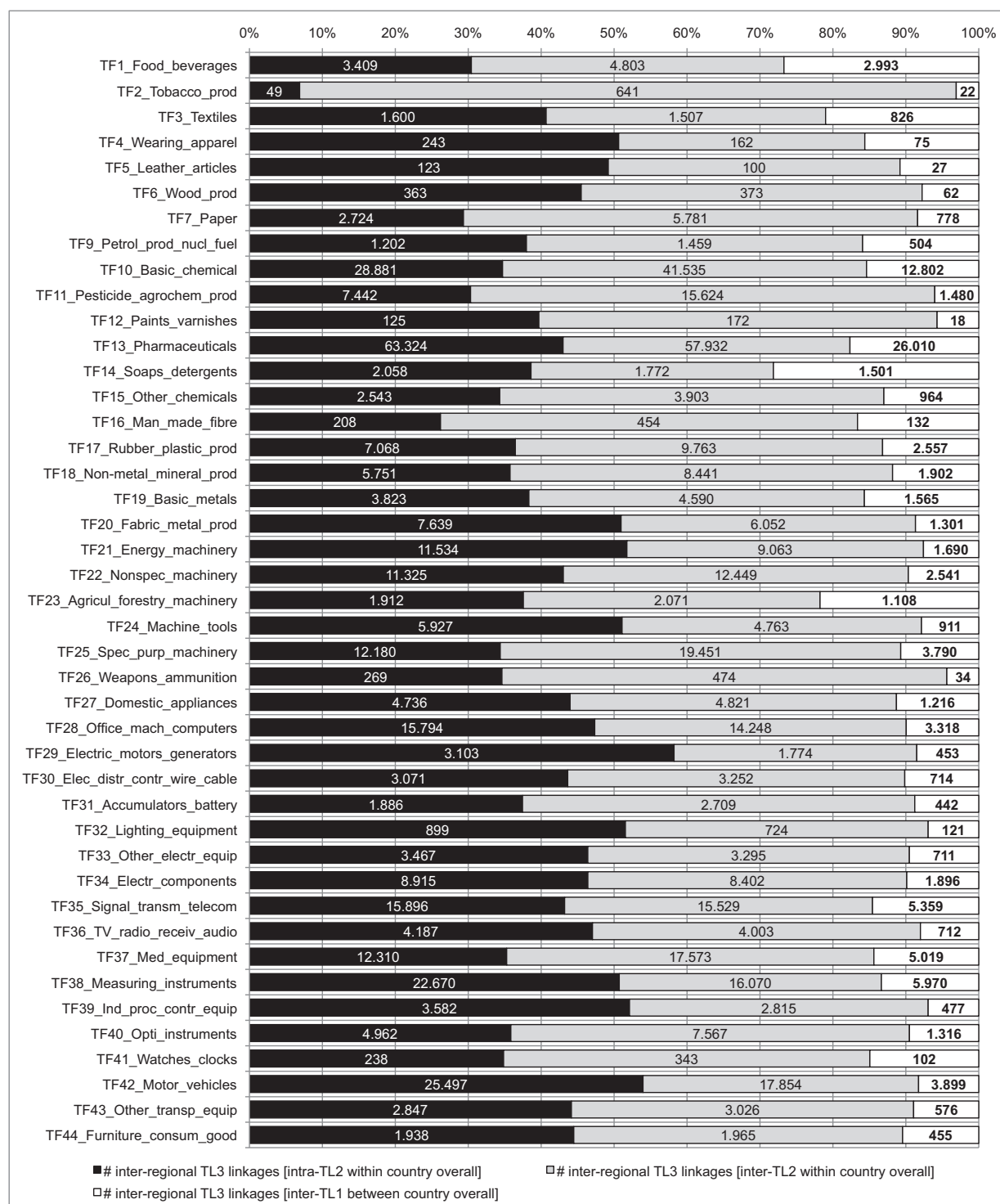


Fig. 4.7. Structure of European co-patenting networks, 2000-2004

Source: own calculations and illustration. *Notes:* Number of linkages by technology-specific co-patenting network (2000-2004).

Table 4.4. Inter-regional linkages by technology field: structural change (1)

Structural change of inter-regional TL3 co-inventor network linkages				
change (%points) 2000-2004 vs. 1990-1994				
technology field	inter-regional TL3 linkages between TL3 within country (%) (1+2)	inter-regional TL3 linkages within TL2 & within country (%) (1)	inter-regional TL3 linkages between TL2 & within country (%) (2)	inter-regional TL3 linkages between country (%) (3)
TF1_Food_beverages	-10%	-3%	-7%	10%
TF2_Tobacco_prod	1%	-9%	10%	-1%
TF3_Textiles	-9%	1%	-10%	9%
TF4_Wearing_apparel	2%	24%	-22%	-2%
TF5_Leather_articles	-2%	-6%	4%	2%
TF6_Wood_prod	0%	17%	-17%	0%
TF7_Paper	1%	-7%	7%	-1%
TF9_Petrol_prod_nucl_fuel	-10%	-1%	-9%	10%
TF10_Basic_chemical	-6%	-1%	-5%	6%
TF11_Pesticide_agrochem_prod	-1%	-12%	11%	1%
TF12_Paints_varnishes	1%	-3%	4%	-1%
TF13_Pharmaceuticals	-5%	3%	-8%	5%
TF14_Soaps_detergents	-8%	-9%	1%	8%
TF15_Other_chemicals	-4%	-2%	-1%	4%
TF16_Man_made_fibre	-11%	-8%	-3%	11%
TF17_Rubber_plastic_prod	-5%	4%	-9%	5%
TF18_Non-metal_mineral_prod	-2%	1%	-3%	2%
TF19_Basic_metals	-6%	4%	-10%	6%
TF20_Fabric_metal_prod	-3%	13%	-16%	3%
TF21_Energy_machinery	-2%	5%	-7%	2%
TF22_Nonspec_machinery	-3%	6%	-9%	3%
TF23_Agricul_forestry_machinery	-16%	-3%	-13%	16%
TF24_Machine_tools	-3%	13%	-16%	3%
TF25_Spec_purp_machinery	-5%	-2%	-3%	5%
TF26_Weapons_ammunition	0%	-5%	5%	0%
TF27_Domestic_appliances	-2%	5%	-7%	2%
TF28_Office_mach_computers	-4%	5%	-9%	4%
TF29_Electric_motors_generators	-4%	19%	-23%	4%
TF30_Elec_distr_contr_wire_cable	-5%	0%	-5%	5%
TF31_Accumulators_battery	-5%	0%	-5%	5%
TF32_Lighting_equipment	-1%	6%	-7%	1%
TF33_Other_electr equip	-6%	-1%	-5%	6%
TF34_Electr_components	-4%	4%	-8%	4%
TF35_Signal_transm_telecom	-8%	1%	-9%	8%
TF36_TV_radio_receiv_audio	1%	5%	-4%	-1%
TF37_Med_equipment	-3%	4%	-8%	3%
TF38_Measuring_instruments	-3%	13%	-17%	3%
TF39_Ind_proc_contr equip	2%	7%	-5%	-2%
TF40_Opti_instruments	-4%	-2%	-2%	4%
TF41_Watches_clocks	-9%	16%	-25%	9%
TF42_Motor_vehicles	-3%	4%	-7%	3%
TF43_Other_transp equip	-3%	10%	-12%	3%
TF44_Furniture_consum_good	-2%	17%	-19%	2%

Source: own calculations and illustration. Notes: Change (percentage points) in the structure of linkages by technology-specific co-patenting networks (1990-1994 and 2000-2004).

Table 4.5. Inter-regional linkages by technology field: structural change (2)

Change (%) of inter-regional co-inventor linkages: 2000-2004 vs. 1990-1994			
technology field	change inter-regional TL3 linkages [overall]	change inter-regional TL3 linkages [within countries]	change inter-regional TL3 linkages [between countries]
TF1_Food_beverages	152%	122%	302%
TF2_Tobacco_prod	134%	136%	83%
TF3_Textiles	43%	28%	148%
TF4_Wearing_apparel	231%	240%	188%
TF5_Leather_articles	69%	65%	108%
TF6_Wood_prod	155%	155%	158%
TF7_Paper	183%	185%	162%
TF9_Petrol_prod_nucl_fuel	47%	31%	294%
TF10_Basic_chemical	48%	38%	146%
TF11_Pesticide_agrochem_prod	147%	145%	190%
TF12_Paints_varnishes	-18%	-18%	-28%
TF13_Pharmaceuticals	188%	170%	317%
TF14_Soaps_detergents	21%	9%	72%
TF15_Other_chemicals	23%	17%	74%
TF16_Man_made_fibre	-7%	-17%	164%
TF17_Rubber_plastic_prod	55%	46%	151%
TF18_Non-metal_mineral_prod	61%	59%	86%
TF19_Basic_metals	56%	46%	145%
TF20_Fabric_metal_prod	82%	77%	164%
TF21_Energy_machinery	186%	179%	296%
TF22_Nonspec_machinery	95%	89%	185%
TF23_Agricul_forestry_machinery	101%	67%	639%
TF24_Machine_tools	119%	112%	246%
TF25_Spec_purp_machinery	58%	50%	175%
TF26_Weapons_ammunition	44%	43%	48%
TF27_Domestic_appliances	124%	118%	182%
TF28_Office_mach_computers	203%	191%	384%
TF29_Electric_motors_generators	201%	188%	496%
TF30_Elec_distr_contr_wire_cable	54%	46%	215%
TF31_Accumulators_battery	415%	388%	1128%
TF32_Lighting_equipment	131%	129%	163%
TF33_Other_electr equip	78%	66%	427%
TF34_Electr_components	159%	148%	334%
TF35_Signal_transm_telecom	216%	190%	586%
TF36_TV_radio_receiv_audio	311%	314%	273%
TF37_Med_equipment	211%	200%	300%
TF38_Measuring_instruments	215%	203%	321%
TF39_Ind_proc_contr equip	187%	193%	125%
TF40_Opti_instruments	125%	115%	293%
TF41_Watches_clocks	51%	37%	278%
TF42_Motor_vehicles	230%	220%	412%
TF43_Other_transp equip	98%	93%	184%
TF44_Furniture_consum_good	44%	41%	72%

Source: own calculations and illustration. Notes: Growth of linkage types by technology-specific co-patenting networks (1990-1994 and 2000-2004).

Table 4.6. Structure of European co-patenting networks: unique linkages

technology field	Structure of inter-regional co-inventor network linkages: unique co-inventor network linkages (total number and % of all possible combinations)										
	1990-1994					2000-2004					
	# unique inter-regional TL3 linkages [within and between country]	# unique inter-regional TL2 linkages [within and between country]	# unique inter-regional TL1 linkages [between country]	# unique inter-regional TL3 linkages [within and between country] [% of all possible]	# unique inter-regional TL2 linkages [within and between country] [% of all possible]	# unique inter-regional TL1 linkages [between country] [% of all possible]	# unique inter-regional TL3 linkages [within and between country]	# unique inter-regional TL2 linkages [within and between country]	# unique inter-regional TL1 linkages [between country]	# unique inter-regional TL3 linkages [within and between country] [% of all possible]	
TF1_Food_beverages	1.174	463	59	0.33%	2.09%	16.81%	2.135	794	84	0.60%	23.93%
TF2_Tobacco_prod	86	46	1	0.02%	0.21%	0.28%	71	39	7	0.02%	1.99%
TF3_Textiles	627	204	28	0.18%	0.92%	7.98%	972	346	53	0.27%	15.10%
TF4_Wearing_apparel	113	40	6	0.03%	0.18%	1.71%	198	89	14	0.06%	3.99%
TF5_Leather_articles	66	34	8	0.02%	0.15%	2.28%	119	49	9	0.03%	2.56%
TF6_Wood_prod	146	67	10	0.04%	0.30%	2.85%	338	112	16	0.09%	4.56%
TF7_Paper	782	256	34	0.22%	1.16%	9.69%	1.211	402	43	0.34%	12.25%
TF9_Petrol_prod_nucl_fuel	1.661	504	44	0.46%	2.27%	12.54%	754	298	31	0.21%	8.83%
TF10_Basic_chemical	5.200	1.262	100	1.45%	5.70%	28.49%	7.840	2.051	138	2.19%	39.32%
TF11_Pesticide_agrochem_prod	766	299	38	0.21%	1.35%	10.83%	915	308	44	0.26%	12.54%
TF12_Paints_varnishes	94	29	4	0.03%	0.13%	1.14%	102	38	5	0.03%	1.42%
TF13_Pharmaceuticals	4.536	1.283	107	1.27%	5.79%	30.48%	9.145	2.537	172	2.56%	49.00%
TF14_Soaps_detergents	744	287	33	0.21%	1.30%	9.40%	983	389	44	0.28%	12.54%
TF15_Other_chemicals	1.325	417	11	0.06%	0.46%	3.13%	1.545	507	55	0.43%	15.67%
TF16_Man_made_fibre	216	102	11	0.06%	0.46%	3.13%	298	138	23	0.08%	6.55%
TF17_Rubber_plastic_prod	2.523	680	61	0.71%	3.07%	17.98%	3.811	1.086	85	1.07%	24.22%
TF18_Non-metal_mineral_prod	2.137	579	55	0.60%	2.61%	15.67%	2.987	903	91	0.84%	25.93%
TF19_Basic_metals	1.661	504	44	0.46%	2.27%	12.54%	2.343	743	74	0.66%	21.08%
TF20_Fabric_metal_prod	1.640	447	45	0.46%	2.02%	12.82%	2.708	678	72	0.76%	20.51%
TF21_Energy_machinery	1.504	378	40	0.42%	1.71%	11.40%	2.950	695	64	0.83%	18.23%
TF22_Nonspec_machinery	2.518	616	55	0.70%	2.78%	15.67%	3.770	1.001	84	1.05%	23.93%
TF23_Agricul_forestry_machinery	637	229	27	0.18%	1.03%	7.69%	1.131	431	50	0.32%	14.25%
TF24_Machine_tools	1.348	349	32	0.36%	1.58%	9.12%	2.044	559	60	0.57%	17.09%
TF25_Spec_purp_machinery	3.258	773	67	0.91%	3.49%	19.03%	4.645	1.275	96	1.30%	27.35%
TF26_Weapons_ammunition	238	87	7	0.07%	0.39%	1.99%	267	105	7	0.07%	1.99%
TF27_Domestic_appliances	1.175	344	34	0.33%	1.55%	9.69%	2.065	613	65	0.58%	18.52%
TF28_Office_mach_computers	1.897	487	51	0.53%	2.20%	14.53%	4.322	1.072	117	1.21%	33.33%
TF29_Electric_motors_generators	481	146	12	0.13%	0.66%	3.42%	1.070	291	37	0.30%	10.54%
TF30_Elec_distr_contr_wire_cable	941	246	34	0.26%	1.11%	9.69%	1.439	407	45	0.40%	12.82%
TF31_Accumulators_battery	370	124	8	0.10%	0.56%	2.28%	1.109	317	38	0.31%	10.83%
TF32_Lighting_equipment	225	85	13	0.06%	0.38%	3.70%	492	126	13	0.14%	3.70%
TF33_Other_electr equip	955	249	24	0.27%	1.12%	6.84%	1.570	449	53	0.44%	15.10%
TF34_Electr_components	1.279	338	42	0.36%	1.53%	11.97%	2.830	796	83	0.79%	26.50%
TF35_Signal_transm_telecom	1.864	485	53	0.52%	2.19%	15.10%	4.782	1.345	128	1.34%	38.47%
TF36_TV_radio_receiv_audio	663	213	28	0.19%	0.96%	7.98%	1.475	432	55	0.41%	15.67%
TF37_Med_equipment	2.739	818	65	0.77%	3.69%	18.52%	5.139	1.410	100	1.44%	28.49%
TF38_Measuring_instruments	2.669	727	69	0.75%	3.28%	19.66%	5.054	1.354	118	1.41%	33.62%
TF39_Ind_proc_contr equip	678	207	21	0.19%	0.93%	5.98%	1.354	347	42	0.38%	11.97%
TF40_Opt_instruments	1.181	305	35	0.33%	1.38%	9.97%	2.070	563	58	0.58%	16.52%
TF41_Watches_clocks	177	50	6	0.05%	0.23%	1.71%	163	57	10	0.05%	2.85%
TF42_Motor_vehicles	2.156	519	45	0.60%	2.34%	12.82%	4.456	1.038	76	1.25%	21.65%
TF43_Other_transp equip	898	311	23	0.25%	1.40%	6.55%	1.528	453	40	0.43%	11.40%
TF44_Furniture_consum_good	773	218	24	0.22%	0.98%	6.84%	1.191	379	43	0.33%	12.25%

Source: own calculations and illustration. Notes: Number of linkages by technology-specific co-patenting networks (1990-1994 and 2000-2004).

Fifth, as the study aims to identify the spatial dynamics of all 43 technology field-specific co-patenting networks, the growth rates of the linkages are computed. Figure 4.8 and tables 4.4 and 4.5 illustrate the growth rates for each technology field for different groups of inter-regional linkages: (i) inter-regional TL3 linkages [overall number]; (ii) inter-regional TL3 linkages [inter-TL2 within country overall]; (iii) inter-regional-TL3 linkages [intra-TL2 within country overall]; (iv) inter-regional-TL3 linkages [inter-TL1 between country overall] (see tables 4.4 and 4.5). Differing dynamics for the 43 technology fields can be observed. Moreover, it is noticeable that especially international linkages have, on average, expanded across almost all technology fields since the 1990s (see tables 4.4 and 4.5) as has been already illustrated in the previous tables and figures. Furthermore, the dispersion of the identified co-patenting networks is very similar to the results regarding Moran's I (see section 4.2.2); larger networks thus seem to support larger distance bands (z-scores).

A more detailed analysis of the two periods unveils potential structural changes of the networks. Figure 4.8 shows that international linkages have replaced intra-national ones. More clearly: the share of inter-regional-TL3 linkages [inter-TL2 within country overall] has decreased, whereas inter-regional-TL3 linkages [intra-TL2 within country overall] and inter-regional-TL3 linkages [inter-TL1 between country overall] have increased their shares. Accordingly, co-patenting linkages have, on average, relatively increased within European regions and between countries; but they have relatively decreased between European regions within national borders.

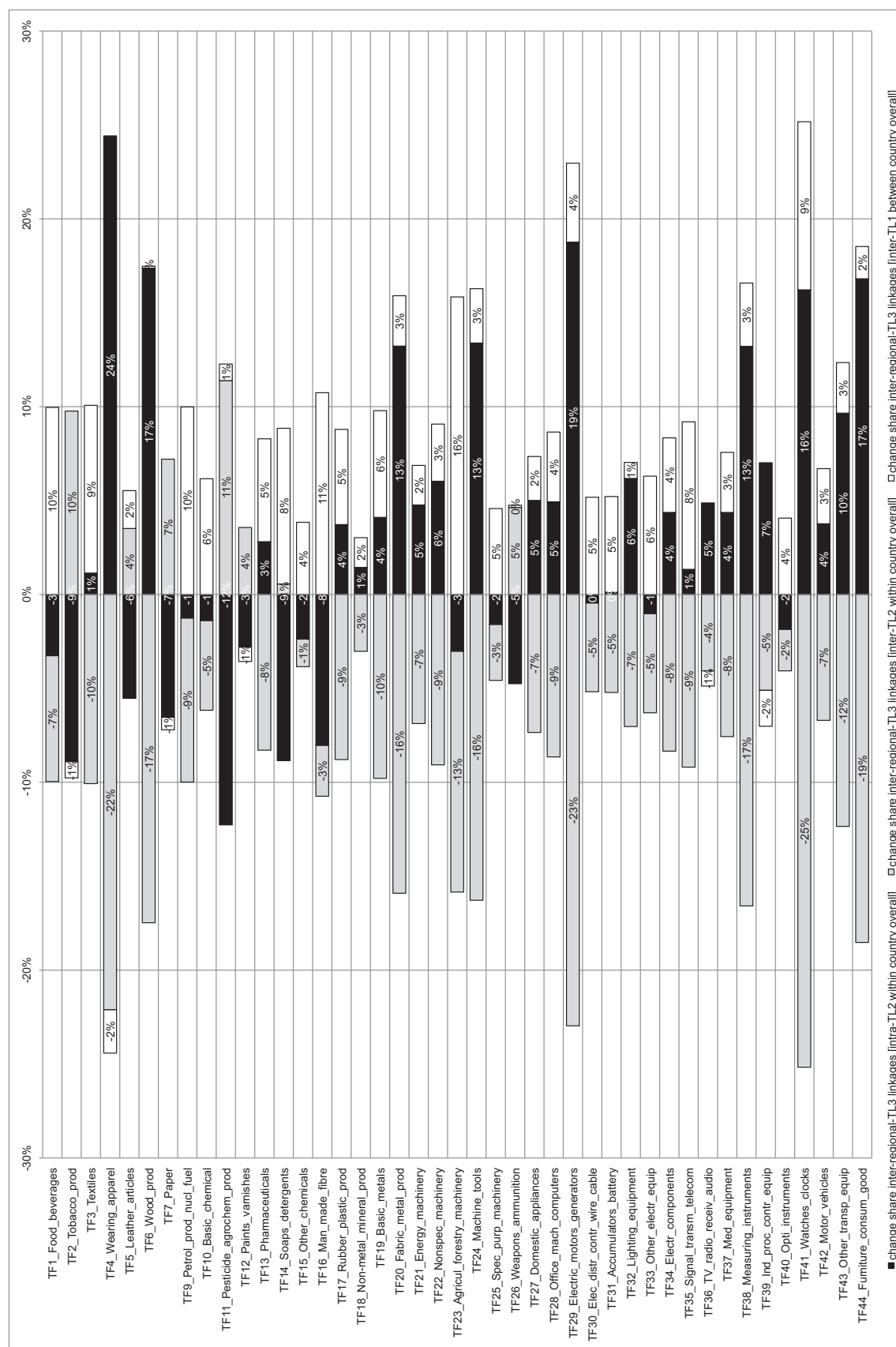


Fig. 4.8. Changing structure of inter-regional network linkages
Source: Own calculations and illustration. *Notes:* Change in share of linkages by technology-specific co-patenting network (1990-1994 and 2000-2004).

4.3.5.3. Core-Periphery Structures and the East-West Gradient

A deeper empirical analysis of the European inter-regional co-patenting linkages gives additional information about the integration of Eastern European regions and countries into the European regional co-patenting network. Therefore, the numbers, shares and growth rates of inter-regional co-patenting linkages between the NMS and the old EU-15 group (including Switzerland and Norway) are calculated. The NMS group consists of eight Central and Eastern European countries (CEEC), i.e., the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, the Slovak Republic, Slovenia and the two Mediterranean countries Malta and Cyprus.⁴⁴¹ The co-patenting network calculations are accomplished for each of the 43 technology fields (Schmoch *et al.*, 2003) and 10 years. Table 4.7 shows the absolute numbers of these linkages and additionally the respective growth rates between the two periods, 1990-1994 and 2000-2004. It is obvious that the eastern part of Europe is increasingly integrated into knowledge-intensive activities and inter-regional research collaborations as reflected by international co-patenting linkages between inventors. A comprehensive overview of the technology-specific growth rates is illustrated in table 4.7 and figures 4.9 and 4.10.⁴⁴² First and foremost, it is essential to note that the absolute number of co-patenting linkages between the eastern and western part of Europe only accounts for 5,308 linkages between 2000 and 2004. The 10 largest technology fields in terms of international east-west co-patenting linkages between 2000 and 2004 are the following: *TF13 Pharmaceuticals* (1,928), *TF10 Basic chemicals* (749), *TF38 Measuring instruments* (517), *TF42 Motor vehicles* (262), *TF35 Signal transm. & telecom.* (277), *TF28 Office mach. & computers* (136), *TF27 Domestic appliances* (111), *TF34 Electr. components* (105), *TF19 Basic metals* (100), *TF22 Nonspec. machinery* (93) and *TF37 Medical equipment* (93).⁴⁴³ Not a single co-patenting linkage between the NMS and the EU-15 group exists for the following technology fields: *TF2 Tobacco prod.*, *TF4 Wearing & apparel.*, *TF5 Leather articles*, *TF12 Paints & varnishes* and *TF41 Watches & clocks*. With respect to the growth rates of international research co-operations between the 1990s and 2000s, the most dynamic technology fields (with the highest growth rates) are the following: *TF3 Textiles* (7000%), *TF27 Domestic appliances* (5450%), *TF7 Paper* (3500%), *TF42 Motor vehicles* (2811%), *TF31 Accumulators & battery* (2700%), *TF20 Fabricated metal prod.* (1775%), *TF14 Soaps & detergents* (1500%), *TF18 Non-metal mineral prod.* (1260%), *TF33 Other electr. equip.* (1200%), *TF13 Pharmaceuticals* (1194%). For comparison purposes, table 4.7 and figure 4.10 summarize the growth rates in co-patenting linkages for all 43 technology fields.

Finally, an alternative way to analyze the size, structure and centrality of European regions is to visualize the European technology-specific co-patenting networks at different spatial levels (TL3, TL2). Network analysis tools are applied in order to calculate and visualize the relative position of European regions in the respective networks (see also section 4.3.6).⁴⁴⁴

⁴⁴¹ These ten countries joined the European Union on 1 May 2004 during the fifth enlargement process.

⁴⁴² For a complete overview and list of abbreviations of all 51 technology field aggregates used in the following graphs and tables see table B.4 (appendix).

⁴⁴³ Again, it is essential to note that technology fields show varying patenting propensities.

⁴⁴⁴ The subsequent network graphs are computed and visualized by using the “Harel-Koren Fast Multi-scale Algorithm” in the *Codeplex NodeXL* software environment. It is a force-directed algorithm that is designed to make all linkages about the same length and to minimize line crossings.

Table 4.7. Structure of network linkages between the NMS and EU-15

Co-inventor network structure: inter-regional TL3 linkages between NMS and EU-15 (and CH and NO)									
technology field	1990-1994			2000-2004			change		
	# inter-regional TL3 linkages [inter-TL1 between country overall]	# inter-regional TL3 linkages [between NMS and EU-15]	share inter-regional TL3 linkages [between NMS and EU-15]	# inter-regional TL3 linkages [inter-TL1 between country overall]	# inter-regional TL3 linkages [between NMS and EU-15]	share inter-regional TL3 linkages [between NMS and EU-15]	inter-regional TL3 linkages [between NMS and EU-15]		
TF1_Food_beverages	745	21	2,82%	2.993	56	1,87%	35	167%	+
TF2_Tobacco_prod	12	0	0,00%	22	0	0,00%	0	-	
TF3_Textiles	333	1	0,30%	826	71	8,60%	70	7000%	+++
TF4_Wearing_apparel	26	0	0,00%	75	0	0,00%	0	-	
TF5_Leather_articles	13	0	0,00%	27	0	0,00%	0	-	
TF6_Wood_prod	24	1	4,17%	62	1	1,61%	0	0%	
TF7_Paper	297	1	0,34%	778	36	4,63%	35	3500%	+++
TF9_Petrol_prod_nucl_fuel	128	8	6,25%	504	20	3,97%	12	150%	+
TF10_Basic_chemical	5.197	98	1,89%	12.802	749	5,85%	651	664%	++
TF11_Pesticide_agrochem_prod	511	11	2,15%	1.480	22	1,49%	11	100%	
TF12_Paints_varnishes	25	0	0,00%	18	0	0,00%	0	-	
TF13_Pharmaceuticals	6.238	149	2,39%	26.010	1928	7,41%	1779	1194%	+++
TF14_Soaps_detergents	873	1	0,11%	1.501	16	1,07%	15	1500%	+++
TF15_Other_chemicals	554	9	1,62%	964	54	5,60%	45	500%	+++
TF16_Man_made_fibre	50	4	8,00%	132	0	0,00%	-4	-100%	-
TF17_Rubber_plastic_prod	1.019	9	0,88%	2.557	38	1,49%	29	322%	+
TF18_Non-metal_mineral_prod	1.020	5	0,49%	1.902	68	3,58%	63	1260%	+++
TF19_Basic_metals	640	8	1,25%	1.565	100	6,39%	92	1150%	+++
TF20_Fabric_metal_prod	493	4	0,81%	1.301	75	5,76%	71	1775%	+++
TF21_Energy_machinery	427	9	2,11%	1.690	75	4,44%	66	733%	++
TF22_Nonspec_machinery	891	18	2,02%	2.541	93	3,66%	75	417%	+
TF23_Agricul_forestry_machinery	150	4	2,67%	1.108	16	1,44%	12	300%	+
TF24_Machine_tools	263	6	2,28%	911	28	3,07%	22	367%	+
TF25_Spec_purp_machinery	1.376	28	2,03%	3.790	87	2,30%	59	211%	+
TF26_Weapons_ammunition	23	16	69,57%	34	0	0,00%	-16	-100%	-
TF27_Domestic_appliances	431	2	0,46%	1.216	111	9,13%	109	5450%	+++
TF28_Office_mach_computers	686	26	3,79%	3.318	136	4,10%	110	423%	+
TF29_Electric_motors_generators	76	6	7,89%	453	50	11,04%	44	733%	++
TF30_Elec_distr_contr_wire_cable	227	7	3,08%	714	41	5,74%	34	486%	+
TF31_Accumulators_battery	36	1	2,78%	442	28	6,33%	27	2700%	+++
TF32_Lighting_equipment	46	6	13,04%	121	16	13,22%	10	167%	+
TF33_Other_electr equip	135	4	2,96%	711	52	7,31%	48	1200%	+++
TF34_Electr_components	437	14	3,20%	1.896	105	5,54%	91	650%	++
TF35_Signal_transm_telecom	781	44	5,63%	5.359	277	5,17%	233	530%	++
TF36_TV_radio_receiv_audio	191	7	3,66%	712	30	4,21%	23	329%	+
TF37_Med_equipment	1.256	20	1,59%	5.019	93	1,85%	73	365%	+
TF38_Measuring_instruments	1.418	61	4,30%	5.970	517	8,66%	456	748%	++
TF39_Ind_proc_contr equip	212	5	2,36%	477	10	2,10%	5	100%	
TF40_Opti_instruments	335	5	1,49%	1.316	32	2,43%	27	540%	++
TF41_Watches_clocks	27	0	0,00%	102	0	0,00%	0	-	
TF42_Motor_vehicles	762	9	1,18%	3.899	262	6,72%	253	2811%	+++
TF43_Other_transp equip	203	2	0,99%	576	12	2,08%	10	500%	++
TF44_Furniture_consum_goods	264	16	6,06%	455	3	0,66%	-13	-81%	-

Source: own calculations and illustration. Notes: Number of linkages by technology-specific co-patenting network (1990-1994 and 2000-2004); network linkages calculated by MySQL database extractions from OECD RegPAT (January 2009).

In the following, network visualization is used to present five selected technology fields, i.e., *TF10 Basic chemicals*; *TF13 Pharmaceuticals*; *TF38 Measuring instruments*; *TF41 Watches & clocks*; *TF42 Motor vehicles*. With regard to European enlargement and the integration of the NMS, the NMS regions are symbolized as red solid triangles. The TOP20 central EU-15 regions are visualized as blue solid squares. Network statistics below the network graphs give additional information. The main objective is to examine the number of NMS regions and the network structure in 1990-1994 and 2000-2004 and to identify the most central EU-15 regions.

Figure 4.11 visualizes the co-patenting network for *TF10 Basic chemicals* for the period 1990-1994. The overall network includes 606 European regions (from 23 countries) and an overall number of 56,363 inter-regional TL3 linkages; 5,197 of these linkages are of international type and 5,200 unique linkages exist between the 606 regions. The number of NMS regions that are incorporated into the spatial network of co-inventors in the 1990s is 34. One decade later (2000-2004), the co-patenting network has grown considerably (see figure 4.12); 697 TL3 regions (within 27 countries) are now active in inter-regional co-patenting. Moreover, the network analysis points to 83,218 inter-regional linkages between European regions. 12,802 of these linkages are of international type; 7,840 unique linkages exist between 697 European regions. 83 NMS regions are identified which are connected to the European inter-regional co-patenting network. A comparison of the two network graphs shows that a significant integration of former CEEC regions has taken place since the 1990s.

Another important technology field represents *TF13 Pharmaceuticals*. Figure 4.13 visualizes the co-patenting network for the period 1990-1994. The overall network includes 573 European regions (23 countries) and an overall number of 51,194 inter-regional TL3 linkages; 6,238 of the linkages are of international type. The number of NMS regions that are incorporated into the European network of co-inventors in the 1990s is 32. Between the 1990s and the 2000s, the co-patenting network has grown considerably (see figure 4.14). The network consists of an overall number of 709 TL3 regions (within 26 EU countries) which are active in the inter-regional co-patenting network. Moreover, 147,266 inter-regional linkages between European regions (intra- and international) are calculated; 26,010 of these linkages are of international type.

Figure 4.15 visualizes the co-patenting network for *TF38 Measuring instruments* for the period 1990-1994. The TL3 network is built upon 515 regions (22 countries) and consists of an overall number of 14,205 inter-regional linkages. 1,418 of these linkages are of international type (and thus border crossing). The number of NMS regions, which are incorporated into the spatial network of co-inventors, is 19. Between the 1990s and 2000s, the co-patenting network has expanded (see figure 4.16). In the 2000s, the network includes an overall number of 632 TL3 regions (24 countries) that are active in the inter-regional co-patenting network. Furthermore, the network analysis identifies 44,710 linkages between these regions; 5,970 are international. 44 NMS regions are involved in co-patenting between the year 2000 and 2004.

Quite different dynamics can be observed in the technology field *TF41 Watches & clocks*. For comparison purpose, figures 4.17 and 4.18 visualize the co-patenting network for the

periods 1990-1994 and 2000-2004. The inter-regional TL3 network is built upon 70 European regions (within 7 countries) and consists of an overall number of 451 inter-regional research linkages. Twenty seven of these linkages are of international type. No single NMS regions is incorporated into the spatial network of co-inventors. Until the 2000s, the co-patenting network slightly expanded its size (refer to figure 4.18). Nevertheless, in the 2000s, the European network only contains 94 TL3 regions (from 9 countries) which are active in inter-regional co-patenting. Furthermore, there exist 683 research linkages between these regions; only 102 are crossing national borders.

Finally, figure 4.19 visualizes the European regional co-patenting network for *TF42 Motor vehicles* for the period 1990-1994. In the 1990s, the overall network consists of 484 European TL3 regions, covering 20 countries. It is built upon an overall number of 14,330 inter-regional TL3 research linkages. 762 of these linkages are crossing national borders. The number of NMS regions, which are incorporated into the spatial network of co-inventors is 12. In the 2000s (refer to figure 4.20), the co-patenting network is much larger compared to the 1990s. 580 TL3 regions (24 countries) can be identified that are active in the inter-regional European co-patenting network. Furthermore, 47,250 linkages exist between these regions; 3,899 of the linkages are crossing national borders compared to 762 in the 1990s. Compared to the small number in the 1990s, 39 NMS regions are active in the 2000s.

To conclude, the network graphs clearly show that the most central European regions are leading research clusters in the EU-15 regions (see also chapter 3, section 3.5.4.2, and chapter 4, section 4.3.6). Besides the well-known fact that offshoring and outsourcing into the NMS has increased since the 1990s, evidence was rather weak regarding the development of border-crossing, knowledge-intensive tasks. It can be concluded from the presented networks and the overview of technology-specific growth rates of linkages in table 4.7 and figures 4.9 and 4.10 that NMS regions seem to be increasingly integrated into inter-regional co-patenting networks. Moreover, it is obvious that the overall number of unique NMS regions (and linkages) in the technology field-specific networks has grown considerably since the 1990s. The visualized networks give additional support to this interpretation. However, the presented results should be enriched by in-depth regional case studies and microeconomic studies in the future in order to identify the place-specific factors that drive co-patenting activity and research collaboration between EU-15 regions and the regions in the NMS.

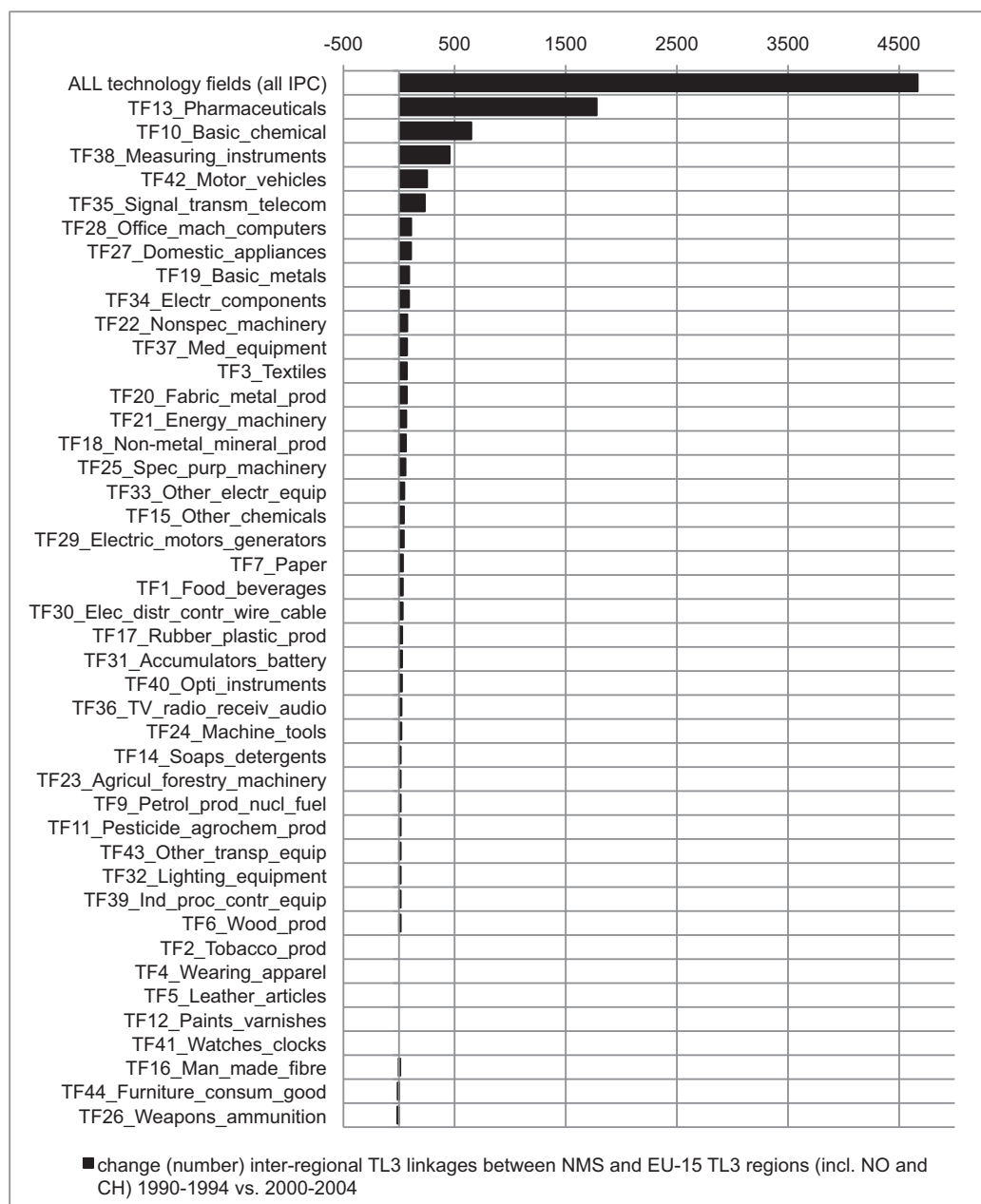


Fig. 4.9. Change (number) of co-patenting linkages between NMS and EU-15

Source: own calculations and illustration. *Notes:* Change of number of linkages by technology-specific co-patenting network (1990-1994 and 2000-2004).

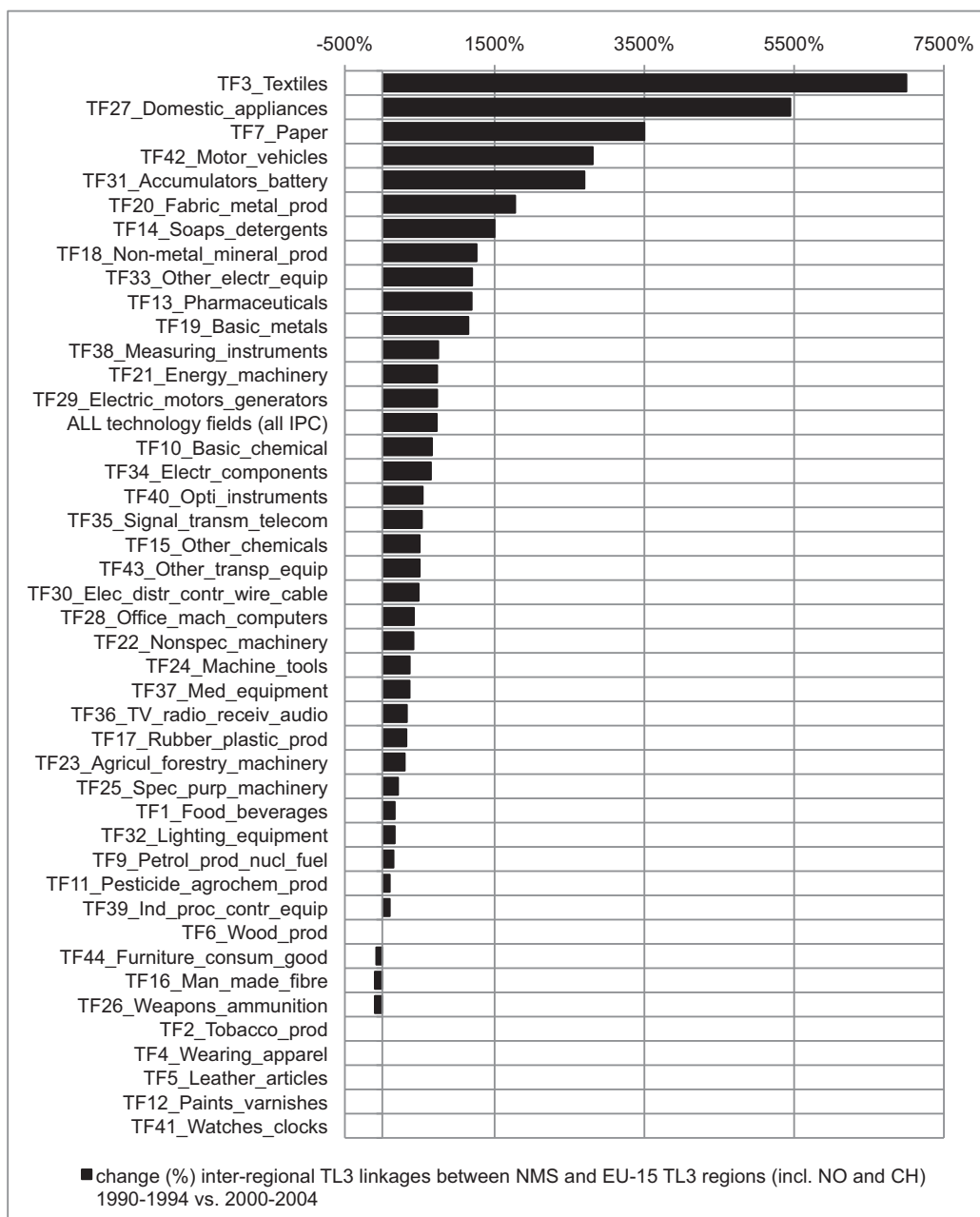


Fig. 4.10. Change (%) of co-patenting linkages between NMS and EU-15
Source: own calculations and illustration. *Notes:* Growth of linkages by technology-specific co-patenting network (1990-1994 and 2000-2004).



Fig. 4.11. European co-inventor network: TF10 Basic chemicals, 1990-1994

Source: Own calculations and illustration; *Notes:* TF10 Basic chemicals at TL3 level; 56.363 overall linkages, 5.200 unique linkages, 606 regions, 410 self-loops, average geodesic distance 2.97; graph density 0.03. Visualization in NodeXL. Triangle: all NMS regions; square: TOP20 (EU-15, CH, NO).



Fig. 4.12. European co-inventor network: TF10 Basic chemicals, 2000-2004

Source: Own calculations and illustration; *Notes:* TF10 Basic chemicals at TL3 level; 83.218 overall linkages, 7.840 unique linkages, 697 regions, 490 self-loops, average geodesic distance 2,74; graph density 0,03. Visualization in NodeXL. Triangle: all NMS regions; square: TOP20 (EU-15, CH, NO).

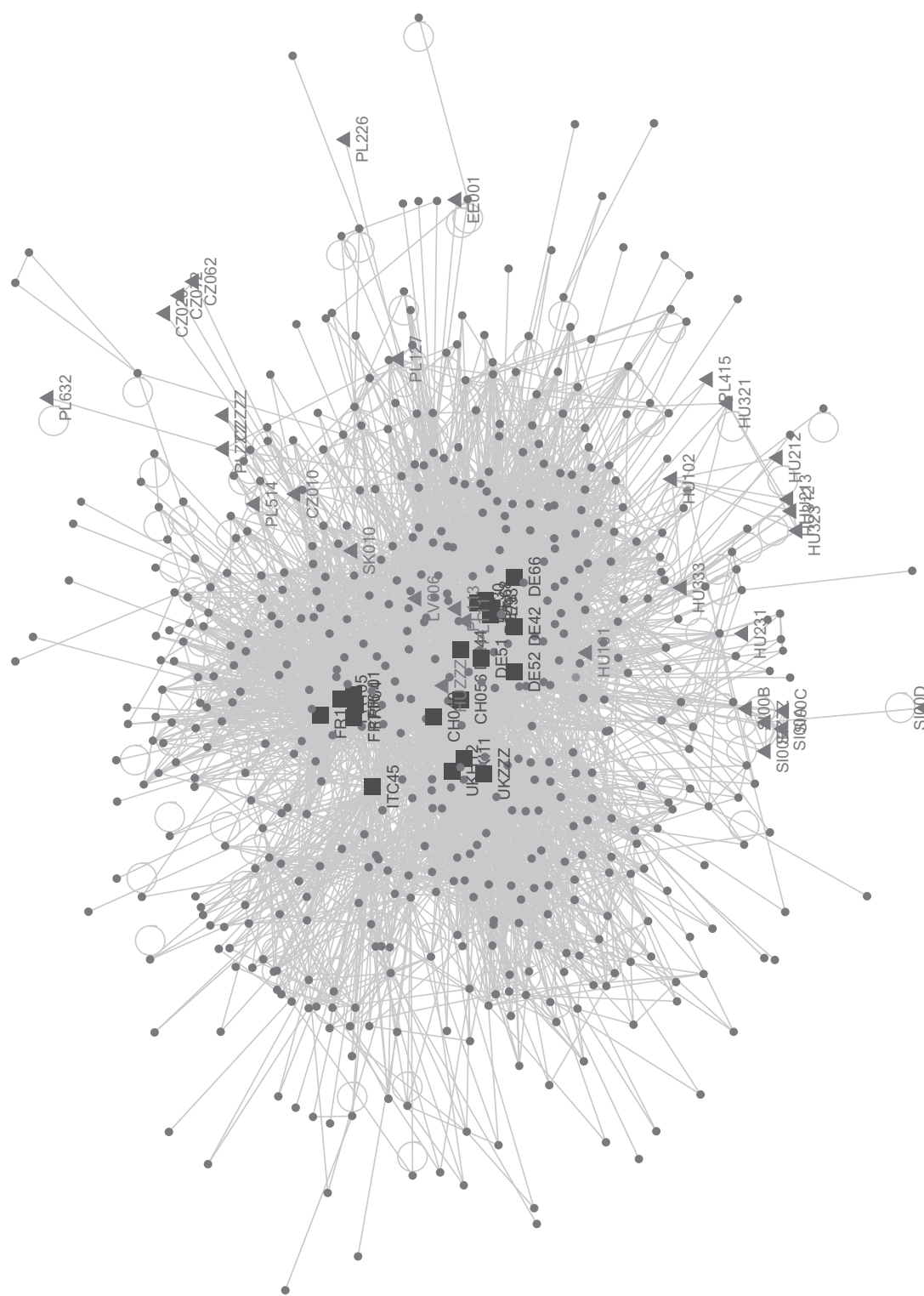


Fig. 4.13. European co-inventor network: TF13 Pharmaceuticals, 1990-1994

Source: Own calculations and illustration; *Notes:* TF13 Pharmaceuticals at TL3 level; 51.194 overall linkages, 4.536 unique linkages, 573 regions, 344 self-loops, average geodesic distance 2,89; graph density 0,03. Visualization in NodeXL. Triangle: all NMS regions; square: TOP20 (EU-15, CH, NO).



Fig. 4.15. European co-inventor network: TF38 Measuring instruments, 1990-1994

Source: Own calculations and illustration; *Notes:* TF38 Measuring instruments at TL3 level; 14.205 overall linkages, 2.669 unique linkages, 515 regions, 316 self-loops, average geodesic distance 3,40; graph density 0,02. Visualization in NodeXL. Triangle: all NMS regions; square: TOP20 (EU-15, CH, NO).

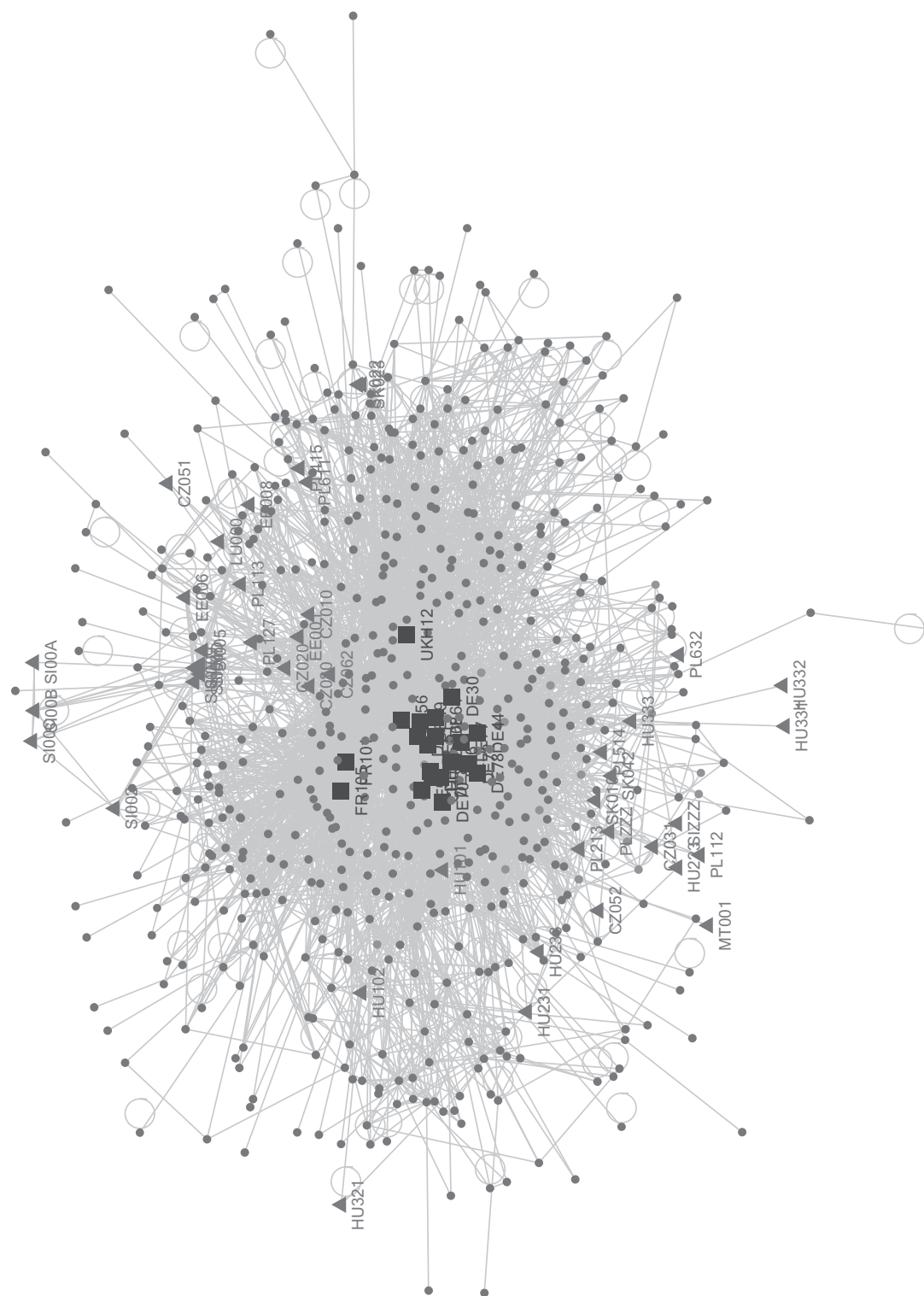


Fig. 4.16. European co-inventor network: TF38 Measuring instruments, 2000-2004
Source: Own calculations and illustration; *Notes:* TF38 Measuring instruments at TL3 level; 44.710 overall linkages, 5.054 unique linkages, 632 regions, 413 self-loops, average geodesic distance 2,98; graph density 0,03. Visualization in NodeXL. Triangle: all NMS regions; square: TOP20 (EU-15, CH, NO):

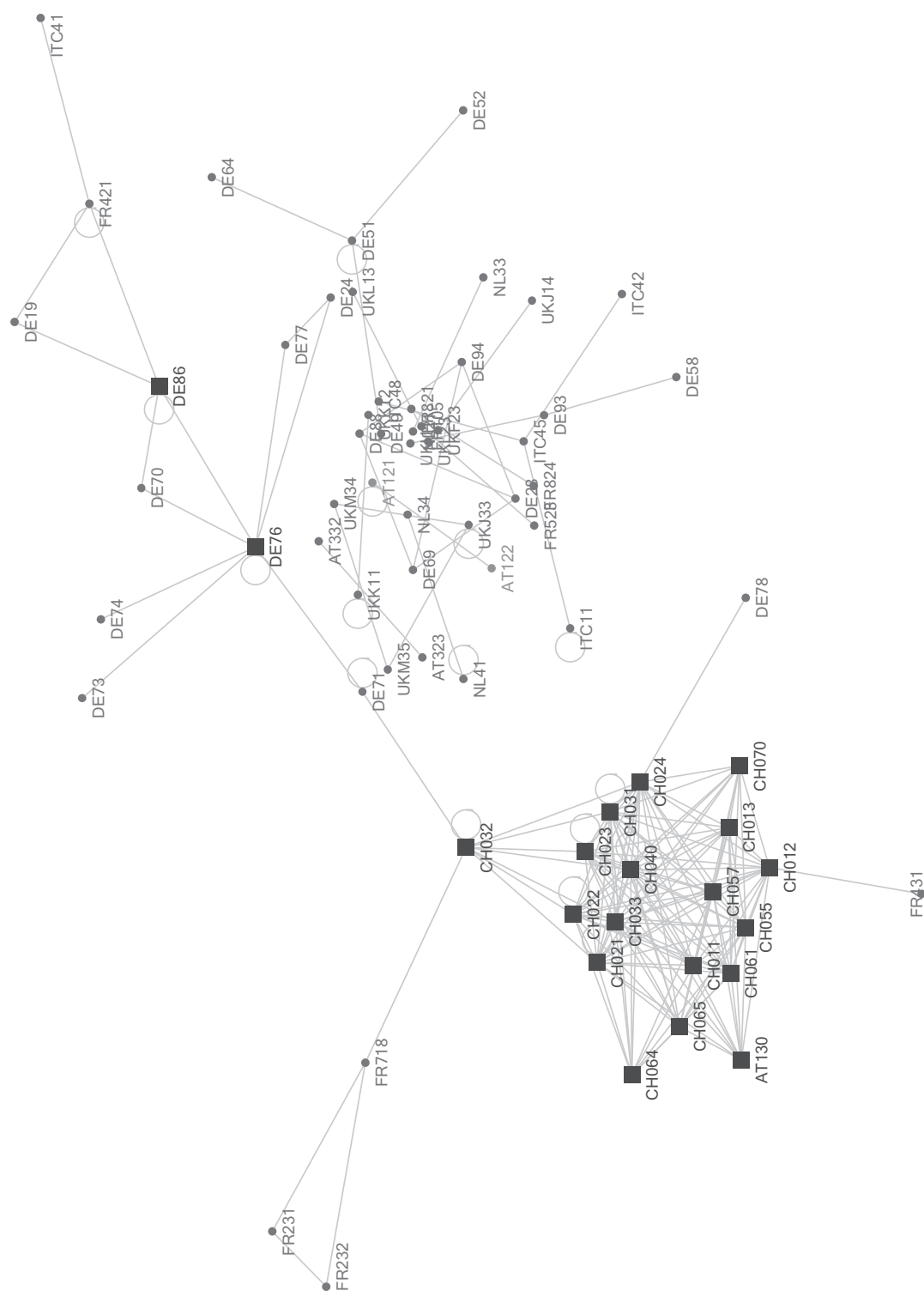


Fig. 4.17. European co-inventor network: TF41 Watches & clocks, 1990-1994
 Source: Own calculations and illustration; Notes: TF41 Watches/ clocks at TL3 level; 451 overall linkages, 177 unique linkages, 70 regions, 16 self-loops, average geodesic distance 3,03; graph density 0,07. Visualization in NodeXL. Triangle: all NMS regions; square: TOP20 (EU-15, CH, NO).

4.3.6. European Regional Co-Patenting Networks: Local Network Statistics

4.3.6.1. Co-Patenting Networks and the Centrality of Regions

The applied methodology in this section explores relational aspects in EPO patent applications, i.e., inter-regional co-patenting networks. The observed spatial dependence in patent statistics is challenged and explored by means of a direct analysis of EPO co-patenting linkages in a technological and spatial context. Local network statistics, i.e., network centrality analyses, complement the global network statistics. This section centers the centrality of European regions based upon inter-regional co-patenting linkages.⁴⁴⁵

In order to understand the complexity and dynamics of industries and their underlying co-inventorship-network structure, the location and centrality of regions within EPO co-inventorship networks have to be evaluated. To accomplish such an analysis, and to answer the proposed research questions, “degree centrality” and “betweenness centrality” indices are calculated for each of the 819 TL3 regions and their TL2 aggregates for the period 2000-2004 as described in section 4.3.3. The results are illustrated in the following tables.⁴⁴⁶

Tables 4.8 and 4.9 provide the ranked order of the TOP10 European TL3 regions for the period 2000-2004 by means of degree centrality in 43 technology fields.⁴⁴⁷ Tables B.9 and B.10 (appendix) additionally present the TOP10 European regions in terms of betweenness centrality for the 43 technology field aggregates. Finally, for comparison purposes, the centrality of regions in the networks at the higher TL2 level have been additionally calculated and the results support the observed structures, however, at a more aggregated level. The results are very similar to the ones reported above.⁴⁴⁸ The analysis clearly unveils that among the most central regions are, e.g., DE72 Stuttgart, DE93 München, DE42 Düsseldorf, DE51 Rhein-Main, DE52 Starkenburg, DE86 Industrieregion Mittelfranken, DE30 Berlin, DE66 Rheinpfalz, DE68 Unterer Neckar, CH011 Vaud, CH057 Thurgau, CH022 Freiburg, CH055 St. Gallen, CH040 Zürich, CH033 Aargau, CH021 Bern, FR105 Haute-de-Seine, FR103 Yvelines, FR623 Haute-Garonne, FR716 Rhone, FR101 Paris, ITC45 Milano, NL33 Zuid-Holland, UKH12 Cambridgeshire CC, UKJ11 Berkshire, DK001 Kopenhavns og Frederiksberg/ DK002 Kopenhagen amt. A comprehensive overview is given in the subsequent tables. The overall picture shows meaningful similarities to the calculated RCI (see chapter 3, section 3.5). It is obvious that the majority of listed European TOP10 regions are located within the leading European countries, i.e., Germany, Switzerland, France, the United Kingdom, the Netherlands, Italy. Furthermore, the identified central

⁴⁴⁵ In this respect, the analysis has to be recognized as a complementary approach to patent citation studies. The analysis is also different from knowledge production function approaches that solely measure potential (and global) inter-regional spillovers. Co-patenting network analysis is considered a complementary approach to econometric estimations in a knowledge production function tradition (refer to section 2.2.3).

⁴⁴⁶ A full listing of all centrality indices for all 819 regions and 43 technology fields is beyond the scope of this study. Detailed information is available from the author upon request.

⁴⁴⁷ For a complete overview and list of abbreviations of all technology field aggregates used in the graphs see table B.4 (appendix).

⁴⁴⁸ Calculations are available upon request from the author.

network regions represent dense urban regions, i.e., capital regions or metropolises. No single NMS region is part within the TOP10 ranking, although NMS regions are increasingly incorporated into the networks.

Table 4.8. Degree centrality ranking of TOP10 regions (1-5)

technology field	TOP10 ranking of TL3 regions (degree centrality in descending order) positions 1-5									
	1	2	3	4	5	1	2	3	4	5
TF1_Food_beverages	CH011	Vaud	DE51	Rhein-Main	DE93	München	CH022	Freiburg	NL33	ZUID-HOLLAND
TF2_Tobacco_prod	DE6	Hamburg	DE5	Schleswig-Holstein Süd	DE21	Lüneburg	UKJ32	Southampton	DE14	Hamburg-Umland-Süd
TF3_Textiles	DE51	Rhein-Main	DE42	Düsseldorf	CH056	Graubünden	CH056	Unterer Neckar	DE72	Stuttgart
TF4_Wearing_apparel	DE84	Oberfranken-Ost	TF13	Pescara	DE75	Neckar-Ab	DE51	Rhein-Main	FR718	Haute-Savoie
TF5_Leather_articles	TFD34	Treviso	DE42	Düsseldorf	DE86	Starkenbourg	DE86	Industrieregion Mittelfranken	DE51	Rhein-Main
TF6_Wood_prod	CH033	Aargau	CH040	Zürich	CH057	Thurgau	CH055	St. Gallen	CH066	Zug
TF7_Paper	DE51	Rhein-Main	DE52	Starkenbourg	DE86	Industrieregion Mittelfranken	DE86	Unter Neckar	DE93	München
TF9_Petrol_prod_nucl_fuel	FR716	Rhône	ITC45	Milano	FR105	Haus-de-Seine	UKJ14	Oxfordshire	FR714	Isère
TF10_Basic_chemical	DE51	Rhein-Main	DE42	Düsseldorf	DE52	Starkenbourg	DE66	Unter Neckar	DE68	Unter Neckar
TF11_Pesticide_agrochem_prod	DE44	Köln	DE42	Düsseldorf	DE51	Rhein-Main	FR716	Rhône	DE66	Rheinpfalz
TF12_Paints_varnishes	DE68	Unter Neckar	DE66	Rheinpfalz	DK003	Frederiksborg amt	DE41	Duisburg/Essex	DE40	Enschel-Lippe
TF13_Pharmaceuticals	DE51	Rhein-Main	DE93	München	FR101	Paris	DE68	Unter Neckar	CH056	Graubünden
TF14_Soaps_detergents	DE42	Düsseldorf	BE24	PROV. VLAAMS-BRABANT	NL33	ZUID-HOLLAND	BE10	REGION DE BRUXELLES-	DE44	Köln
TF15_Other_chemicals	DE42	Düsseldorf	DE66	Rheinpfalz	DE44	Köln	DE68	Unter Neckar	DE41	Duisburg/Essex
TF16_Man_made_fibre	DE51	Rhein-Main	FR716	Rhône	DE66	Rheinpfalz	DE34	Halle/S.	DE70	Mittler Oberrhein
TF17_Rubber_plastic_prod	DE93	München	DE51	Rhein-Main	DE42	Düsseldorf	DE52	Starkenbourg	DE64	Rheinessen-Nahe
TF18_Non-metal_mineral_prod	DE51	Rhein-Main	DE42	Düsseldorf	DE93	München	DE52	Starkenbourg	DE64	Rheinessen-Nahe
TF19_Basic_metals	DE42	Düsseldorf	DE42	Düsseldorf/Essex	DE72	Stuttgart	DE93	München	DE86	Industrieregion Mittelfranken
TF20_Fabric_metal_prod	DE93	München	DE42	Düsseldorf	DE72	Stuttgart	DE51	Rhein-Main	DE43	Bochum/Hagen
TF21_Energy_machinery	DE72	Stuttgart	DE93	München	DE51	München	DE70	Mittler Oberrhein	DE86	Industrieregion Mittelfranken
TF22_Nonspec_machinery	DE72	Stuttgart	DE51	Rhein-Main	DE93	München	DE42	Düsseldorf	DE68	Unter Neckar
TF23_Agricul_forestry_machinery	FR101	Paris	FR103	Yvelines	DE93	München	DE68	Unter Neckar	DE62	Mittlerhein-Westenwald
TF24_Machine_tools	DE72	Stuttgart	CH057	Thurgau	CH057	Thurgau	CH040	Zürich	DE42	Düsseldorf
TF25_Spec_purp_machinery	DE42	Düsseldorf	DE51	Rhein-Main	DE72	Stuttgart	DE93	München	DE52	Starkenbourg
TF26_Weapons_ammunition	DE3	Schleswig-Holstein Mitte	DE20	Südheide	DE66	Industrieregion Mittelfranken	DE42	Düsseldorf	DE48	Nordhessen
TF27_Domestic_appliances	DE93	München	DE72	Stuttgart	DE51	München	DE70	Mittler Oberrhein	DE97	Sudostoberbayern
TF28_Office_mach_computers	DE93	München	DE72	Stuttgart	DE68	Unter Neckar	DE52	Starkenbourg	DE86	Industrieregion Mittelfranken
TF29_Electric_motors_generators	DE72	Stuttgart	DE93	München	DE70	Mittler Oberrhein	DE86	Industrieregion Mittelfranken	CH057	Thurgau
TF30_Elec_distr_contr_wire_cable	DE51	Rhein-Main	DE72	Stuttgart	CH033	Aargau	DE36	Bielefeld	DE86	Industrieregion Mittelfranken
TF31_Accumulators_battery	DE72	Stuttgart	DE51	Rhein-Main	DE93	München	DE52	Starkenbourg	DE45	Aachen
TF32_Lighting_equipment	DE93	München	DE72	Stuttgart	CH031	Basel-Stadt	CH022	Freiburg	CH055	St. Gallen
TF33_Other_electr equip	DE93	München	DE72	Stuttgart	CH040	Zürich	DE30	Berlin	DE86	Industrieregion Mittelfranken
TF34_Electr components	DE93	München	DE72	Stuttgart	DE68	Oberes Elbtal/Osterzgebirge	DE86	Industrieregion Mittelfranken	DE51	Rhein-Main
TF35_Signal_transm_telecom	DE93	München	DE72	Stuttgart	SE010	Stockholms län	ITC45	Milano	FR181	Uusimaa
TF36_TV_radio_recviv_audio	DE93	München	FR101	Paris	DE86	Industrieregion Mittelfranken	UKH12	Cambridgeshire CC	CH011	Vaud
TF37_Med_equipment	DE51	Rhein-Main	DE68	Unter Neckar	DE93	München	FR101	Paris	CH040	Zürich
TF38_Measuring_instruments	DE93	München	DE68	Unter Neckar	DE51	Rhein-Main	DE72	Stuttgart	DE30	Berlin
TF39_Ind_proc_contr equip	DE72	Stuttgart	DE86	Industrieregion Mittelfranken	DE93	München	DE68	Unter Neckar	DE70	Mittler Oberrhein
TF40_Opt_instruments	DE93	München	DE73	Oswürttemberg	DE51	München	DE72	Stuttgart	CH056	Graubünden
TF41_Watches_clocks	CH012	Valais	CH021	Bern	CH021	Basel-Landschaft	CH024	Neuchâtel	CH024	Neuchâtel
TF42_Motor_vehicles	DE72	Stuttgart	DE93	München	DE70	Mittler Oberrhein	CH011	Vaud	FR103	Yvelines
TF43_Other_transp equip	DE93	München	DE30	Berlin	CH057	Thurgau	DE6	Hamburg	CH040	Zürich
TF44_Furniture_consum_good	DE72	Stuttgart	CH033	Aargau	CH022	Freiburg	CH021	Bern	UK111	Inner London - West

Source: own calculations and illustration. Notes: Degree centrality ranking of TL3 regions (descending order).

Table 4.9. Degree centrality ranking of TOP10 regions (6-10)

technology field	TOP10 ranking of TL3 regions (degree centrality in descending order) positions 6-10									
	6	7	8	9	10	6	7	8	9	10
TF1_Food_beverages	FR103	Yvelines	CH021	Bern	FR101	Paris	FR105	Hauts-de-Seine	DE68	Unterer Neckar
TF2_Tobacco_prod	DE15	Bremen-Umland	UKJ33	Hampshire CC	DE30	Berlin	DE19	Hannover	SE044	Skåne län
TF3_Textiles	DE66	Rheinpfalz	DE44	Köln	DE52	Starkenburg	CH022	Freiburg	BE23	PROV. OOST-VLAANDEREN
TF4_Weaving_apparel	DE71	Nord Schwarzwald	FR105	Hauts-de-Seine	FR222	Oise	DE72	Stuttgart	DE87	Westmittelfranken
TF5_Leather_articles	ITD35	Venezia	UKF23	Northamptonshire	CH040	Zürich	DE72	Stuttgart	DE41	Duisburg/Essex
TF6_Wood_prod	DE58	Oberes Elbtal/Osterzgebirge	CH022	Freiburg	CH031	Basel-Stadt	DE93	München	DE72	Stuttgart
TF7_Paper	FI181	Lusimaa	CH011	Vaud	CH022	Freiburg	CH056	Graubünden	DE42	Düsseldorf
TF9_Petrol_prod_nucl_fuel	UKD22	Cheshire CC	DE42	Düsseldorf	DE51	Rhein-Main	FR101	Paris	DE64	Rheinhesen-Nahe
TF10_Basic_chemical	TF10	Köln	DE93	München	ITC45	Milano	FR716	Rhône	CH056	Graubünden
TF11_Pesticide_agrochem_prod	DE68	Unterer Neckar	CH056	Graubünden	DE64	Rheinhesen-Nahe	UKJ11	Berkshire	DE70	Mittlerer Oberrhein
TF12_Paints_varnishes	DE5	Schleswig-Holstein Süd	DK002	Kobenhavn amt	DK001	Kobenhavn og Frederiksberg kommune	FR623	Hauts-Garonne	PT171	Grande Lisboa
TF13_Pharmaceuticals	DE42	Düsseldorf	DE30	Berlin	FR105	Hauts-de-Seine	DE44	Köln	ITC45	Milano
TF14_Soaps_detergents	DE66	Rheinpfalz	DE51	Rhein-Main	UKC22	Tyneside	CH040	Zürich	UKD54	Wirral
TF15_Other_chemicals	DE61	Rhein-Main	DE93	München	FR716	Rhône	CH021	Bern	DE6	Hamburg
TF16_Man_made_fibre	DE64	Rheinhesen-Nahe	DE72	Köln	FR612	Gronde	DE68	Unterer Neckar	DE56	Ostthüringen
TF17_Rubber_plastic_prod	DE66	Rheinpfalz	DE44	Köln	DE68	Unterer Neckar	ITC45	Milano	DE44	Köln
TF18_Non-metal_mineral_prod	ITC45	Milano	CH021	Bern	FR103	Yvelines	DE72	Stuttgart	DE68	Unterer Neckar
TF19_Basic_metals	DE51	Rhein-Main	CH040	Zürich	CH057	Thurgau	DE92	Starkenburg	DE44	Köln
TF20_Fabric_metal_prod	CH040	Zürich	DE44	Köln	DE86	Industrieregion Mittelfranken	CH055	St. Gallen	DE41	Duisburg/Essex
TF21_Energy_machinery	DE79	Bodensee-Oberschwaben	DE42	Düsseldorf	DE71	Nord Schwarzwald	DE30	Berlin	DE69	Franken
TF22_Nonspec_machinery	DE44	Köln	DE66	Rheinpfalz	DE64	Rheinhesen-Nahe	DE30	Berlin	CH057	Thurgau
TF23_Agricul_forestry_machinery	DE51	Rhein-Main	DE36	Bielefeld	DE35	Münster	FR105	Hauts-de-Seine	DE52	Starkenburg
TF24_Machine_tools	DE58	Oberes Elbtal/Osterzgebirge	CH055	St. Gallen	DE51	Rhein-Main	FR105	Hauts-de-Seine	DE79	Bodensee-Oberschwaben
TF25_Spec_purp_machinery	DE41	Duisburg/Essex	DE68	Unterer Neckar	DE73	Ostwürtemberg	DE78	Hochrhein-Bodensee	DE44	Köln
TF26_Weapons_armmunition	DE78	Schwarzwald-Baar-Heuberg	DE93	München	FR241	Cher	CH040	Zürich	DE6	Hamburg
TF27_Domestic_appliances	DE86	Industrieregion Mittelfranken	DE42	Düsseldorf	DE52	Starkenburg	DE88	Augsburg	DE30	Berlin
TF28_Office_mach_computers	UKH12	Cambridgeshire CC	DE51	Rhein-Main	DE30	Berlin	ITC45	Milano	DE45	Aachen
TF29_Electric_motors_generators	DE83	Oberfranken-West	CH055	St. Gallen	DE68	Unterer Neckar	DE90	Regensburg	CH040	Zürich
TF30_Elec_distr_contr_wire_cable	CH055	St. Gallen	CH057	Thurgau	DE42	Düsseldorf	CH040	Zürich	DE43	Bochum/Hagen
TF31_Accumulators_battery	CH011	Vaud	CH057	Thurgau	DE74	Donau-ller (BW)	DE42	Düsseldorf	CH065	St. Gallen
TF32_Lighting_equipment	DE38	Arnsberg	DE51	Rhein-Main	CH011	Vaud	CH040	Zürich	FR101	Paris
TF33_Other_electr equip	DE22	Braunschweig	DE68	Unterer Neckar	CH057	Thurgau	DE23	Hildesheim	DE70	Mittlerer Oberrhein
TF34_Electr components	ITC45	Milano	DE30	Berlin	DE52	Starkenburg	DE88	Unterer Neckar	FR714	Isère
TF35_Signal_transm_telecom	DE30	Berlin	FR105	Hauts-de-Seine	DE45	Aachen	FR101	Paris	UKJ11	Berkshire
TF36_TV_radio_recv_audio	CH040	Zürich	FR523	Ile-et-Vilaine	CH022	Freiburg	CH055	St. Gallen	CH012	Valais
TF37_Med_equipment	DE52	Starkenburg	DE30	Berlin	FR716	Rhône	DE42	Düsseldorf	DE70	Mittlerer Oberrhein
TF38_Measuring_instruments	FR101	Paris	UKH12	Cambridgeshire CC	DE52	Starkenburg	DE70	Mittlerer Oberrhein	FR105	Hauts-de-Seine
TF39_Ind_proc_contr equip	DE90	Regensburg	DE52	Ingolstadt	DE51	Rhein-Main	CH040	Zürich	DE83	Oberfranken-West
TF40_Opt_instruments	CH055	St. Gallen	DE89	Starkenburg	CH021	Bern	DE30	Berlin	DE86	Industrieregion Mittelfranken
TF41_Watches_clocks	CH040	Zürich	CH023	Solothurn	CH033	Aargau	CH022	Freiburg	FR431	Doubs
TF42_Motor_vehicles	DE52	Starkenburg	DE69	Franken	DE22	Braunschweig	DE44	Köln	DE68	Unterer Neckar
TF43_Other_transp equip	DE51	Rhein-Main	CH055	St. Gallen	DE66	Rheinpfalz	DE74	Donau-ller (BW)	DE86	Industrieregion Mittelfranken
TF44_Furniture_consum_goods	CH055	St. Gallen	CH011	Vaud	CH012	Valais	DE93	München	CH057	Thurgau

Source: own calculations and illustration. Notes: Degree centrality ranking of TL3 regions (descending order).

4.3.6.2. Co-Agglomeration of Co-Patenting Networks

Another serious research issue that is approached in this study is to what extent innovative European regions have a similar (perhaps central) network position with respect to different technology fields (geographical coincidence). Assuming that leading innovative regions obtain a central position in different technology fields, “co-inventor network centrality” can be used to analyze co-agglomeration of technology fields. In this respect, the analysis in this section challenges (analogous to section 3.5.5) the following crucial question: Are some European regions central multi-technology network hubs? Therefore, regions’ ranking positions in technology-specific networks are compared to the positions in all other technology-specific networks. Spearman rank correlation coefficients for co-inventor centrality indices are calculated for all 43 technology fields.⁴⁴⁹ Finally, the calculated rankings are used to calculate the correlation matrices for the reference period 2000-2004. The obtained Spearman correlation coefficients illustrate to what degree the respective co-inventor network centrality rankings of regions in two technology fields overlap. Therefore, the obtained results can be used as a proxy to discuss the existence of “multi-technology” network hubs and thus “diversified” network regions in Europe.

To illustrate the results, correlograms are used to visualize the spatial pattern of co-location of technology-specific co-inventorship networks (see also chapter 3). Such correlograms are constructed for all 43 co-patenting networks based on different centrality indices (degree centrality, eigenvector centrality, betweenness centrality). The correlation coefficients are again shaded; coefficients between 0.5 and 0.7 in light grey, coefficients above 0.7 in dark grey. In case that the centrality rankings are very similar, the coefficients should exhibit high correlation. Thus, high Spearman rank correlation coefficients between two technology fields then mean that the two technology fields are similar in their network centrality patterns (ranking). It can be interpreted as a possible proxy for geographical coincidence/co-agglomeration of co-patenting networks.

Figure 4.21 (and figures A.44 and A.45, appendix) highlights the computed Spearman rank correlation matrices by centrality index and technology field.⁴⁵⁰

⁴⁴⁹ If a region has a low network centrality in terms of co-inventorship compared to other regions, a low ranking position is given to this unit. If a region is not connected to the respective network at all, a centrality parameter value of zero is assigned to this unit. This happens for a certain number of regions. Therefore, the higher TL2 level was chosen for the correlation analysis.

⁴⁵⁰ It is worth remembering that the centrality indices are calculated from inter-regional co-patenting linkages at the TL2 level. The TL2 level treats linkages within the same TL2 region as a self loop; moreover, it controls for inventor commuting and skewness of the distribution (averaging process).

To conclude, the empirical analysis in this section yields the following results. The correlogram for degree centrality (importance of regions in terms of overall number of unique linkages) shows empirical evidence for the “multi-technology hub” hypothesis (see figure 4.21). Most networks co-locate in those regions that are central in several technology-specific co-patenting networks (in terms of heterogeneous linkages), which supports the diversification hypothesis. High correlation coefficients can be observed for the following technology fields: *TF28 Office mach. & computers* and *TF35 Signal transm. & telecom.* (0.92); *TF10 Basic chemicals* and *TF13 Pharmaceuticals* (0.94).

Innovative regions also exhibit a “gatekeeping position” (betweenness centrality) in several technology fields as shown by high Spearman coefficients (see figure A.44, appendix). *TF10 Basic chemicals* and *TF13 Pharmaceuticals* show a very high Spearman coefficient (0.83), which means that the central regions in the co-patenting network in *TF10 Basic chemicals* also dominate the *TF13 Pharmaceuticals* co-patenting network and are essential for the overall connectedness of the two networks. Similarly, the centrality ranking of *TF38 Measuring instruments* and *TF13 Pharmaceuticals* is highly correlated (0.84).

Finally, the eigenvector correlation matrix (see figure A.45, appendix) highlights the correlation coefficients for all 43 technology fields in terms of important linkages (to the most central regions). High Spearman coefficients then mean that the technology-specific co-patenting networks are determined by the same regions. These regions have many important linkages to other highly connected (and innovative) regions, which represents empirical evidence for dense networks.

With regard to the hypotheses, the correlograms illustrate that there is indeed some kind of evidence for co-location/ co-agglomeration of technology fields in Europe, meaning that the centrality rankings of the regions show similarities. Comparing degree centrality indices, the results of this study suggest that leading innovative regions are indeed central for the majority of technology field-specific co-patenting networks (TF1 to TF44). Centers of co-patenting activity seem to co-locate, on average, in identical regions, which gives first support to the hypothesis that European regions are “multi-field” network nodes. Moreover, the Spearman rank correlation coefficients are much higher for eigenvector centrality indices than for betweenness or degree centrality, which may be interpreted as evidence for the presence of dense networks between leading innovative regions and the existence of meaningful core-periphery structures.

5. Research Clustering, Income Disparities and the Growth of Regions in Europe

5.1. Analyzing Regional Disparities and Growth

Having explored spatial concentration, clustering and inter-regional co-patenting networks across Europe and the ERA in the former chapters 3 and 4, the following analysis will be shifted towards regional income disparities and regional growth.

Spatial income inequality (i.e., non-normal spatial distribution of income) is a phenomenon that determines the structure of both leading industrialized regions and regions in transition. According to Scott and Storper (2003), considering globalization as a simple spreading out of economic activity into a fluid “space of flows” seems to be a fundamental mistake. The analyses in the former chapters have already pointed out the persistence of clustering and geographic concentration of research activity across European regions. Thus, globalization is supposed to be accompanied by persistent agglomerative tendencies. As Scott and Storper (2003, 582) argued,

“[i]n sum, large-scale agglomeration - and its counterpart, regional economic specialization - is a worldwide and historically persistent phenomenon that is identifying greatly at the present time as a consequence of the forces unleashed by globalization. This leads us to claim that national economic development today is likely not to be less but rather more tied up with processes of geographical concentration compared with the past.”

With respect to the European regional development, it is especially important to analyze the spatial distribution of the gross domestic product (GDP) at the regional level. Although the European member countries seem to converge with respect to economic activity at the national level, several existing regional studies point to divergence and increasing within-subgroup inequality (Frenken and Hoekman, 2006; Paas and Schlitte, 2007; Crespo Cuaresma *et al.*, 2009b).⁴⁵¹ European enlargement activities have to deal with the issue of considerable income disparities within and between the European member states and their regions, as has already been discussed in the introductory chapter. Accordingly, there may be a crucial implication for the explicit target of regional convergence, especially at the regional level where several European policy tools are applied (e.g., NUTS2 and TL2/TL3) (OECD, 2003, 2006; European Commission, 2007c). The European Community’s objective is to enhance economic and social cohesion and to achieve equity (Articles 2 and 4, and Title XVII of the Treaty establishing the European Community).⁴⁵²

⁴⁵¹ See also Duro (2004), Combes and Overman (2004), Brühlhart and Traeger (2005) and Combes *et al.* (2008).

⁴⁵² For a comprehensive review of the European structural policies refer to Rodríguez-Pose and Fratesi (2007) and European Commission (2011f) and European Commission (2011h).

The European Cohesion Policy and the objectives have their roots in Articles 2 and 4 and Title XVII of the Treaty of the European Community. According to Article 2, European cohesion policy should contribute to “[p]romote economic and social progress as well as a high level of employment, and to achieve balanced and sustainable development.” Moreover, article 158 adds that “[i]n particular, the Community aims to reduce the disparities between the levels of development of the different regions and the backwardness of the least favored regions or islands, including rural areas.” The European cohesion policy represents the second-largest item in the European Union’s budget. The largest amount of European regional policy funding (over 80%) is applied to European regions that are falling under the European convergence objective. This policy objective generally focuses on NUTS2 regions. Financial support is given if regional per capita GDP is less than 75% of the EU-25 average (and, respectively, of the EU-27 average).⁴⁵³ Box 5.1 summarizes key information about the European cohesion policy.

A strong motivation and solid argument for analyzing the structure and dynamics of European income distribution and European regional growth is based upon the fact that economic activity seems to show a persistent non-normal distribution as well as regional interdependence (Fotheringham *et al.*, 2002; Hauser *et al.*, 2008; Andersson and Gråsjö, 2009).⁴⁵⁴ Regarding the OECD TL3 level, pan-European disparities and regional growth have not been very well studied so far. The majority of studies ignore variation at the level of smaller units as they are restricted to the NUTS1 or NUTS2 level (approximately 50-250 large aggregates) (Combes and Overman, 2004; Monfort, 2008). Therefore, one objective of the analysis in this chapter is to provide a systematic measurement of the distribution of economic activity and the regional components of inter- and intra-regional disparities of GDP per capita (PPP) over time and across the entire population of 819 European regions.

According to Maggioni and Uberti (2009), a crucial and worrying aspect of the European integration process is that the productive capacity agglomeration process, which emerges from market forces, may become too strong and may lead to social debates due to effects on wages, production, productivity and employment structures. There is evidence that countries that have experienced diverging regional income disparities tended to have, on average, higher national real GDP levels and growth rates, which is in line with the theoretical results of NEG models, as presented and discussed in chapter 2 (see sections 2.1.5.5 and 2.1.6.7).⁴⁵⁵

With respect to the European case, there is evidence that regions within the group of the 10 NMS are rather diverging compared with the EU-15 group of regions (Szörfi, 2007; Paas and Schlitte, 2008). Regarding cohesion, the core of European growth and the gravity center of future regional European cohesion policy is considered to have relocated to other parts of the European landscape of regions (see Box 5.1). The eastern enlargement process has induced an increase of about 30% of the European areal surface, an increase of more than 25% of the European population, but no significant increase in average per capita

⁴⁵³ The NUTS2 level represents the level for structural cohesion policy. From an economic perspective, however, the NUTS2 level is problematic for several reasons (see also the discussion in chapter 3 and 4).

⁴⁵⁴ See also Anselin (2007).

⁴⁵⁵ See also Williamson (1965) and Baldwin and Martin (2004).

GDP (European Commission, 2003, 2004). Until the 1990s, the European regional growth poles were mainly concentrated in EU-15 metropolises, e.g., Munich, Berlin, Brussels, Vienna, Hamburg, Paris, Madrid, Milan, Rome. In the 1990s, new growth poles emerged in the capital towns and urban regions in Scandinavian countries, Spain, Ireland and recently in the NMS (Heidenreich, 1998). Moreover, it has been argued that economic growth and income is characterized by bi- or tri-modal distributions, originating from strong secondary growth poles (e.g., Naples, Barcelona, Stuttgart, Hamburg, Frankfurt in the EU-15). Nevertheless, the existing regional studies are mainly restricted to large macro regions (Abrham and Vosta, 2006; Melchior, 2008).⁴⁵⁶

This first part of chapter 5 analyzes income inequality dynamics. The analysis represents a pure quantitative approach that makes use of regional GDP per capita and population data. The section approaches the spatial inequality of per capita income for the period 1995 to 2006 by explicitly measuring the distribution and the structural dynamics across European regions (i.e., up to 819 TL3 regions). Several studies have shown that inequality increases with disaggregation from the macro to the micro level (Openshaw and Taylor, 1979). Therefore, the analysis decomposes the overall inequality/disparity (global spatial inequality) of GDP per capita (PPP) into a within-subgroup and between-subgroup component. Besides Gini computation, this study also applies generalized entropy measures. The analysis centers on EU-25 countries, but it also includes Switzerland and Norway, as they are geographically part of the European continent. Applying the statistical tools at the very disaggregated OECD TL3 level should help to depict spatial income disparities much better than using the European regional classification system (NUTS1/2-level), which is generally used for analyses of the European convergence objective. Moreover, the TL3 regions resemble functional regions and minimize potential spatial autocorrelation (see also chapter 4, section 4.2). The OECD definition should be aggregated enough to represent functional units.

In the first part of the chapter, the analysis tries to find empirical evidence for the following research questions: (i) Is GDP per capita still highly concentrated and unequally distributed within and between the European countries? (ii) Do the EU-15 countries show different patterns of regional disparity in terms of GDP per capita compared with the 10 NMS? (iii) Have regional disparities been persistent, decreasing or increasing since the 1990s? The analysis is related to the theoretical concepts and models on core-periphery structures reviewed in chapter 2, section 2.1, and contributes to the empirical studies presented in section 2.2.2.

Furthermore, besides the above-described inequality analysis at the level of European regions, the empirical analysis in the second part of this chapter also places emphasis on the question of whether patenting activity and the regional settlement structure do have a significant effect on regional growth and whether the EU-15 and the NMS regions show convergence of per capita income.

⁴⁵⁶ Refer also to Heidenreich (1998) and Duro (2004).

Box 5.1: European Regional Policy

The European Fund for Regional Development (ERDF), the European Social Fund (ESF) and the Cohesion Fund (CF) are organized around three central objectives: (i) convergence, (ii) regional competitiveness and employment, and (iii) European territorial co-operation (European Commission, 2011g,f,h). The overall budget between 2007-2013 is Euro 347bn; Euro 201bn for the ERDF, Euro 76bn for the ESF, and Euro 70bn for the CF. The convergence objective is financially based on the ERDF, the ESF and the CF (European Commission, 2011g,f). The CF has been implemented in order to support European member countries whose gross national income per inhabitant is less than 90% of the EU average. The main target is to improve the economic and social conditions in backward member countries and to stabilize their economies (European Commission, 2011h). For the years 2007 to 2013, the CF is targeting Bulgaria, Cyprus, the Czech Republic, Estonia, Greece, Hungary, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Slovakia and Slovenia. Spain receives a phase-out fund if its GNI per inhabitant is less than the EU-15 average (national comparison) (European Commission, 2011g,e).

The ESF aims to improve European employment and job opportunities. The program intervenes in the framework of the convergence and regional employment and competitiveness objectives (European Commission, 2011g,f,h).

The ERDF is implemented to strengthen social and economic cohesion in the European Union by addressing imbalances between EU regions. Regarding the 2007-2013 funding program, the European Union's policy at the regional level is based upon three objectives: (i) convergence, (ii) regional competitiveness and employment, and (iii) European territorial co-operation. The three pillars replace the previous policy objectives of the period 2000-2006 (i.e., the antecedent *Objectives 1, 2 and 3*) (European Commission, 2011h).

The (regional) convergence objective covers those regions whose GDP per capita is below 75% of the regional EU average. Nearly all the regions of the NMS and many regions in Spain, Southern Italy, Greece, Portugal and in the New Laender (Germany) correspond to this criterion. The main priorities under the convergence objective are (i) human and physical capital, (ii) innovation output, (iii) the knowledge society, (iv) environment and (v) administrative efficiency. The budget allocated to the convergence objective is Euro 283bn (current prices). The past enlargement rounds (2004: 10 countries; 2007: 2 countries) have led to a decrease of the European average GDP per capita (section 5.3) (European Commission, 2011e). That being the case, several regions in the "old" EU-15 member states, which used to be authorized to receive funding under the convergence objective, are now beyond the 75% threshold level of the enlarged European Union. These regions can receive "phasing out" funding until the year 2013 (European Commission, 2011e).

The European Commission additionally advances European inter-regional co-operation in order to support European regions (and cities) in member states for joint programmes, projects and networks (European Commission, 2011d).

According to Barro and Sala-i-Martin (1991), among others, β -convergence is a necessary condition for σ -convergence, and usually the former process generates the latter. However, it is also possible for initially poor regions and countries to grow faster than initially rich ones, meaning that cross-sectional dispersion is either constant or increasing in the course of time (Barro and Sala-i-Martin, 2003; Hagemann, 2004). Since the famous cross-country studies of Baumol (1986), Abramovitz (1986), Barro (1991), Barro and Sala-i-Martin (1991), Barro and Sala-i-Martin (1992) and Mankiw *et al.* (1992), the convergence-

divergence debate has also reached the level of regions (Abreu *et al.*, 2004, 2005; Harris, 2008).⁴⁵⁷

Barro and Sala-i-Martin (1991, 154) have analyzed a cross-section of 85 European regions for the period 1950-1985, and have found some kind of

“[e]mpirical regularity that the rate of beta-convergence is roughly 2% a year in a variety of circumstances [...] the half-life of this convergence process is 35 years.”

Moreover, Barro and Sala-i-Martin (2003, 496) concluded that

“[t]he unconditional beta-convergence is the norm for these regional economies.”

The existence and economic and political consequences of industry agglomerations, research clustering and spatial concentration of research in general are nowadays increasingly challenged. Furthermore, the issues of convergence and divergence are highly visible in the European policy agenda (Acs, 2002; Fujita and Krugman, 2003; Fujita and Mori, 2005).⁴⁵⁸ The question is whether the initial income levels of poorer regions converge to the level of industrialized regions, which has some implications for regional growth paths and leads to normative conclusions.

According to the economic theories, convergence and/or divergence may occur depending on several structural factors. Neoclassical growth theory mainly argues for unconditional β -convergence due to decreasing returns of input factors (capital, labor) in the production function and homogeneous steady-state paths, whereas adherents to the endogenous growth theory and new economic geography argue for conditional convergence or even divergence (Martin and Ottaviano, 1999; Baldwin and Martin, 2004; Hagemann, 2004). The conditional convergence hypothesis is in general highly pessimistic with respect to homogeneous steady states. Absolute convergence to a unique steady state seems only plausible when analyzing within-country convergence; in this case, it is most likely to assume similar saving rates, technology bases, population growth, governmental policy, property rights and other conditions (Harris, 2008). In respect of between-country convergence, especially at the regional level, the units appear to have different steady-state paths (Solow, 2007; Brakman and van Marrewijk, 2008; Battisti and Vaio, 2008). However, the number of growth estimations at the regional level is still quite small compared with the overall number of cross-country studies at the national level. Regarding the origins of regional divergence, the spatial distribution of knowledge stocks and researchers is considered a crucial factor for regional development. Chapters 3 and 4 already demonstrated that the distribution of knowledge stocks (i.e., patenting activity) in Europe shows core-periphery structures. Persistent core-periphery structures in patenting activities should then be reflected in significant differences regarding regional growth rates (see sections 2.1.6.6 and 2.1.6.7), meaning that regions (and countries) exhibit divergence. This hypothesis will be tested in section 5.4.

The convergence-divergence hypothesis has been frequently tested by application of a σ -convergence measure. σ -convergence happens if the disparity of regional income levels

⁴⁵⁷ Baumol (1986) has used data for the period 1870-1978 to show convergence of productivity of sixteen industrialized countries.

⁴⁵⁸ Baldwin and Krugman (2001) and Fujita *et al.* (2001).

decreases in the course of time (Bräuninger and Niebuhr, 2005, 2008).⁴⁵⁹ Further to this, β -convergence does not necessarily mean that regional inequalities are decreasing (Quah, 1993; Arbia *et al.*, 2005). Additionally, it has been shown in studies that spatial effects (i.e., spatial autocorrelation) have to be considered in regional convergence analyses, especially when large spatial aggregates are used (Dewhurst and McCann, 2007). Neglecting spatial effects between regions would reduce regions to isolated islands in a non-interdependent space (Paas and Schlitte, 2008).⁴⁶⁰ Nevertheless, some studies already reported that the implementation of national and regional controls might reduce spatial dependence (Bräuninger and Niebuhr, 2005; Geppert and Stephan, 2008).⁴⁶¹

From an empirical perspective, the determinants of regional growth and income disparities in Europe have received increasing attention in recent years (Harris, 2008; Geppert and Stephan, 2008; Petrakos and Artelaris, 2009).⁴⁶² Box 5.2 offers a short overview of regional studies.⁴⁶³

The great majority of authors restricted their research efforts on the level of administratively defined macro regions, which sometimes consist of spatial units representing the nation state (e.g., Cyprus, Denmark, Estonia, Latvia, Lithuania, Luxembourg, Malta and Slovenia). It is obvious that such classifications are by definition not suited for an analysis of regional settlement structures, agglomeration economies, commuting effects and various forms of spatial spillovers (Brakman *et al.*, 2005). Moreover, several researchers followed the predefined NUTS classification, although empirical evidence has suggested that the NUTS2 level is inferior for many reasons. The perhaps most serious issue is that spatial dependence is present in most NUTS1/2 regressions; the autocorrelation of dependent variables and covariates appears as a result of the averaging process in the context of data aggregation.⁴⁶⁴ In general, the averaging process via spatial aggregation is considered to reduce the variance within the population of spatial units (Dewhurst and McCann, 2007).

⁴⁵⁹ See also Durlauf and Quah (1999), Niebuhr and Schlitte (2004) and Paas *et al.* (2007).

⁴⁶⁰ See also Quah (1996), Rey and Montouri (1999) and Le Gallo and Dall'erba (2003).

⁴⁶¹ Ezcurra *et al.* (2007, 403), among others, recently explained their decision to rely on NUTS2 units as follows: "It should be noted, however, that, as in any analysis of spatial data involving different geographical units, our results may be sensitive to the level of territorial disaggregation adopted (see Ertur *et al.* (2006) for further details on this issue). In any event, it is worth mentioning that our decision to work with NUTS-2 regions is justifiable in terms of European regional policy considerations. In fact, this is the spatial level at which eligibility under Objective 1 of Structural Funds is determined since the reform of the European regional policy in 1989."

⁴⁶² See also Duro (2004) and Arbia *et al.* (2005).

⁴⁶³ For an extended overview see Baumont *et al.* (2003), Le Gallo and Dall'erba (2003), Magrini (2004), Niebuhr and Schlitte (2004), Abreu *et al.* (2005), Fischer and Stirböck (2006), Feldkircher (2006), Frenken and Hoekman (2006), Paas and Schlitte (2008), Battisti and Vaio (2008), Petrakos and Artelaris (2009), Crespo Cuaresma *et al.* (2009a), Crespo Cuaresma *et al.* (2009b) and Crespo Cuaresma *et al.* (2010).

⁴⁶⁴ Refer also to chapter 4, section 4.2 for more details.

Box 5.2: Regional Growth Studies - A Short Overview

The majority of existing regional studies have examined the European growth process at an aggregated spatial level (large regional administrative units), e.g., at the NUTS1/NUTS2 level (Magrini, 2004; OECD, 2009a). Studies in this line are, among others: Baumont *et al.* (2002) (138 NUTS2 regions, 1980-1995); Feldkircher (2006) (246 NUTS2 regions, 1995-2002); Bräuninger and Niebuhr (2005) (192 NUTS2 regions, 1980-2002); Debarsy and Ertur (2006) (237 NUTS2 regions, 1993-2002); Brakman and van Marrewijk (2008) (257 NUTS2 regions, 1995-2005); Brühlhart and Traeger (2005) (236 NUTS2 regions, 1975-2000); Fischer and Stirböck (2006) (256 NUTS2 regions, 1995-2000); Petrakos *et al.* (2007) (249 NUTS2 regions, 1990-2003); Crespo Cuaresma *et al.* (2009b) (255 NUTS2 regions, 1995-2005); Martin (2001) (195 NUTS regions, 1975-1998); Rodríguez-Pose and Fratesi (2004) (195 regions, 1988-1999); Ezcurra *et al.* (2007) (197 NUTS2 regions, 1977-1999).

It is obvious that all listed studies are conceptualized at the more aggregated NUTS1/2 level, which enforces spatial dependence in regressions due to data averaging via the aggregation process. Moreover, the majority of studies are based on the “Cambridge Econometrics regional database”, which represents a workhorse database in European growth-convergence studies at the NUTS1/2 level.

The studies of Niebuhr (2001), Christopoulos and Tsionas (2004) and Dall’Erba (2005), among a few others, are restricted on within-country growth patterns for selected countries at the much smaller NUTS3 level, which is, however, closest to the theoretical ideas and empirical issues related to agglomeration economies, clustering and proximity effects (see chapter 2). In this respect, it seems essential to note that the approach applied in this study is different to the large fraction of existing studies as it uses a different spatial classification system, including regions at a smaller level than the common NUTS2 level. Accordingly, the only quantitative studies, to the author’s knowledge, which analyzed the convergence issue at a smaller level than the NUTS2 level, for the EU-15 group, the NMS and the enlarged group of the EU-25, have been conducted by Frenken and Hoekman (2006), Paas and Schlitte (2007), Falk and Sinabell (2008) and Petrakos and Artelaris (2009).⁴⁶⁵

To sum up, it can be concluded that (i) most studies are accomplished at the aggregated level of administrative NUTS2 units but not at a more disaggregated regional level, which is mainly a result of data limitations and an unbalanced NUTS3 classification; (ii) empirical evidence on the different linkages between regional growth, spatial spillovers and especially the role of regional typologies, regional disparities and research activity are still scarce at the level of European regional classifications below NUTS2. Following theoretical models in the new economic geography and growth tradition, regional income disparities and divergence phenomena are foremost reflections of spatial distributions, i.e., the co-location and co-agglomeration of agents, technology fields, production factors and markets. Moreover, these disparities can be based upon different spillover effects from neighboring regions as has been theoretically discussed in chapter 2 (Martin and Ottaviano, 1999, 2001; Fujita and Thisse, 2003; Baldwin and Martin, 2004).

⁴⁶⁵ Similarly, Le Gallo and Dall’erba (2003), Fischer and Stirböck (2006), Ertur and Koch (2006), Feldkircher (2006) and Crespo Cuaresma *et al.* (2010), among a few others, have analyzed the European convergence process of GDP per capita in the light of spatial models that account for spatial spillovers and/or spatial regimes.

The growth analysis in the second part of chapter 5 tries to find empirical evidence for the following open research questions: (i) Are European regions and their sub-groups converging to different steady-state paths according to the conditional convergence theory? (ii) Are the regional growth rates of GDP per capita affected by inter-regional spillovers at a proximate distance? (iii) Do urban areas and metropolitan and capital regions exhibit higher growth rates compared to rural regions? (iv) Is the regional research density, i.e., the patenting activity, significant and positive in regional growth regressions? (v) Do the NMS show differing growth paths vis-à-vis the EU-15 group? The growth regressions are related to the theoretical concepts and models on core-periphery structures reviewed in chapter 2, with special emphasis on regional growth (section 2.1), and contribute to the empirical studies presented in section 2.2.2.

From an empirical point of view, the following empirical analysis applies cross-sectional unconditional and conditional β -convergence estimations/ growth regressions for European TL3 regions. Since spatial dependence could play a role in regional data, the analysis incorporates spatial econometric techniques. Dummy variables for the regional typology are additionally introduced into the growth regressions, i.e., urban, intermediate and rural regions, and metro and capital regions, in order to control for the level of urbanization and for the population density, the population size, and the size of the local market, respectively. Due to the MAUP, the econometric results may differ from the aforementioned growth/convergence studies. Unfortunately, several causalities, mechanisms and factors cannot be analyzed because of the very limited availability of additional data in the context of more than 800 European regions. Accordingly, due to the chosen research methodology and the large number of regions, the empirical analysis has to abstract from place-specific factors and path dependencies (i.e., formal and informal institutions, culture, place-specific history, first-nature geography, epistemic communities, regional policy).

The remainder of chapter 5 is as follows. The underlying database is described in section 5.2. The first empirical part in section 5.3 analyzes income inequality dynamics. Descriptive statistics and the results of the global income inequality/disparity analysis are presented and discussed. The results of within- and between-subgroup income inequality decomposition at the level of European regions are demonstrated in section 5.3.3. The second part of the chapter presents and discusses growth regressions for European regions (section 5.4). After a short introduction to growth estimations in section 5.4.1, the results from the unconditional convergence estimations are presented and discussed in section 5.4.2. Afterwards, conditional growth regressions for the NMS and EU-15 regions are discussed in section 5.4.3. In section 5.4.4, the regression set-up is extended to conditional spatial regression models.⁴⁶⁶

⁴⁶⁶ Disparity/ inequality measures have been performed with STATA 11; growth regressions in this chapter have been run with STATA 11, OpenGeoDA and ArcGIS 9.3.1.

5.2. The Database: Regions, Patents and the Settlement Structure

One severe issue with empirical investigations of core-periphery structures, spatial dynamics and geographic concentration is the question of aggregation from a sectoral and spatial perspective (see also chapter 3). Geographical economics always suffers from the issue of defining and defending the correct and meaningful industrial and geographical scale of analysis (Audretsch and Feldman, 1996; Brakman *et al.*, 2005). The same issue exists for technology correspondence tables. Brakman *et al.* (2005) argued that industries and regions correspond to their theoretical counterparts and that there is a tradeoff between industrial and regional detail. Some scholars address 36 manufacturing industries (NACE, SIC) which are available at the NUTS0 level (national level); other scholars, instead, prefer smaller levels, e.g., 17 industries, which exist at more disaggregated spatial levels. Therefore, a serious problem in geographical economics and the geography of innovation literature is the definition and usage of spatial units (see chapter 3).⁴⁶⁷ Brakman *et al.* (2005, 7) recently suggested that

“[t]he geographical scope of the NEG is by and large restricted to sets of NUTS3 regions. This suggests that there is something to gain from sacrificing some industrial detail for the sake of regional detail.”

The underlying database in this chapter includes raw data extractions for 819 TL3 regions (see table B.3, appendix).⁴⁶⁸ The regional cross-sectional population consists of the TL3 regions within the EU-25 member states and Norway and Switzerland (OECD, 2003, 2006). Thus, the population in this study covers 774 TL3 micro regions, which form the EU-25 member states; additionally, 45 TL3 units from Norway (19 TL3) and Switzerland (26 TL3) are included. From the 774 regions, 651 represent the EU-15 and 123 belong to the NMS. Switzerland is included to avoid black holes in the spatial structure. However, Norway is eliminated from the regressions for several reasons. Moreover, Croatia, Romania and Liechtenstein are abandoned due to data constraints. Additionally, Luxembourg and Cyprus are excluded from the inequality decomposition. Finally, the French and Portuguese overseas regions (islands) as well as Spanish Atlantic islands are excluded from the growth regressions.

⁴⁶⁷ The geographical scope of the NEG literature is, according to Brakman *et al.* (2005), by and large restricted to empirical analyses at the NUTS2 and NUTS3 level.

⁴⁶⁸ The only difference between the TL3 and NUTS3 in this study results from aggregating the 439 “Stadt-/Landkreise” in Germany (NUTS3) to 97 so called “Raumordnungsregionen” (planning regions) and aggregating Dutch and Belgian NUTS3 units to the NUTS2 level (which is OECD TL3). Similarly, Greek islands and small units are aggregated to Greek NUTS2 units and solve several issues. (i) Several NUTS3 units are relatively small and numerous in comparison with other EU NUTS3 units. The application of, e.g., 439 German NUTS3 regions would increase the influence of German regions in the analysis as they account for one-third of all NUTS3 observations (see also Magrini, 2004). (ii) Additionally, when using NUTS3 GDP data, the existence of relatively small regional units may induce the issue of commuting of workers between their place of residence and place of work and thus mean biased GDP measures (e.g., Berlin, London, Paris).

The study uses purchasing power (PPP) adjusted GDP per capita data as dependent variable in the regression (Monfort, 2008).⁴⁶⁹

The majority of existing regional studies on the enlarged European Union and the ERA primarily analyze the larger administrative NUTS2 units.⁴⁷⁰ Frenken and Hoekman (2006) concluded that the NUTS2 level, which has been applied in the majority of convergence and inequality studies, is poorly defined in terms of regional typologies, as large NUTS2 regions contain urban centers and rural regions at the same time, which means that the administrative spatial classification system largely differs from the real functional boundaries of regions. Similarly, Abreu *et al.* (2005, 34) concluded that

“[a]ggregating several smaller units into larger ones makes matters worse, since it averages out the variation in the variables of interest (the modifiable areal unit problem). One solution may be to redefine boundaries of the spatial units from scratch, using highly disaggregated data and Geographical Information Systems. [...] the level of aggregation should be chosen according to the theoretical model under consideration.”

Therefore, studies on spatial disparities, agglomeration economies and research clustering at the NUTS2 level are problematic as spatial variation generally disappears due to aggregation (and averaging) (Arbia and Petrarca, 2010).⁴⁷¹ Taking all these concerns into account, it has to be argued that the OECD TL3 level (OECD, 2003, 2006) fits best to the proposed research questions and the theoretical background (see chapter 2), because the TL3 level gives the opportunity to test the hypothesis of growth disparities between capital regions, urban areas and rural regions. Moreover, it represents an established regional classification system which enables future comparisons with other studies.

5.3. The Development of Income Disparities in Europe

5.3.1. A Descriptive Overview

Analyzing regional income distribution across the 819 TL3 regions of the enlarged European Union (including Switzerland and Norway) shows remarkable regional disparities between the NMS and the EU-15; but also within the EU-15 and NMS groups. The analysis places the emphasis on the distribution of GDP per capita in purchasing power standards (PPP), where income is adjusted for price level differences across countries.

⁴⁶⁹ Generally, PPP corrected data are adjusted for differences in national price levels but they do not consider within-country price differences, although there might exist considerable regional differences. GDP data at the TL3 level have been collected, and if necessary, calculated and/or transformed for the period 1995 to 2006; e.g., Switzerland and Norway.

⁴⁷⁰ To the author’s knowledge, Frenken and Hoekman (2006), Paas and Schlitte (2008) and Melchior (2008), among a few other studies, contributed with a similarly detailed spatial classifications system.

⁴⁷¹ Arbia and Petrarca (2010, 10) concluded that “*[t]he efficiency loss connatural to aggregation is, generally speaking, mitigated by the presence of a positive spatial correlation parameter and conversely exacerbated by the presence of a negative spatial correlation parameter. This result is coherent with the theoretical expectation. Positive spatial correlation implies that we aggregate between similar values thus preserving variability.*” See also Abreu *et al.* (2005) and Burger *et al.* (2008).

A first descriptive analysis shows that there exists (i) a core-periphery structure with relatively high income levels in the center of the European Union and (ii) relatively low levels of GDP per capita in peripheral areas and regions at the borderline of the enlarged European Union. Figures 5.1 and 5.2 highlight the development of regional per capita income (PPP) in Europe between 1995 and 2006 in maps.⁴⁷² European regions widely differ by means of the spatial distribution of per capita income and thus show strong regional disparities. Moreover, it is clearly visible that the enlarged European Union (EU-25, CH, NO) also yields country-specific income levels, meaning that regions only differ to some degree from their national average. Thus, variance seems to be rather modest within countries, compared to the between-country differences in the early years.

The first map (figure 5.1) displays the distribution of regional per capita income relative to the EU-27 average in the year 1995 (including Switzerland and Norway). The illustrated distribution of regional GDP per capita differentiates the more successful regions of Europe, which are located in the core of Europe, from the more backward and underdeveloped ones. The high-income regions form a functional area that is commonly known as the European “blue banana” (Heidenreich, 1998; Martin, 1998b; Maggioni *et al.*, 2007). Accordingly, most of the relatively rich regions belong to the northern part of the European continent, including Northern Italy, Southern Germany, Southeast France, Ile-de-France, the southern regions of Great Britain, Belgian regions and Dutch regions, among others. Low income regions, with a GDP level below 75% of the EU-27 average, can be found in the eastern part of Germany, in Greece, in Southern Italy, in Ireland and in the Western parts of Spain and Portugal (at least in the 1990s). Moreover, it is argued that areas accompanied with high levels of GDP per capita are often those that are hosting the capital cities. Furthermore, metropolises and capital regions represent the locations of diversified high-technology industries and service sectors (see chapter 3, section 3.5); e.g., Southern Ireland (Dublin), Denmark (Copenhagen), Germany (Berlin, Stuttgart, Frankfurt), France (Paris), the UK (London), Southern Finland (Helsinki), or the Southeast of Sweden (Stockholm). Within low performing EU countries, capital regions are identified to serve as “growth poles” since the 1990s, e.g., Lisbon, Madrid, Prague or Warsaw (see also OECD, 2009a,b).⁴⁷³

The second map (figure 5.2) visualizes European regional per capita income levels for the year 2006. Very high income levels can be observed in the southern parts of Ireland, in the eastern regions of Spain and Southern UK areas, whereas other regions in the mentioned countries are still lagging behind. A remarkable north-south gradient is still present in Italy. In addition, the map seems to support the hypothesis, that particularly metropolitan regions and/or capital regions show relatively higher per capita income levels compared to the European average, similarly to the 1990s.⁴⁷⁴

⁴⁷² See figure A.47 in the appendix for the visualization of the regional GDP per capita distribution in the year 2000.

⁴⁷³ The second map (figure A.47, appendix) illustrates regional GDP per capita (PPP) for the year 2000. Very low levels of per capita income exist in, e.g., Western regions of Spain and Portugal, Southern Italy and some Northern areas in the United Kingdom. Similarly, the Greek regions and some of the New German Laender still suffer from relatively low income levels. Moreover, most parts of Ireland have developed above the European average since the year 1995 in terms of regional GDP per capita.

⁴⁷⁴ This hypothesis will be additionally challenged in the second part of this chapter (see section 5.4).

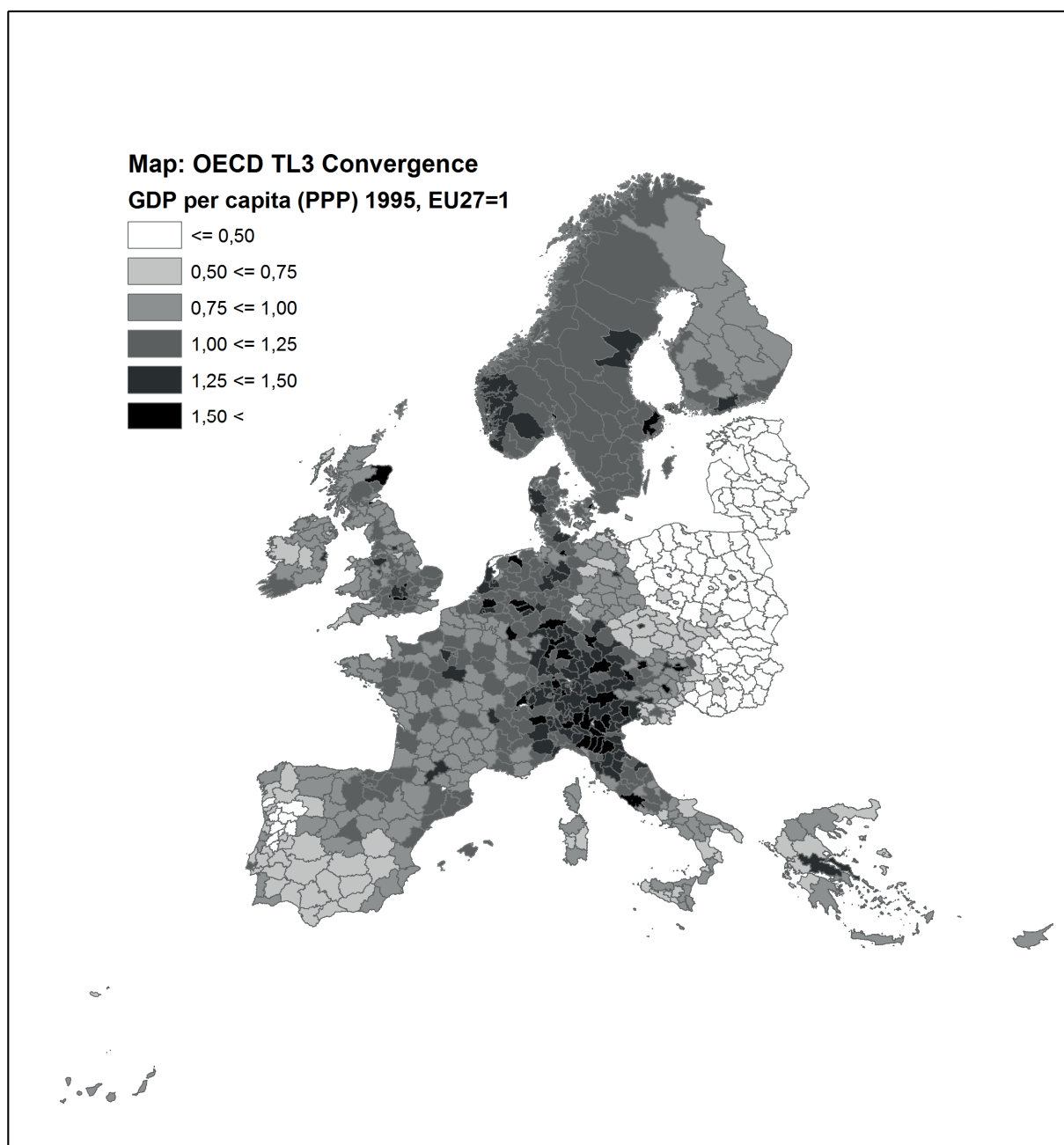


Fig. 5.1. GDP per capita (PPP) year 1995

Source: own calculations and illustration. *Notes:* Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.

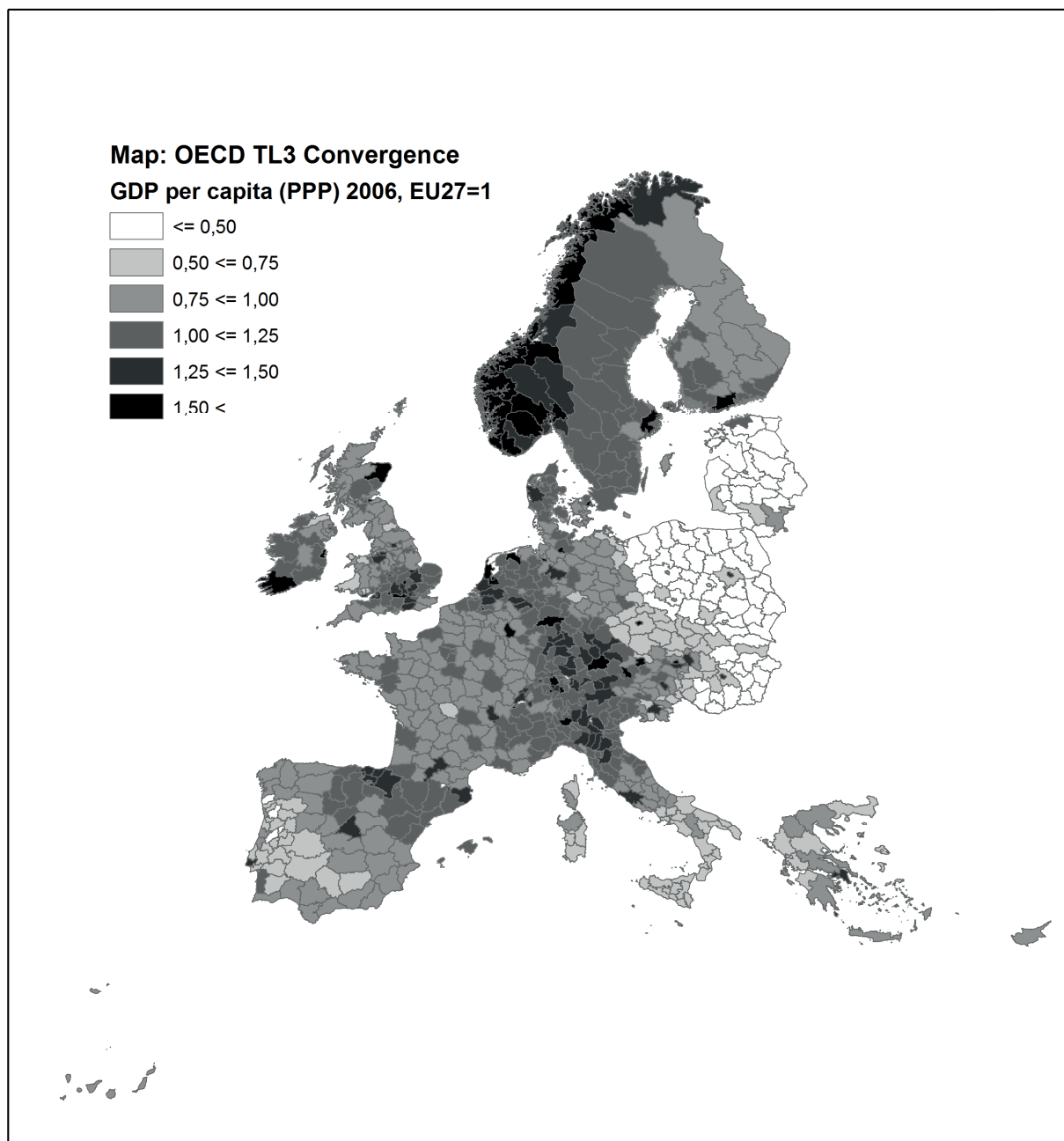


Fig. 5.2. GDP per capita (PPP) year 2006

Source: own calculations and illustration. *Notes:* Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.

The third map (figure 5.3) highlights the GDP per capita (PPP) growth rates of all 819 European regions between 1995 and 2006, expressed in relation to the EU-27 average. Comparing the regional GDP per capita growth rates of European regions shows again a north-south and east-west gradient that has already been identified in the research clustering study in chapters 3 and 4. Nevertheless, almost all eastern and southern European regions are characterized by higher GDP growth rates, compared to European core regions. The map seems to support the well-known hypothesis that per capita growth between 1995 and 2006 was, on average, higher in the peripheral and economically backward regions of Europe. This hypothesis originates from the well-known and well-described catching-up theory, i.e., β -convergence concept, that is based on the canonical neoclassical growth model (Solow, 2007) and the related discussion on social capabilities and additional factors that determine regional (and national) development (Abramovitz, 1986; Barro and Sala-i-Martin, 1991; Harris, 2008). High growth rates, above the EU-27 average, can be observed in, e.g., Ireland, Spain, the NMS, the northern part of Greece and Portugal. Besides this development, medium-high growth rates are observable within the so-called “blue banana” (mainly high-growing regions of the EU-15), e.g., Dutch regions, Southern UK and several central European regions such as Milan, Munich, Stuttgart, Noord-Brabant or Düsseldorf.⁴⁷⁵ Accordingly, it can be argued that there is something to gain from a closer look at the regional typology and at the development within the NMS group.

The box plots (see graphs in figure 5.4) depict that the development of European countries' average growth rates depend on the growth rates of a few leading regions, which have also reached a much higher level of GDP per capita compared to the national average. These are typically capital regions, metropolises and urban regions. Some of them serve as secondary growth poles (see also Williamson, 1965; Arbia *et al.*, 2005; Szörfi, 2007). Such high-growing capital regions are located in Hungary, Estonia, Poland, the Czech Republic, Latvia, Lithuania, Slovenia and Slovakia. The box plots show the inter-quartile distances and the lower and upper quartiles for the EU-15 and NMS countries for several years (1995 and 2006). Besides the structure in the year 1995, the figure also highlights the year 2006 and the average yearly growth rates for the EU regions. It is evident that the 0.25 quartile has increased in almost all countries between 1995 and 2006, which means that the lower tail of the income distribution has increased in absolute terms. Besides the quartiles and the inter-quartile distances, the study also analyzes if regions with initially high levels of GDP per capita (PPP) in 1995 suffer from very low average yearly growth rates, which would be in line with the canonical neoclassical convergence approach and the assumed decreasing returns and lower growth rates near the unique steady-state (see also section 5.4).

National Gini coefficients and a decomposition of overall regional income disparities (GDP per capita) into within- and between-subgroup components are performed in the following analysis in order to gain more information about the spatial structures of the growth process. Finally, the aforementioned picture of catching-up regions is additionally highlighted by distribution functions (kernel density) in figure 5.5. Three groups of regions are illustrated: (a) the EU-25 and Switzerland and Norway, (b) the EU-15 and (c) the NMS. It is obvious from the graphs that the distribution of the EU-25 group (with Switzerland and Norway) has changed between 1995 and 2006 due to remarkable shifts in the lower

⁴⁷⁵ For similar results at a higher aggregation level see OECD (2009a,b).

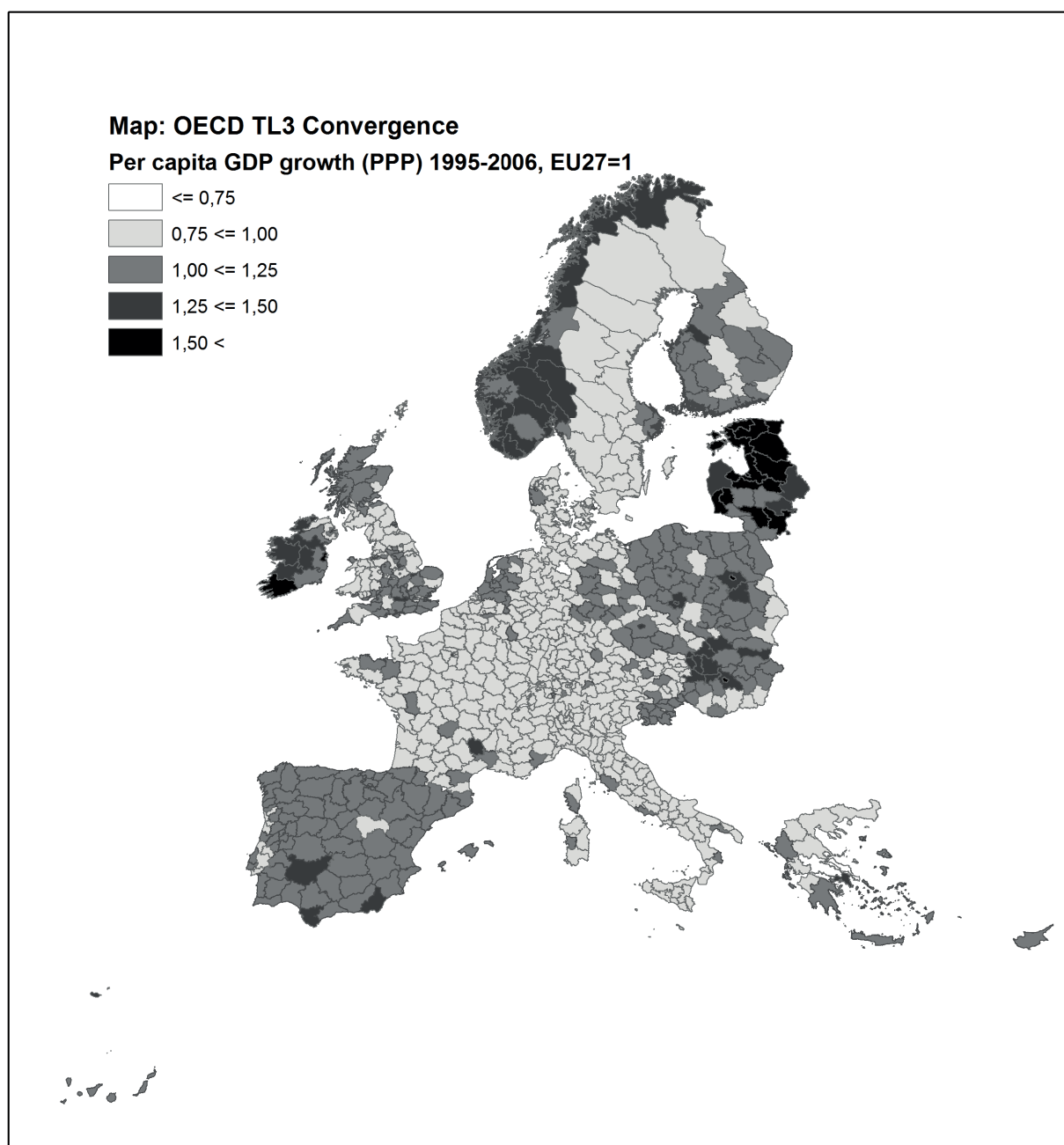


Fig. 5.3. Growth Rates of GDP per capita (PPP) 1995-2006

Source: own calculations and illustration. *Notes:* Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.

tail of the income distribution, i.e., a catching-up process of several poor regions (see also Geppert and Stephan, 2008).

5.3.2. Measures of Concentration, Disparity and Inequality

5.3.2.1. Regional Disparities and the Gini Coefficient

After the introductory analyses and data presentation in the previous section, the following analysis addresses the distributional characteristics and regional disparities of GDP per capita by means of quantitative methods. Geographic concentration and regional disparities are a general phenomenon in regional economics (Hinloopen and van Marrewijk, 2004; Arbia *et al.*, 2005).

Furthermore, concentration (disparity) measures are assessed in a similar manner compared to specialization. The sole difference to specialization measures is that instead of a comparison of industrial structures within a single region, concentration measures involve a comparison of regions' industrial structures in the context of a larger spatial aggregate (Krugman, 1991; Ellison and Glaeser, 1997).⁴⁷⁶ According to the aforementioned issues, the literature on geographic concentration and spatial inequality has developed some common empirical measures and indices. Regional disparities can be measured by application of various indices. The most common statistical approaches are the Herfindahl-/ Herfindahl-Hirschman index, the location quotient (Hoover-Balassa index), the Gini coefficient, the Krugman index, Theil's T and Theil's L index, and modifications of the generalized entropy index (Litzenberger, 2007; Monfort, 2008; Jenkins and Kerm, 2009).⁴⁷⁷ Some of these indices have been already presented and discussed in chapter 3.

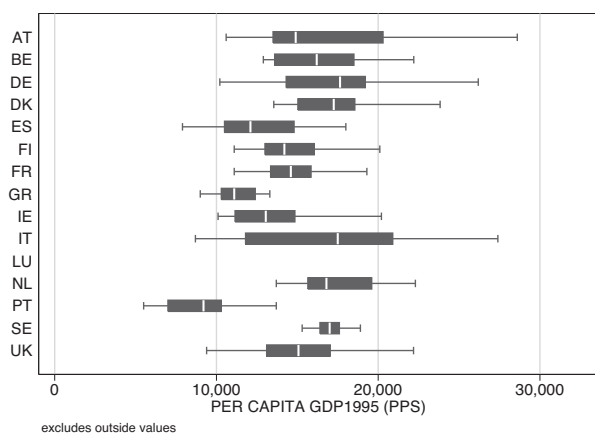
However, disparity or inequality indices should satisfy several axioms (Jenkins and Kerm, 2009).⁴⁷⁸ For measuring overall disparity (inequality), the study makes use of the locational Gini coefficient and the generalized entropy measure (i.e., the Theil and Atkinson index). Generally, the Gini coefficient (see also chapter 3, section 3.4), which is applied in the following analysis, is a measure of statistical disparity or inequality. According to the traditional methodology, studies commonly used the Gini coefficient as a measure of inequality of income or wealth (Dewhurst and McCann, 2007; Jenkins and Kerm, 2009). The Gini coefficient is defined mathematically based on the Lorenz curve concept. However, in the context of regional disparities, Gini computations at the level of regions have to include weights for the treatment of spatial heterogeneity (e.g., population, surface). In this respect, relative shares for each subspace are computed with $g_j = [s_j/y_j]$; with s_j being the GDP share of region j and y_j being the population share of the region.⁴⁷⁹ Equation

⁴⁷⁶ See Amiti (1997), Amiti (1999), Laursen (1998), Midelfart-Knarvik *et al.* (2000) and Jenkins and Kerm (2009) for further details.

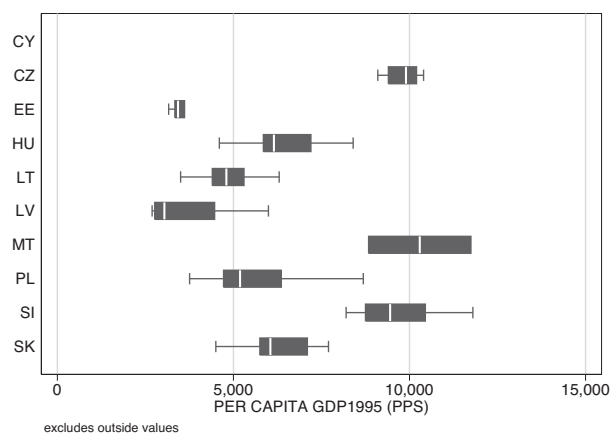
⁴⁷⁷ See also Kim (1995), Amiti (1999), Keilbach (2000), Aiginger and Pfaffermayr (2004), Combes and Overman (2004).

⁴⁷⁸ See also section 3.4. For further details see Cowell (1995).

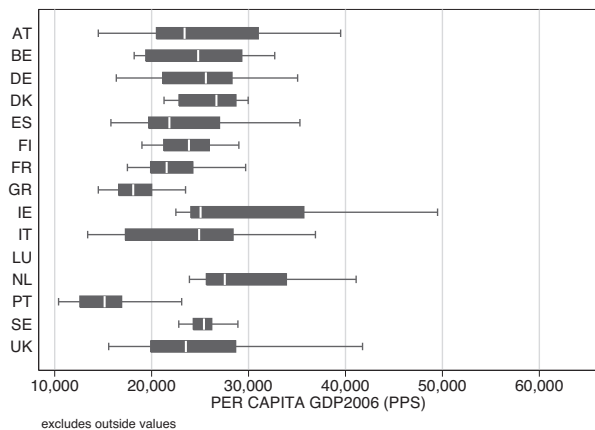
⁴⁷⁹ It should be noted that the obtained Gini from g_j is identical to the usage of GDP per capita of region j divided by the GDP per capita of the aggregate of regions \sum_j .



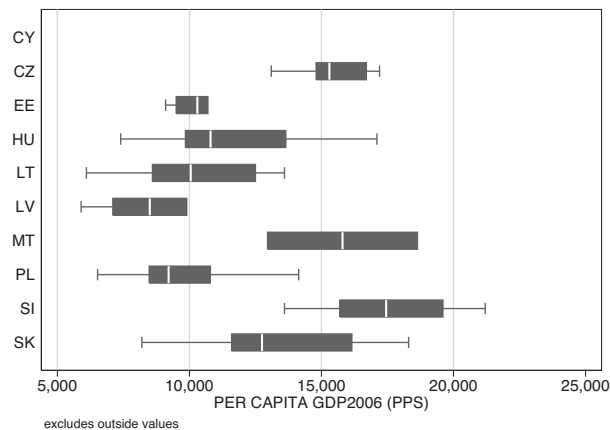
(a) EU-15 GDP per capita (PPP) in 1995



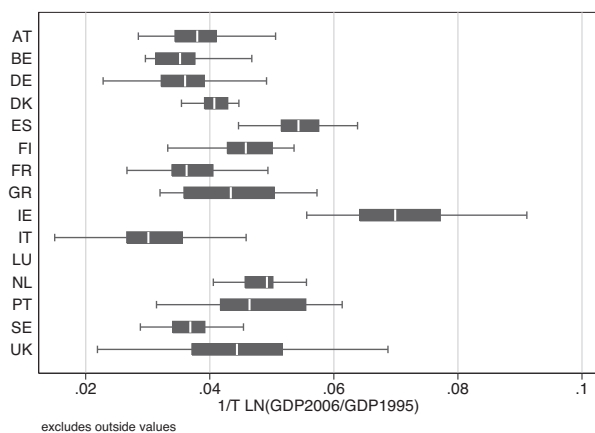
(b) NMS GDP per capita (PPP) in 1995



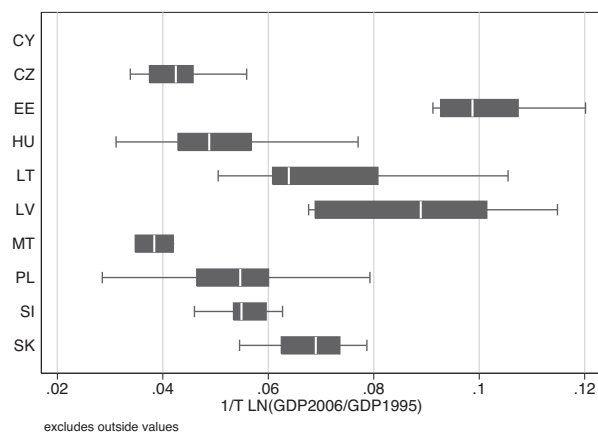
(c) EU-15 GDP per capita (PPP) in 2006



(d) NMS GDP per capita (PPP) in 2006

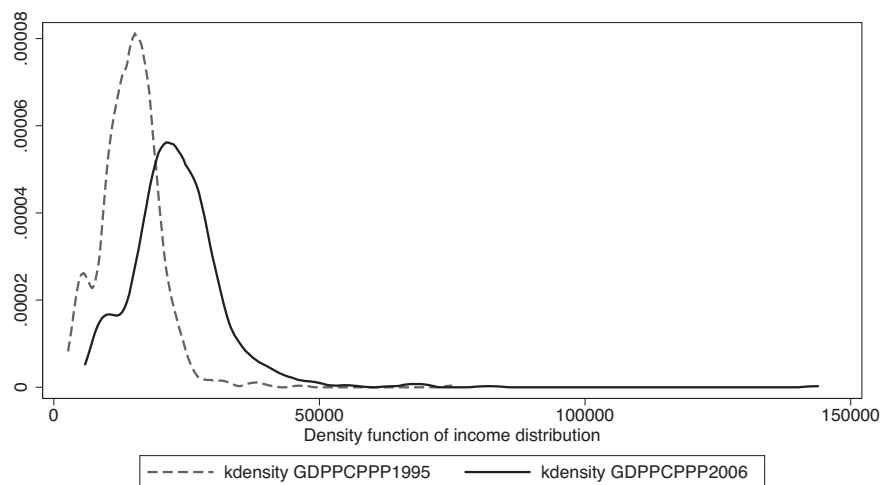


(e) EU-15 GDP per capita (PPP) Growth Rates 1995-2006

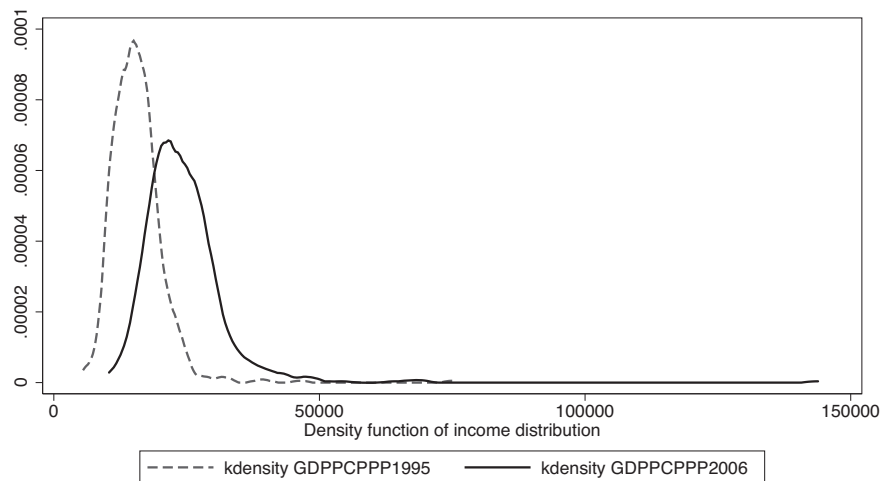


(f) NMS GDP per capita (PPP) Growth Rates 1995-2006

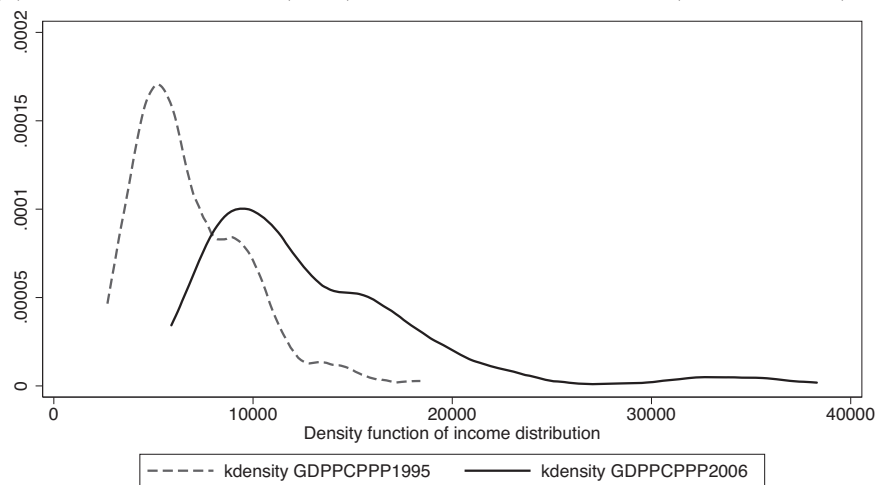
Fig. 5.4. Boxplot: GDP per capita (PPP) level vs. growth rate
Source: own calculations and illustration.



(a) Kernel density GDP (PPP) per capita, regions in the EU-25, CH, NO (1995 vs. 2006)



(b) Kernel density GDP (PPP) per capita, EU-15 regions (1995 vs. 2006)



(c) Kernel density GDP (PPP) per capita, NMS regions (1995 vs. 2006)

Fig. 5.5. Kernel density: density function of income distribution TL3 regions by group
Source: own calculations and illustration.

5.3.1 represents the locational Gini as has been already introduced, discussed and applied in chapter 3 (see section 3.4).

$$G_{LOC}^* = \left[2 \left[\frac{1}{2} - \left[\sum_{j=1}^n \left(\frac{1}{2} y_j s_j \right) + \sum_{j=1}^n \left(y_j \sum_{k=j+1}^n s_k \right) \right] \right] \right] \left[\frac{1}{1 - \min y_j} \right] \quad (5.3.1)$$

G_{LOC}^* is a population weighted Gini coefficient in terms of y_j , which needs a normalization procedure. Normalization is accomplished by correcting for the minimum populated European region (with $\min(y_j)$), which guarantees a maximum concentration surface as presented in equation 5.3.1. In case that the regional share of GDP, s_j , across subspaces j is identical to the share of the reference distribution, y_j , we observe an equal distribution and no disparity (i.e., $g_j = 1$ and $G_{LOC}^* = 0$). The Lorenz curve is then identical to the bisecting line. However, the more the distribution of the economic activity under analysis, s_j , differs from the reference distribution, y_j , the larger is G_{LOC}^* . In this respect, G_{LOC}^* takes s_j and y_j for each region and computes the cumulated sum of GDP shares of all subspaces, ordered by g_j (see chapter 3, section 3.4 for more details).

5.3.2.2. Measures of Regional Disparity and Inequality Decomposition

Besides the above described Gini index, which represents a global measure of inequality (disparity), the study aims to identify the origin of overall inequality in the EU-25, the EU-15 and the NMS. Following Sala-i-Martin (2006) and Brakman and van Marrewijk (2008), among others, no final consensus has been worked out with respect to the development of within- and between-country income disparities in Europe due to differing spatial classification systems used in existing studies. There is some indication that especially within-country income inequality has increased, which is against the idea of general convergence as postulated by, e.g., Friedman (2005) and Sala-i-Martin (2006).⁴⁸⁰ Moreover, increasing regional disparities are inconsistent with the European convergence objective (see Box 5.1). Preliminary empirical evidence against regional convergence in Europe has been claimed by Duro (2004), who has analyzed the period 1982-1995. Duro pointed to divergence patterns across European NUTS1/2 regions.⁴⁸¹

Another complementary measure of inequality, besides the conventional global indices, is the generalized entropy index, $GE(\alpha)$, as highlighted in equation 5.3.2 (Novotný, 2007; Haughton and Khandker, 2009):⁴⁸²

$$GE(\alpha) = \frac{1}{\alpha(1-\alpha)} \frac{1}{n} \sum_{i=1}^n \left[1 - \left(\frac{y_i}{\bar{y}} \right) \right], \text{ for } 0 < \alpha < 1, \text{ where } \bar{y} = \frac{1}{n} \sum_{i=1}^n y_i = \frac{Y}{N}. \quad (5.3.2)$$

⁴⁸⁰ See OECD (2009a) for an income concentration analysis at the more aggregated TL2 level for OECD countries. For further details see Arbia *et al.* (2005), Dewhurst and McCann (2007) and Monfort (2008).

⁴⁸¹ See also Combes and Overman (2004), Arbia *et al.* (2005), Frenken and Hoekman (2006), OECD (2009a).

⁴⁸² An important aspect with regard to the different indicators is their sensitivity on differing sample sizes. To overcome the issues arising from this property, the overall number of observations in this study is constant (819 TL3 regions). However, a direct comparison between subgroups is complicated; the study only shows the time trends and the dynamics of national inequality indices.

with n = number of groups, N_i = cumulative population, N = total population, Y_i = cumulative income and Y = total income and with $\alpha = 1$ as the Theil Index T .⁴⁸³ Theil's T is a particular case of the generalized entropy index. In its aggregated form, Theil's T is a measure of overall inequality/disparity (Brülhart and Traeger, 2005). When population shares equal the respective GDP shares in all regions, GDP would be distributed completely evenly, and hence, Theil's T index would be equal to zero. The index is useful in analyzing regional disparities and, most importantly, in calculating between- and within-subgroup inequality (United Nations, 2005; Novotný, 2007; Haughton and Khandker, 2009). Theil's T index, $GE(1)$, is defined as in equation 5.3.3:

$$GE(1) = T = \frac{1}{n} \sum_{i=1}^n \frac{y_i}{\bar{y}} \ln \left(\frac{y_i}{\bar{y}} \right) \quad (5.3.3)$$

For grouped data, a typical way to rewrite the Theil index T is presented in 5.3.4:

$$GE(1) = T = \sum_i \sum_j \left(\frac{Y_{ij}}{Y} \right) \ln \left(\frac{Y_{ij}/Y}{n_{ij}/N} \right) \quad (5.3.4)$$

with Y_{ij} being the income of the ij -group; n_{ij} being absolute frequency of population in the ij -group; $Y = \sum_i \sum_j Y_{ij}$ is total income over all groups; and $N = \sum_i \sum_j n_{ij}$ is total population. Thus, the Theil index compares the relative share in the population (n_{ij}/N) with the income share of each group (Y_{ij}/Y). It is argued that the Theil index is very sensitive to the sample size. To reduce this problem, the number of observations has been held constant over time (Brülhart and Traeger, 2005; Haughton and Khandker, 2009).

It is essential to note that inequality indices show significant variation in their sensitivity to differences in different parts of the income distribution. The higher the parameter α in $GE(\alpha)$, the more sensitive is $GE(\alpha)$ to income differences at the top of the distribution; however, the more negative α is, the more sensitive is $GE(\alpha)$ to differences at the bottom of the distribution. Thus, inequality/disparity indices differ in their sensitivity to changes in the lower and upper tails of the distribution (Brülhart and Traeger, 2005). The Gini coefficient, that has been presented in the last section, is most sensitive to income differences in the middle part of the distribution. However, its sensitivity depends on the relative position of the observation in comparison to other observations. Therefore, if more regions are in the lower part of the income distribution, as is usually the case, they should obtain a stronger weight (Duro, 2004; Novotný, 2007; Haughton and Khandker, 2009).

Another frequently used measure of regional disparity is $GE(2)$, which is half the squared coefficient of variation (CV) and sensible to changes in the upper parts of the distribution. Similarly, a change of the sensitivity index in $GE(\alpha)$ to $\alpha = 0$ leads to the mean log deviation (MLD) measure, the so-called Theil's L index, $GE(0)$. With respect to different sensitivity parameters (α), it is generally argued that the dynamics of $GE(-1)$ mainly show changes of income of the poorer regional units at the bottom of the distribution, whereas $GE(2)$ is mainly responsive to changes at the upper end/tail of the distribution. $GE(1)$ is said to represent the standard case in empirical studies (Brülhart and Traeger,

⁴⁸³ In the following, only Theil's T is presented (see equations 5.3.3 - 5.3.6). For details on $GE(-1)$, $GE(0)$ and $GE(2)$ refer to Brülhart and Traeger (2005) or Haughton and Khandker (2009).

2005; Haughton and Khandker, 2009). Accordingly, income disparity measures and their decomposition will be provided for $GE(1)$, i.e., Theil's T.

Regarding the origins of overall regional disparities in per capita income, it is fruitful to decompose global income inequality into between- and within-subgroup inequality.⁴⁸⁴ The properties of the (non-negative) Theil index $GE(1)$ make it possible to break down overall regional disparities in such a way that the weighted sum of the index components is identical to the overall inequality index as highlighted in equation 5.3.5 (Brülhart and Traeger, 2005). Furthermore, it is argued that another advantage is that census information of the countries and regions involved are not needed (Duro, 2004; Sala-i-Martin, 2006; Brakman and van Marrewijk, 2008).

$$GE(\alpha) = GE_W(\alpha) + GE_B(\alpha), \text{ for } \alpha = 1. \quad (5.3.5)$$

Theil's T is then defined as in equation 5.3.6:

$$GE(1) = T = T_B + T_W = \left[\sum_i \left(\frac{Y_i}{Y} \right) \ln \left(\frac{Y_i/Y}{n_i/N} \right) \right] + \left[\sum_i \left(\frac{Y_i}{Y} \right) T_i \right] \quad (5.3.6)$$

with $Y_i = \sum_j Y_{ij}$ as total income of the i^{th} group and $n_i = \sum_j n_{ij}$ as absolute frequency of population in the i^{th} group and $T_i = \sum_j \left(\frac{Y_{ij}}{Y_i} \right) \ln \left(\frac{Y_{ij}/Y_i}{n_{ij}/n_i} \right)$ as the Theil index for the i^{th} group. $GE_B(\alpha)$ measures the share of inequality that originates from income inequality between subgroups (e.g., between countries). Within-subgroup inequality, $GE_W(\alpha)$, represents the share of inequality (or disparity) that originates from inequality within the groups under analysis (e.g., within countries) (Brülhart and Traeger, 2005; Novotný, 2007; Haughton and Khandker, 2009). Inequality decomposition is computed for several groups, i.e., the NMS, the EU-15 and the EU-25 (incl. Switzerland and Norway).

To repeat a point made earlier, the Theil index is considered to be very useful for the purpose of analyzing the origins of regional disparities. The decomposition into within- and between-subgroup disparities offers additional information in the context of divergence/convergence developments that are taking place within and between certain groups of regions. To challenge the presented research questions, global income inequality (disparity) of GDP per capita income (PPP) is decomposed into (i) inequality within nation states (within-subgroup inequality); and (ii) inequality between nation states in Europe (between-subgroup inequality). That being the case, the TL3 regions are grouped into $i \in \{1, 2, \dots, n\}$ subgroups. The following group classifications are analyzed in the subsequent empirical analysis: (i) the group of the EU-25+2 countries with 27 subgroups; (ii) the NMS with 10 subgroups; (iii) the EU-15 group with 15 subgroups; (iv) the group of the EU-15 and NMS with two subgroups.

⁴⁸⁴ Inequality decomposition measures should, however, require two decomposition properties (Brülhart and Traeger, 2005; Brakman and van Marrewijk, 2008): (i) subgroup consistency: the positive responsiveness of the overall inequality measure to changes in the inequality levels of constituent group as a minimum requirement; (ii) additive decomposability: overall inequality is the sum of between- and within-subgroup inequality. The mentioned properties are only satisfied by $GE(0)$ and $GE(1)$ (Duro, 2004; Arbia *et al.*, 2005; Monfort, 2008). The Gini coefficient is not decomposable in the sense of subgroup consistency. However, given the popularity and favorable properties of the Gini index, it will be used in this study as a measure for global income disparities (European and national aggregates).

5.3.3. The Development of European Income Disparities

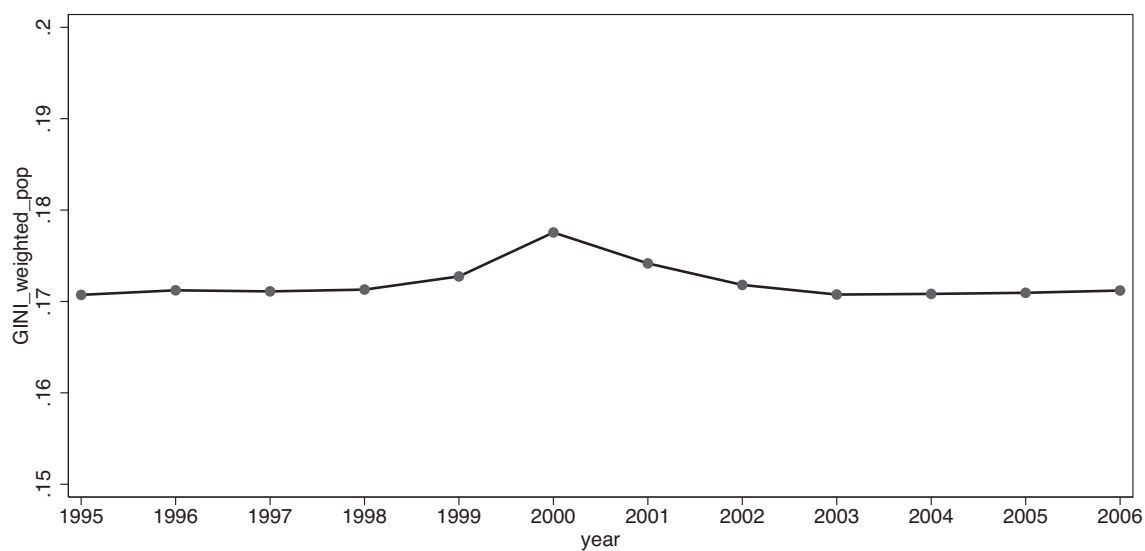
5.3.3.1. Global Income Disparities in Europe

In order to maintain a detailed and dynamic understanding of the development of European and national income disparities, the income inequality (disparity) measures for each European country since 1995 are plotted at a yearly base in figures 5.6, 5.7 and 5.8.⁴⁸⁵ Income disparity remained rather constant within the EU-15 group, whereas the former CEE-10 (NMS) group suffered from increasing regional disparities as shown by the population weighted Gini indices (see figure 5.6). Figures 5.7 and 5.8 show the national (population weighted) Gini coefficients of GDP per capita income for the period 1995 to 2006. Countries have experienced dynamics very different from the global European trend and can be classified into three categories: (i) a decrease in inequality in Austria and Italy; (ii) a general increase in inequality in Switzerland, the Czech Republic, Denmark, Estonia, Greece, Hungary, Ireland, Lithuania, Netherlands, Portugal, Slovenia, Slovakia and the United Kingdom; (iii) an inverted U-shaped trend of income inequality in Belgium, Germany, Spain, Finland, France and Sweden. However, there is a general trend of decreasing inequality for the global sample (EU-25).

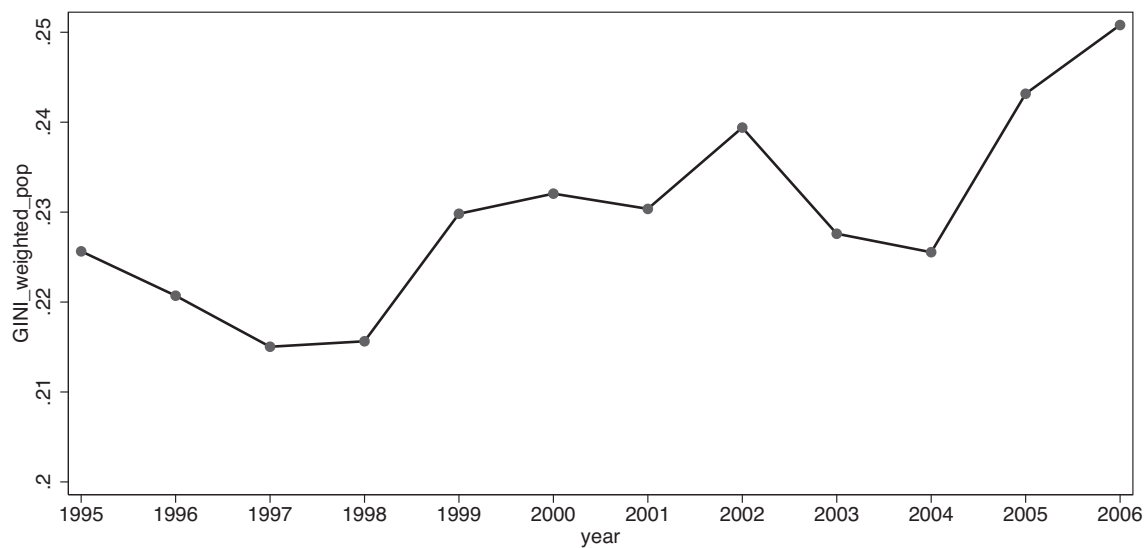
Similar to results at the TL2 level (OECD, 2009b,a), it can be argued that between-country income convergence at the TL3 level is accompanied by within-country income divergence, meaning that there is a significant increase in income inequality within several European countries.⁴⁸⁶ However, within-country divergence is stronger at the TL3 level; TL2 disparities are weaker due to aggregation/averaging (Arbia and Petrarca, 2010). Besides the varying dynamics of Gini coefficients of GDP per capita, figures 5.6, 5.7 and 5.8 also show a trend of increasing within-country income disparities for several countries, which is in line with conclusions from new economic geography frameworks (see theoretical considerations in chapter 2) (see also Puga, 2002; Rodríguez-Pose and Fratesi, 2007). It is visible that several European countries have experienced a significant increase in income inequality, meaning that convergence within countries does not dominate the European picture. Cross-country convergence (between countries) is in most cases accompanied by significant regional divergence within countries (Williamson, 1965). According to a recent study of the OECD, the European TL2 regions can be divided into two groups in terms of average yearly growth rates: (i) a “convergence” group which shows the following growth rate characteristics: minimum 1.5%, maximum 6.6%, median 2.5%, average 2.7%; (ii) a “divergence” group which shows the following values: minimum 1.7%, maximum 5.4%, median 2.9%, average 3.1%. These results support the findings in this study, i.e., evident divergence in several backward countries (OECD, 2009b,a).

⁴⁸⁵ For similar results regarding inequality decomposition refer to Paas and Schlitte (2007). Nevertheless, the authors applied a different spatial classification system and offered only results regarding GE(1).

⁴⁸⁶ In opposition to this study, the OECD (2009a,b,c) predominantly centers the TL2 level (i.e., NUTS1/2 level), which is much more aggregated compared to the TL3 level used in this study. The OECD concluded that “countries that have experienced diverging regional income disparities tended to show faster real GDP growth rates at the national level” (OECD, 2009b, 21; see also OECD, 2009c, 32-35).



(a) Weighted Gini coefficient GDP/capita (PPP) EU-15 (1995-2006)



(b) Weighted Gini coefficient GDP/capita (PPP) NMS (1995-2006)

Fig. 5.6. Development of regional disparities in GDP/capita (PPP) by group
Source: own calculations and illustration.

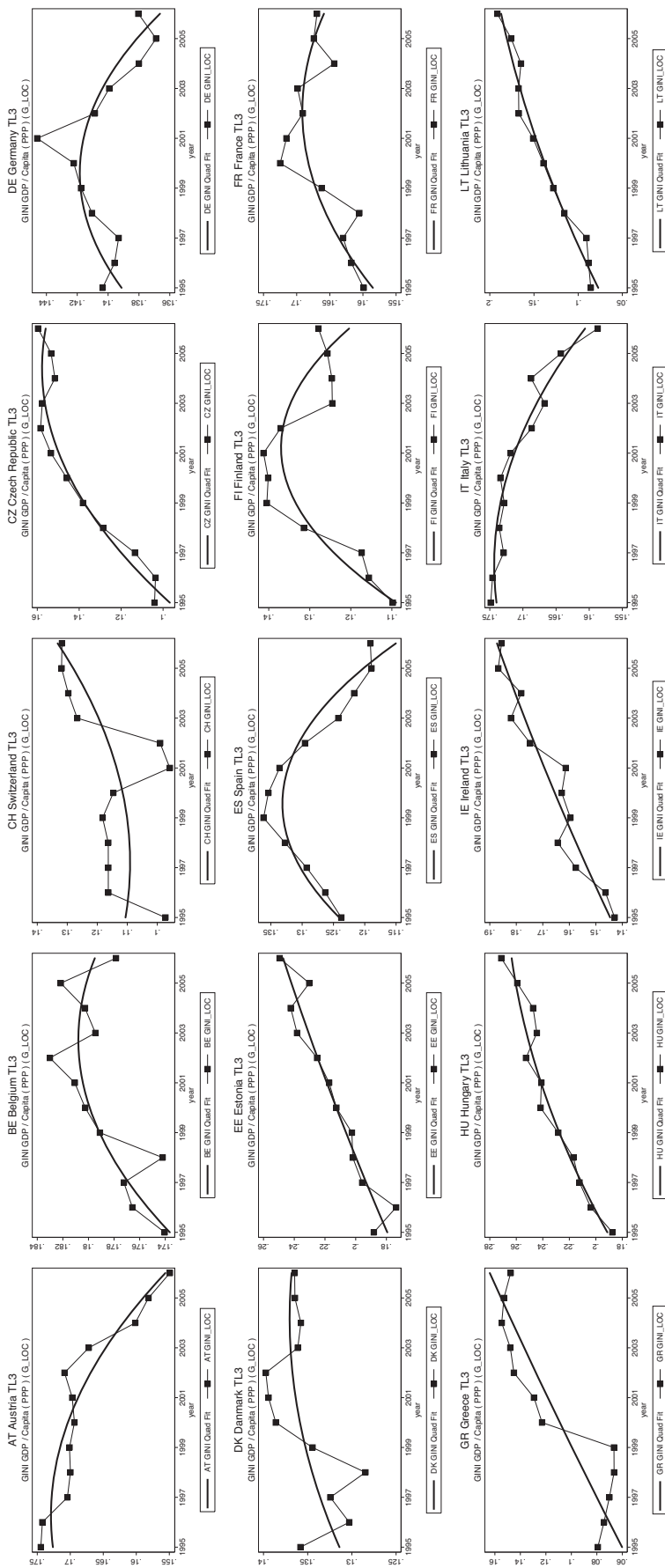


Fig. 5.7. Locational Gini coefficients of GDP per capita (PPP) (a)
 Source: own calculations and illustration.

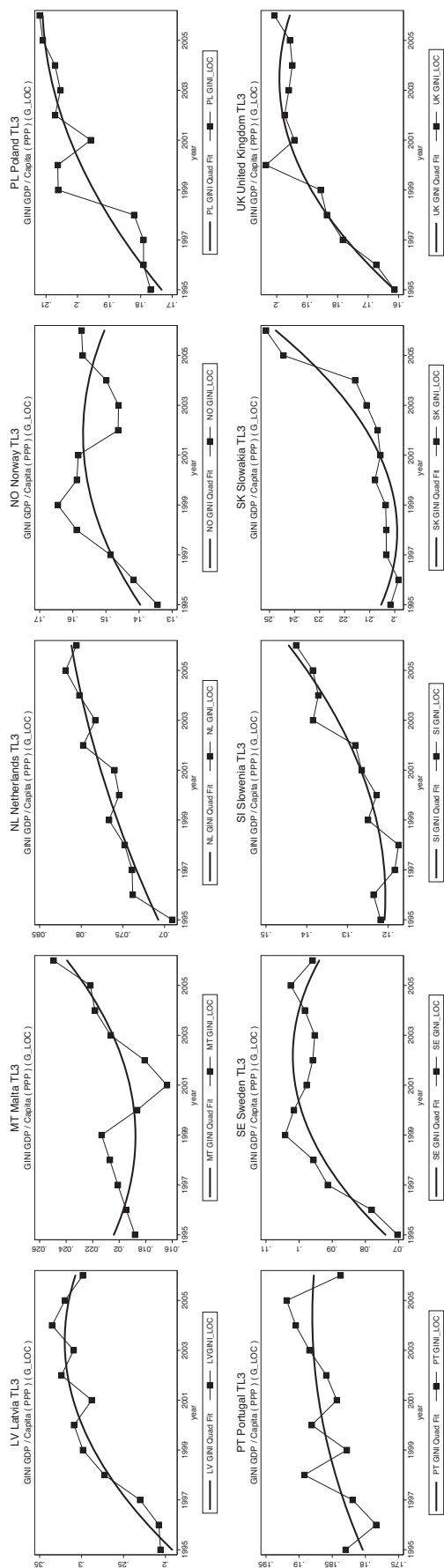


Fig. 5.8. Locational Gini coefficients of GDP per capita (PPP) (b)
 Source: own calculations and illustration.

5.3.3.2. Regional Disparities within and between European Countries

As has been argued in the previous sections, another pivotal consideration concerns the development of regional disparities within and between European member countries. The following figures illustrate the development of income inequality by subgroups as proposed in the previous section 5.3.2.2; special emphasis is placed on Theil's T, i.e., GE(1).

The graphs in figure 5.9 focus on the development of GDP per capita inequality of the entire population of European regions (i.e., the 817 TL3 regions, except Cyprus and Luxembourg, that represent the EU-23, Switzerland and Norway) between the years 1995 and 2006. It is obvious from the graphs that between- and within-subgroup disparities matter for the development of overall (global) disparity. Besides the fact that overall regional disparities (graphs on the left) have decreased in the entire population, i.e., GE(-1) to GE(2), the share of between-subgroup disparities (graphs on the right) has decreased by approximately 15% since the year 1995 (GE1between819TL3), meaning that on average convergence between countries took place. At the same time, within-subgroup disparities (GE1within819TL3) have relatively increased, which means that Europe consists of a meaningful number of countries that suffer from considerable increases in regional income inequality within national borders (i.e., within-country regional divergence).

However, in order to analyze the development of regional disparities more closely with respect to the European integration process, the entire population of the 819 European regions is divided into two groups; the group of EU-15 regions with countries as subgroups (see figure 5.10) and the group of NMS regions with countries as subgroups (see figure 5.11).⁴⁸⁷ One should expect different developments and dynamics, similar to differences regarding EPO patenting activity and research networks (see chapter 3 and 4).

Figure 5.10 shows that the EU-14 group (650 regions, without Luxembourg) features a very similar overall development of regional income disparities compared to the entire population of the 817 European regions. A decrease in overall income inequality (disparity) since 1995 is visible. Between-subgroup inequality (GE1betweenEU-15) and within-subgroup inequality (GE1withinEU-15) have decreased. However, between subgroup inequality is at a much lower level compared to within-subgroup inequality, indicating that overall income inequality stems mainly from inequality within countries.⁴⁸⁸

A very different picture emerges from the decomposition of income inequality in the case of the NMS regions. Figure 5.11 highlight the results based on the inequality decomposition. The subgroups are again defined with respect to national borders (122 NMS regions in 9 countries).⁴⁸⁹ The graphs in figure 5.11 clearly show a significant increase of within-subgroup inequality (GE1withinNMS), which has been accompanied by a strong decrease in between-subgroup inequality (GE1betweenNMS). However, the decrease in between-subgroup inequality, which represents cross-country convergence, could not compensate for the strong increase in within-subgroup inequality, that has led to an overall increase in

⁴⁸⁷ For a similar interpretation at the more aggregated level of NUTS2 regions see Monfort (2008).

⁴⁸⁸ For a comprehensive review of existing inequality studies at the national level see Novotný (2007) and de Dominicis *et al.* (2008). Refer also to Combes and Overman (2004).

⁴⁸⁹ Cyprus is a single regions and thus within-country inequality cannot be decomposed into a within- and between-country component.

income disparities in the NMS group. Thus, the graphs in figure 5.11 clearly exhibit an increase in income disparities, which stems predominantly from divergence at the regional level within countries.⁴⁹⁰

Finally, in an alternative analysis, the subgroup borders are redefined in terms of administrative borders of the EU-15 and NMS groups. Between-subgroup inequality originates from differences between the EU-15 and NMS group. Within-subgroup inequality originates from regional disparities within the two groups. Figure A.46 (appendix) summarizes the results of this inequality decomposition, which are quite similar to the ones already presented above. Again, it is visible that regional disparities among regions within the groups have increased since the 1990s, whereas regional disparities between the two groups have decreased.

To conclude, the inequality decomposition demonstrates that regional income disparities have in general decreased within Europe, which is mainly a result of decreasing disparities between European member states, reflecting the closing of income gaps among European countries. On the contrary, income disparities among regions within the borders of European countries have increased since the mid 1990s, indicating the emergence of national core-periphery structures relating to GDP. It is evident from the above presented results that the global decline in income disparities among European countries, and in Europe as a whole, coincides with increasing regional disparities within member states. Consequently, the developments since the 1990s have not prevented disparities to increase in some countries; particularly in those countries that recently joined the European Union.

Another shortcoming of empirical studies on the European case is the lack of growth regressions at the TL3 level (Paas and Schlitte, 2007). Therefore, a final consideration of this chapter concerns European regional growth regressions. Section 5.4 presents regional growth regressions for the same spatial classification system as has been described and discussed above and analyzed in chapters 3 and 4 (i.e., TL3 regions in the EU-15 and NMS). Besides a short review of the canonical absolute and conditional convergence concept, the following part primarily contributes with regression models that extend the standard conditional convergence model with several covariates that control for (i) the regional neighborhood structure and potential spatial interdependence, (ii) regional typologies (i.e., urban, rural, intermediate, metro and capital regions), and (iii) regional technology structures and research activities (i.e., regional EPO patenting activity).

5.4. Research Activity, Settlement Structure and Regional Growth

5.4.1. Income Levels and Regional Growth: A Descriptive Overview

A still controversial research question is whether or not European regions are converging or diverging since the 1990s and which factors are the drivers of divergent regional growth.

⁴⁹⁰ Note that the results are supported by a recent study of the OECD, although their study centers the more aggregated TL2 level (OECD, 2009a,b).

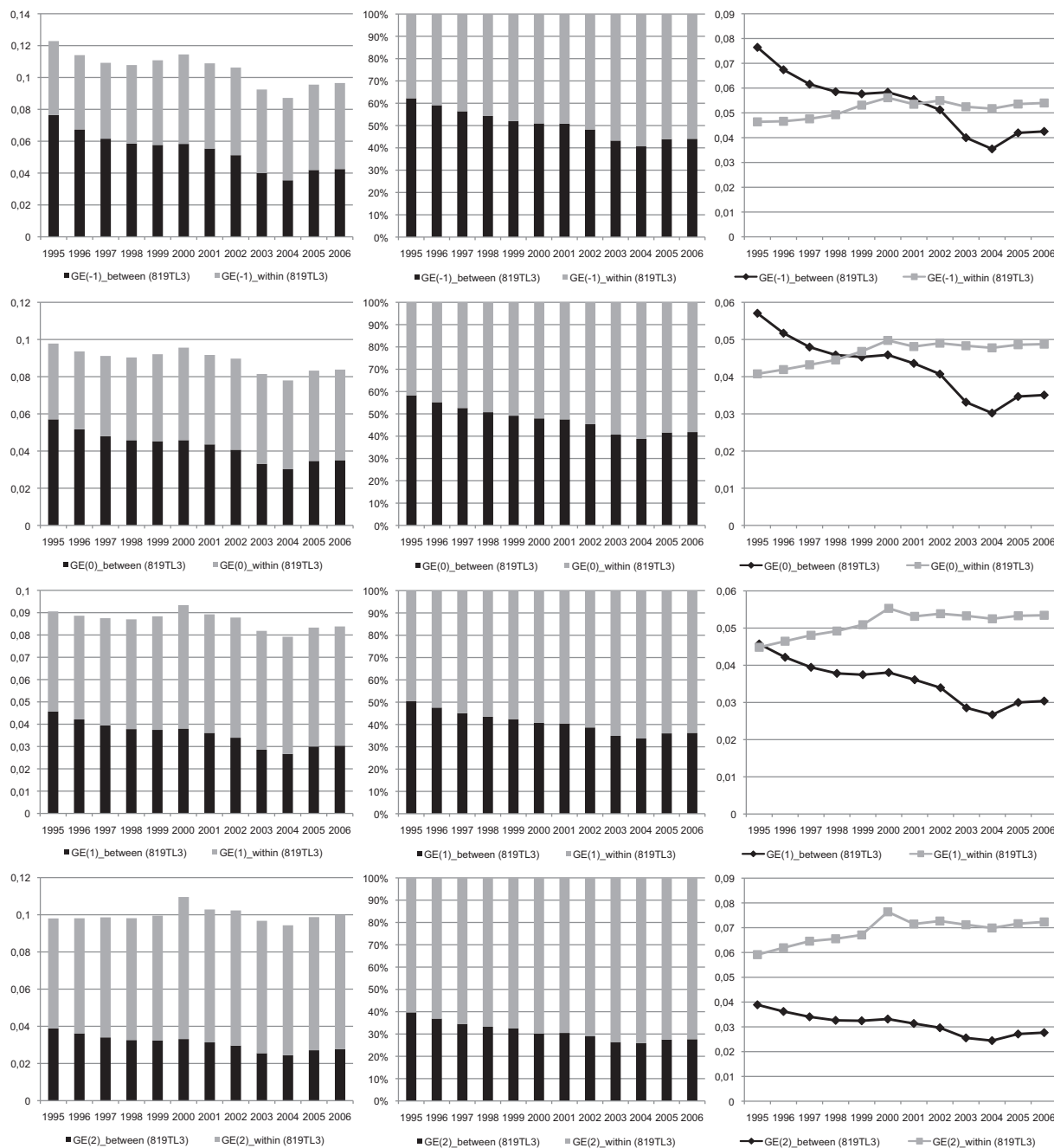


Fig. 5.9. Income inequality decomposition: EU-23, CH, NO
 Source: own calculations and illustration. Notes: GDP per capita in the EU; inequality composition is done for GE(-1), GE(0), GE(1), GE(2). Sample includes 773 EU-23 regions and Switzerland and Norway. Cyprus and Luxembourg excluded due to impossible within-country inequality decomposition. Subgroups represented by country ID.

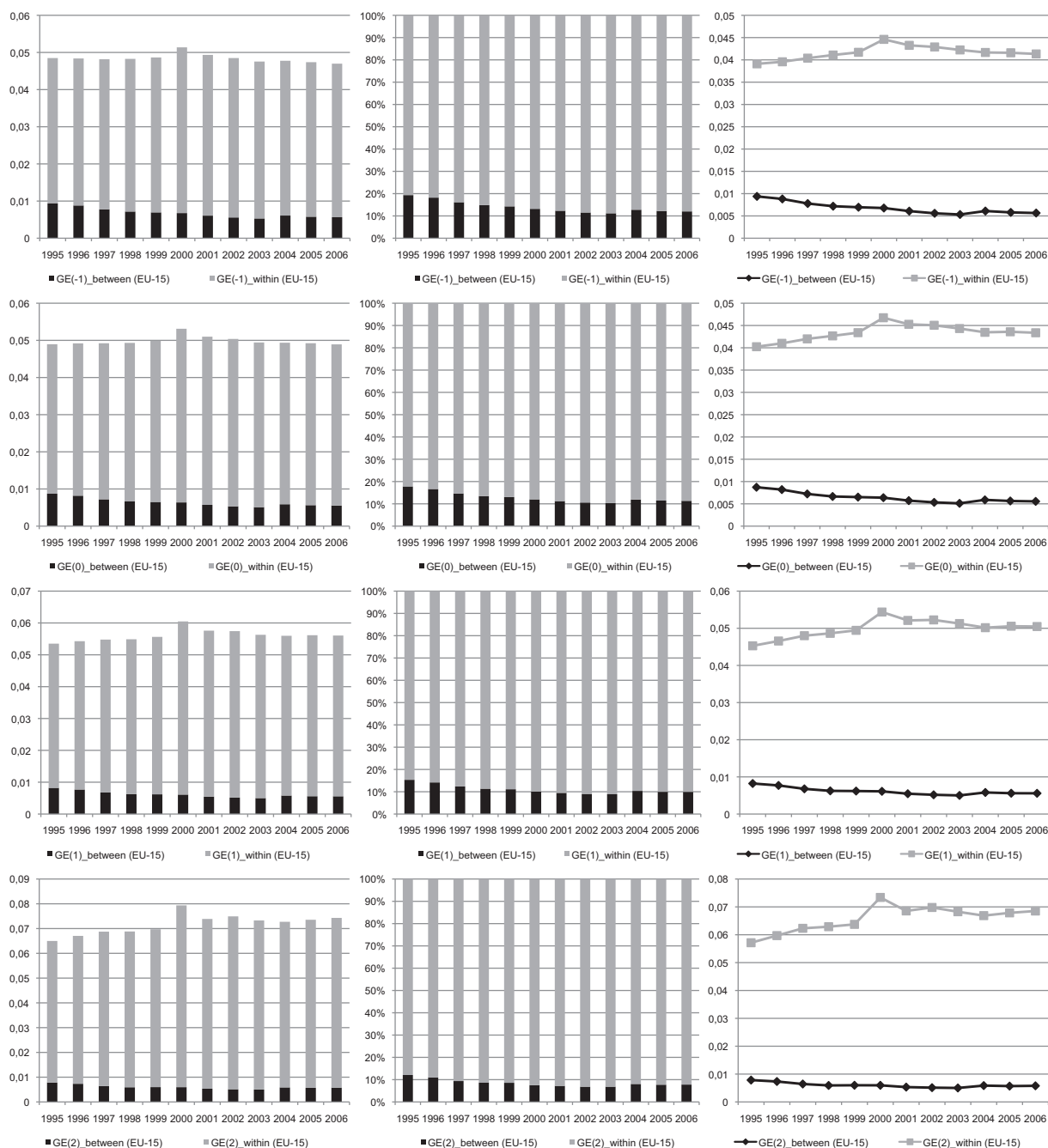


Fig. 5.10. Income inequality decomposition: EU-14 group

Source: own calculations and illustration. Notes: GDP per capita in the EU; inequality composition is done for GE(-1), GE(0), GE(1), GE(2). Sample includes 650 EU-14 regions. Luxembourg excluded due to impossible within-country inequality decomposition. Subgroups represented by country ID.

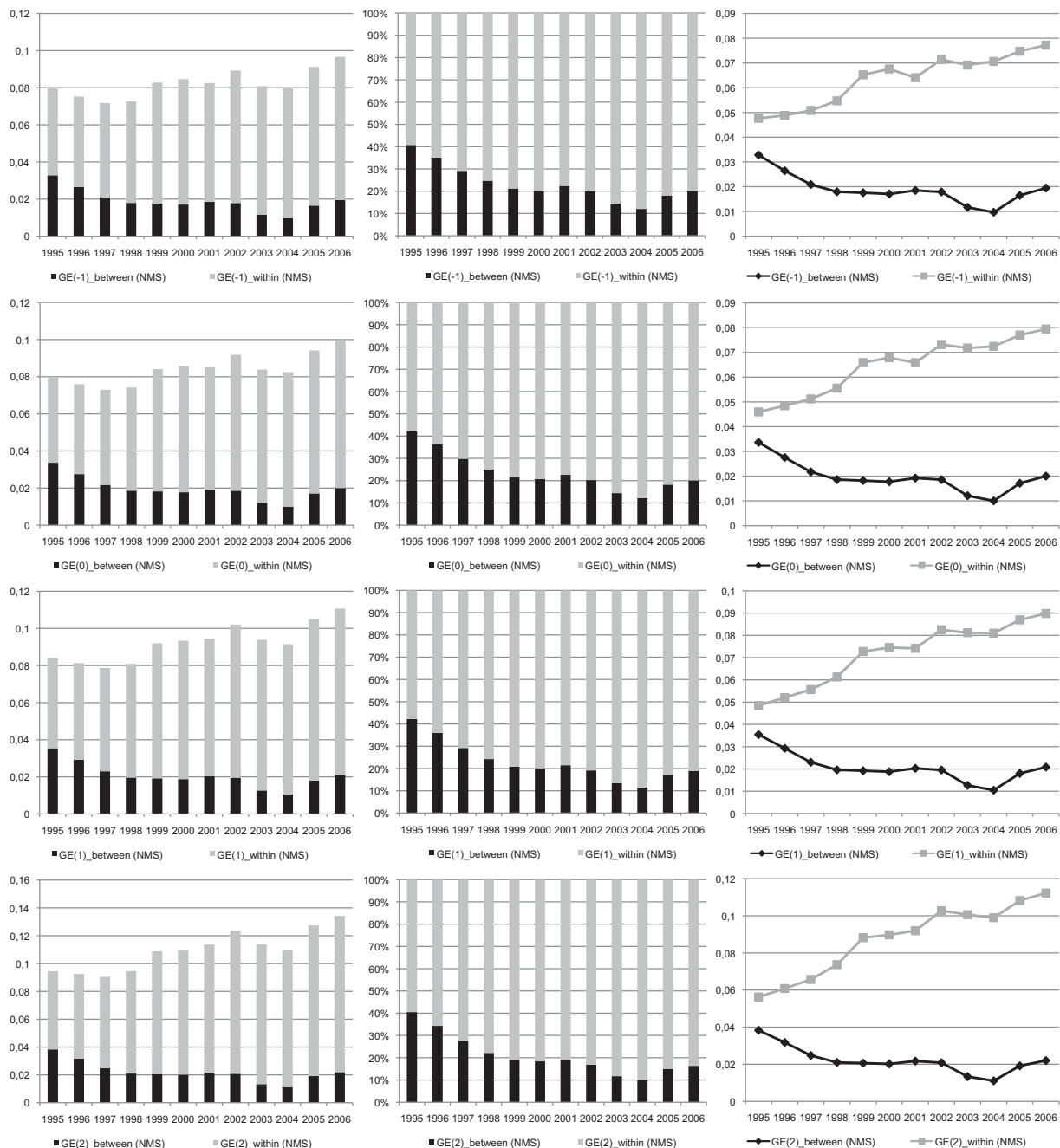


Fig. 5.11. Income inequality decomposition: NMS group
Source: own calculations and illustration. *Notes:* GDP per capita in the NMS; inequality composition is done for GE(-1), GE(0), GE(1), GE(2). Sample includes 122 NMS regions. Cyprus excluded due to impossible within-country inequality decomposition. Subgroups represented by country ID.

The subsequent scatter plot (figure 5.12) illustrates initial GDP per capita levels in 1995 (abscissa) for 651 regions (the EU-15 group) and their growth rate (ordinate). The figure seems to illustrate a kind of regional convergence, although we cannot draw statistically robust conclusions from simple scatter plots. Identically, figure 5.13 highlights this relationship for NMS regions. Finally, both subgroups are combined (figure 5.14). It is visible from the combined scatter plot, that the enlarged group of EU-25 regions (entire population) suffers from structural differences. Mainly all NMS regions are located in the upper-left corner of the figure; the EU-15 regions are determined by rather smaller growth rates, although they have reached very similar levels of GDP per capita. Related to this observation, several studies have analyzed the two groups of regions separately (Paas and Schlitte, 2007, 2008).

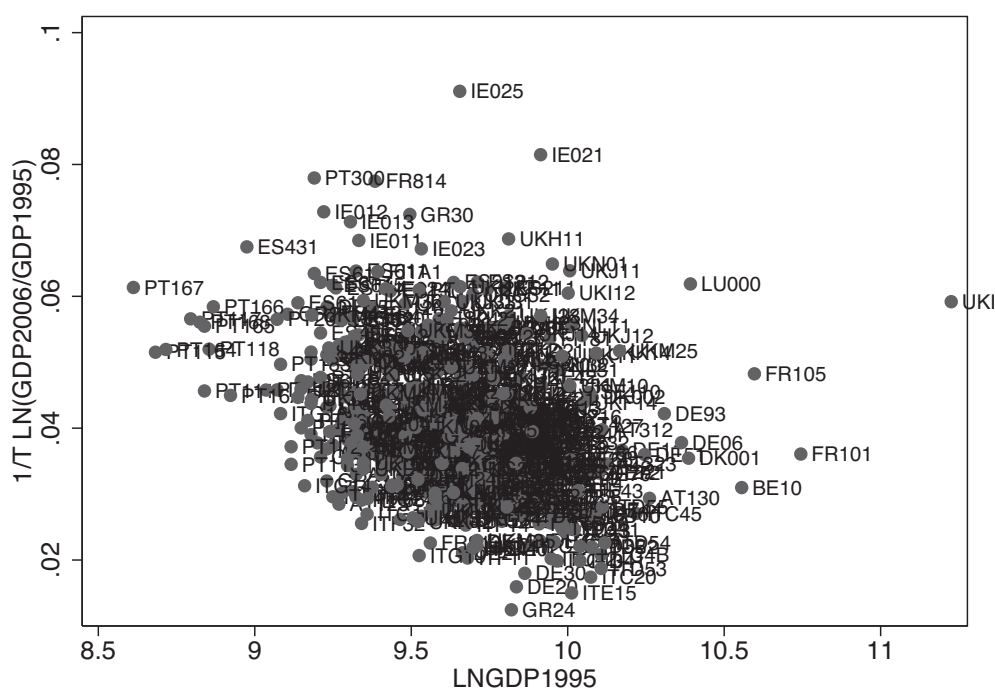


Fig. 5.12. Scatterplot GDP/capita level (1995) vs. growth rate (1995-2006), EU-15
Source: own calculations and illustration. *Notes:* 651 observations included; GDP in PPP.

5.4.2. Unconditional Convergence and European Regional Growth

The relationship between the initial level of GDP per capita and growth in per capita GDP is generally estimated by application of a standard econometric growth model (log-linear specification). It includes the income growth parameter $\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right)$ as dependent variable and the initial level of income $\ln(y_{i,t})$ as explanatory variable (see equation 5.4.1). This corresponds to the concept of unconditional (absolute) β -convergence and can be applied in a spatial context to regions ($i = 1, \dots, N$), derived from the neoclassical growth model (Barro and Sala-i-Martin, 2003; Hagemann, 2004; Solow, 2007). It applies to the case of similar structural characteristics between observations (Mankiw *et al.*, 1992; Barro and Sala-i-Martin, 1992). Results of studies conducted at the regional level have been reported

by Bräuninger and Niebuhr (2005), Abreu *et al.* (2005), Bräuninger and Niebuhr (2008), OECD (2009a) and Crespo Cuaresma *et al.* (2009b), among others.

$$\frac{1}{T} \ln \left(\frac{y_{t+T}}{y_t} \right) = \beta_0 + \beta_1 \ln(y_t) + \varepsilon \quad (5.4.1)$$

$$\varepsilon \sim N(0, \sigma_\varepsilon^2 I)$$

T is the length of the analyzed period (here 11 years); ε_i is a $(n \times 1)$ vector of independently and identically distributed disturbances.⁴⁹¹ Tests of absolute β -convergence are generally plausible when the object of study is within-country convergence, because knowledge and technology bases, institutions, geography and standard of living are assumed to be quite similar within countries.⁴⁹²

Table 5.1 summarizes absolute convergence regression results for the EU-25, the EU-15 and the NMS group (TL3 regions). In addition, national convergence estimates are reported in the subsequent tables, if the initial GDP level coefficient is significant (see tables 5.2 and 5.3).⁴⁹³ A first result is that growth regressions without national controls (models 1-3) show significant convergence tendencies (initial GDP level is significant and negative) (see also Frenken and Hoekman, 2006). However, when national controls are included, the convergence speed in the EU-15 and EU-25 group slows down (models 4, 5). Moreover, the coefficient of initial GDP completely changes its sign for the NMS group when national dummy variables are incorporated, meaning that regions in the NMS group are diverging (model 6). This result is in line with the aforementioned results regarding Gini indices and inequality decomposition.

Furthermore, regional growth regressions (absolute convergence) are reported for selected countries in tables 5.2 and 5.3. It is obvious that especially NMS countries, e.g., the Czech Republic, Estonia, Hungary, Latvia, the Slovak Republic, Slovenia, show significant and positive coefficients of the initial GDP per capita level, meaning that these countries are determined by regional divergence.⁴⁹⁴ Absolute convergence seems to be absent as regional units differ in several ways (e.g., patenting activity, regional size, population density, GDP level). The varying levels of technological knowledge and research activities of European regions, i.e., patenting and co-patenting activities, have been already presented and discussed in the previous chapters. Therefore, the standard empirical approach has to be

⁴⁹¹ Convergence speed is not of central interest in this study. According to the standard growth regression methodology, the rate of convergence is obtained by estimating β_1 for the initial income level and re-parameterizing it via $b = -\ln(1 + \beta T)/T$ in order to compute convergence speed and half-life (Bräuninger and Niebuhr, 2005).

⁴⁹² Given the cross-sectional data in this study, there might exist three types of departures from this assumption: (i) heteroscedasticity, (ii) spatial autocorrelation, (iii) outliers and parameter heterogeneity. While the first deviation leads inefficiency of OLS, the last two might seriously bias the estimates (see also Bräuninger and Niebuhr, 2005; Geppert and Stephan, 2008; OECD, 2009a).

⁴⁹³ Insignificant estimations are not reported. The regressions are generally based upon heteroscedasticity-consistent standard errors (Huber–White standard errors) to control for potential heteroscedasticity of unknown form (Stata, 2009, 2010).

⁴⁹⁴ See Frenken and Hoekman (2006) for very similar results.

Table 5.1. Unconditional and conditional convergence for EU-25, EU-15 and NMS

Model	(1)	(2)	(3)	(4)	(5)	(6)
	EU-15	EU-25	NMS	EU-15	EU-25	NMS
<i>dependent variable:</i> $1/T\ln(y_{i,2006}/y_{i,1995})$						
CTRYDUMMY	no	no	no	yes	yes	yes
GDPLEVEL	-0,0118*** (0,0118)	-0,0164*** (0,0014)	-0,0132** (0,0046)	-0,0054*** (0,0017)	-0,0116*** (0,0016)	0,0203*** (0,0044)
t-value	-6,31	-11,68	-2,86	-3,16	-7,21	4,62
R-squared	0,0958	0,2691	0,08	0,50	0,48	0,59
N	645	768	123	645	768	123

Source: own estimations. *Notes:* growth regressions for the period 1995-2006 with and without national controls (CTRYDUMMY); country dummy variables (4-6) and constant (1-6) not reported; robust standard errors in parentheses. Huber and White robust-sandwich estimator reported in table. HC3, robust and clustered regressions were additionally executed; signs and significance did not change. Details available upon request.

extended in order to deal with regional heterogeneity; i.e., national controls and several covariates.⁴⁹⁵

Table 5.2. Robust OLS estimation results: national growth regressions (1)

Model	(7)	(8)	(9)	(10)	(11)	(12)
	CZ	DE	EE	ES	HU	IT
<i>dependent variable:</i> $1/T\ln(y_{i,2006}/y_{i,1995})$						
GDPLEVEL	0,0355*** (0,0072)	-0,0126*** (0,0034)	0,0328*** (0,0101)	-0,0079* (0,0044)	0,0304*** (0,0096)	-0,0137*** (0,0017)
t-value	4,95	-3,73	3,25	-1,80	3,18	-8,26
R-squared	0,3798	0,1597	0,6314	0,0768	0,2358	0,3707
N	14	97	5	50	20	103

Source: own estimations. *Notes:* National cross-sectional growth regressions for the period 1995-2006; robust standard errors in parentheses; constant not reported; Huber and White robust-sandwich estimator reported in table. HC3, robust and clustered regressions were additionally executed; signs and significance did not change. Details available upon request.

5.4.3. Conditional Convergence and Regional Growth in Europe

5.4.3.1. Conditional Convergence and Regional Growth

Testing for conditional convergence means to incorporate regions' internal factors, which assumes different steady states with a $k \times 1$ vector of regions' internal factors ($X_{i,t}$) as in the testable model 5.4.2 (Mankiw *et al.*, 1992; Hagemann, 2004; Arbia *et al.*, 2005). $X_{i,t}$ is a standard vector of exogenous explanatory variables (exogenous covariates), which primarily determines the growth rate with the parameter β_2 (besides the effect from the

⁴⁹⁵ In case of conditional convergence estimations the choice of the explanatory variables is crucial as they differentiate regions' steady states.

Table 5.3. Robust OLS estimation results: national growth regressions (2)

Model	(13)	(14)	(15)	(16)	(17)
	LT	PT	SK	SL	UK
<i>dependent variable:</i> $1/T \ln(y_{i,2006}/y_{i,1995})$					
GDPLEVEL	0,0703*** (0,2345)	-0,0119* (0,0063)	0,0175*** (0,0062)	0,0157** (0,0070)	0,0070** (0,0028)
t-value	3,00	-1,91	2,84	2,24	2,50
R-squared	0,4721	0,1075	0,5744	0,1532	0,0285
N	10	30	8	12	133

Source: own estimations. *Notes:* National cross-sectional growth regressions for the period 1995-2006; robust standard errors in parentheses; constant not reported; Huber and White robust-sandwich estimator reported in table. HC3, robust and clustered regressions were additionally executed; signs and significance did not change. Details available upon request.

initial GDP level via β_1).⁴⁹⁶

$$\frac{1}{T} \ln \left(\frac{y_{t+T}}{y_t} \right) = \beta_0 + \beta_1 \ln(y_t) + \beta_2 \ln(X_t) + \varepsilon \quad (5.4.2)$$

$$\varepsilon \sim N(0, \sigma_\varepsilon^2 I)$$

Regarding regional studies, growth regressions normally incorporate regional and national dummy variables (see table 5.4).⁴⁹⁷ Besides national dummy variables (CTRYDUMMY), which are in general applied in international convergence estimations, growth regressions additionally include several covariates and controls as presented in table 5.4. The study implements dummy variables for national border regions (NATBORDER) and European border regions (EUBORDER), testing the hypothesis that border regions suffer from lower growth rates due to their peripheral geographic location. Additionally, several agglomeration controls are included, e.g., population density (POPDENSITY), level of urbanization and closeness to a large city/a large local market (URBAN, METRO), rural/peripheral areas (RURAL). Accordingly, regions are classified into metro regions (METRO), urban regions (URBAN), intermediate regions (INTERMEDIAT) and rural areas (RURAL).⁴⁹⁸ Metro regions are those units, which are highly populated and incorporate a large city center with sufficient population size and density (European Union, 2009). Urban, intermediate and rural areas are defined according to an alternative classification with respect to population density, absolute population and market size, and closeness to a city center

⁴⁹⁶ Note that β is the marginal effect from x on y with $\partial y / \partial x = \beta$.

⁴⁹⁷ The general model description in this study is related to the regression setup proposed by OECD (2009a). In comparison to the TL2 level regressions in OECD (2009a), this study offers TL3 level regressions. Furthermore, several ideas for covariates and methodological aspects are related to the regressions in Arbia *et al.* (2005), Bräuning and Niebuhr (2005), Paas and Schlitte (2007), Bräuning and Niebuhr (2008), Geppert and Stephan (2008) and Paas and Schlitte (2008).

⁴⁹⁸ Figure A.47 in the appendix highlights the OECD (2010) definition of urban, intermediate and rural areas for the analyzed sample. It shows that most European regions correspond to the intermediate and rural classification. All spatial dummy variables in the regressions represent the regional typology in the year 1995.

with specific numbers of inhabitants (OECD, 2010).⁴⁹⁹ Moreover, a capital region control variable (CAPITAL) is used, which controls for the attribute that the TL3 region hosts the administrative center of the national economy.⁵⁰⁰ The hypothesis is, that the capital region dummy should be at least significant and positive in the regressions for the NMS group if capital regions exhibit higher growth rates. A small number of studies confirmed strong core-periphery structures in the NMS at the regional level, originating from high growth rates in capital regions and poor peripheral regions (see, e.g., Paas and Schlitte, 2008).⁵⁰¹

Besides the regional typology, which controls for the average state of settlement between 1995 and 1997, the study additionally controls for employment (and thus implicitly for production) structures by application of a very simple sectoral classification (due to data constraints). The employment shares in industry (INDUSTRY) and services (SERVICES) are implemented for all European TL3 regions for the initial year (OECD, 2003, 2009d).⁵⁰²

Finally, the analysis controls for the region-specific technology and knowledge bases and research activity in terms of population corrected EPO patent applications in non-high-technology (NHTEPOPAT) and high-technology fields (HTEPOPAT) at the regional level (OECD, 2009a,f,e). The rationale is that technologically leading regions show in general higher levels of EPO patent applications, which serve as a proxy for codified (analytic) knowledge bases. Moreover, these covariates implicitly control for human capital in high-technology and non-high-technology fields (see OECD, 2009a,b). Besides the distinction into non-high-technology and high-technology EPO patents, the analysis also incorporates the overall number of EPO patent applications (per capita). The hypothesis is that there is a significant relationship between European regions' average annual growth rates in GDP per capita (PPP) and regions' technology structure, which is proxied by regions' EPO patent applications (codified knowledge). The hypothesis is that EU-15 and NMS regions' EPO high-technology patent application densities are significant and positive in growth regressions. Non-high-technology EPO patent applications are assumed to show a significant and positive coefficient in NMS regressions, as these regions are on average technologically backward compared to EU-15 regions (see also chapter 3, sections 3.4 and 3.5).⁵⁰³ As has been already shown in chapters 3 and 4, leading innovative European regions are located in the western part of Europe. These places are responsible for the major fraction of European patent applications and are hosting the majority of EPO inventors. EPO patent applications represent an established approximation for research activity and are assumed to be associated with regional human capital structures (Griliches, 1990; OECD, 2009a).

⁴⁹⁹ Statistically, metro regions are agglomerations of at least 250.000 inhabitants and represent a combination of NUTS3 regions. An agglomeration is represented by at least one NUTS3 region; however, in most cases the metro regions consist of several units. If in an adjacent NUTS3 region more than 50% of the population also lives within this agglomeration, it is included into the metro unit.

⁵⁰⁰ Due to the level of aggregation, several neighboring regions may share this attribute.

⁵⁰¹ According to this study, the capital region dummy in the NMS regressions is significant and positive.

⁵⁰² Unfortunately, there exist no 2-digit or 3-digit industry employment data at the TL3 regional level for the whole population of 819 regions; neither for all EU-15 countries.

⁵⁰³ For visualization purpose, figure A.48 in the appendix show the spatial distribution of EPO patent applications per million inhabitants (patent densities) for the initial year (average value 1994-1996). For further details refer to chapter 3 and 4.

Regarding the methodological design of regional growth analyses, panel studies generally center changes within countries over time, while cross-sectional studies examine differences between countries and regions. Moreover, it is also argued that cross-sectional studies investigate long-run relationships, whereas panel studies look at relationships at a short/medium viewpoint (see, e.g., Arbia *et al.*, 2005; Geppert and Stephan, 2008). Since the explanatory variables of the growth regression models in this study rather represent time-invariant characteristics of European regions, e.g., regional typology, time-invariant employment shares, national controls (dummy variables), and extremely time-invariant patent densities, the focus is restricted on cross-sectional regressions. Accordingly, the following regressions are rather interested in broad categories of factors rather than in the influence of specific growth determinants. Although information on regional capital stocks does not exist, the regional typology is considered to implement additional information (and variation), i.e., infrastructure, capital stock, human capital, local market size (Bräuninger and Niebuhr, 2005; Geppert and Stephan, 2008).⁵⁰⁴ Similarly, Geppert and Stephan (2008, 198) argued that,

“[as] most of the explanatory variables, country and settlement-type dummies, represent time-invariant characteristics of regions, it is not possible to apply the standard approaches of panel data analysis. The influence of these broad categories of factors on regional income has to be evaluated in a cross-sectional setting.”

Accordingly, the following empirical analysis depicts the significance of regional dummy variables, especially of the regional typology (i.e., settlement structure), in a cross-sectional econometric setting. The distribution of EPO patenting activity is highly skewed but persistent and thus represents another time-invariant feature of the TL3 regions under analysis. Covariates and dummy variables are presented and defined in table 5.4; the expected signs of the estimates are presented in table 5.5.

It can be concluded from the previously presented national growth regressions in tables 5.2 and 5.3 that the EU-15 and NMS group show very different growth patterns (see also Paas and Schlitte, 2007). Therefore, this study follows several contributions and splits the EU-25 group into an EU-15 and NMS regression group for which regressions are run separately. The results of the a-spatial conditional convergence regressions are reported in tables 5.6 (EU-15) and 5.7 (NMS). Due to potential heteroscedasticity, the conditional growth models are estimated with White-robust heteroscedasticity-consistent standard errors for inference purpose.⁵⁰⁵

Another issue in regional regressions is potential spatial interdependence of observations (see also chapter 4, section 4.1). Spatial econometrics can handle this issue with the help of (i) spatial lags of the dependent variable, or (ii) by allowing interdependence within the

⁵⁰⁴ For similar interpretations refer to Geppert *et al.* (2005) and OECD (2009a). Moreover, several covariates could not be incorporated into a panel analysis due to severe data constraints at the TL3 level.

⁵⁰⁵ Although coefficients should not be biased, inference of classical least square estimations would lead to biased standard errors and thus unreliable inference. HC3 least-square estimator and the intragroup-cluster correlation estimator have also been applied; the latter estimator allows for intra-group interdependence between observations, which represents an alternative to spatial models (group ID equals country ID), i.e., all regions within a country form a cluster.

Table 5.4. Dependent variable, covariates and controls

<i>dependent variable:</i>		
GDPGROWTH	$1/T \ln(y_{i,2006}/y_{i,1995})$	average annual GDP per capita growth rate (PPP)
<i>explanatory variables:</i>		
GDPLEVEL	$\ln(y_{i,t})$	GDP per capita level (PPP)
$\rho GDPLEVEL$	$W[1/T \ln(y_{i,t+T}/y_{i,t})]$	spatial lag of average annual GDP per capita growth rate (PPP)
INDUSTRY	$\ln(E_{1i}/\sum_1^3 E_i)$	share of total regional employment in industry sector
SERVICES	$\ln(E_{2i}/\sum_1^3 E_i)$	share of total regional employment in service sector
EPOPAT	$\ln(PAT_i/pop_i)$	total EPO patent applications per million population; proxy for research activity and technological development
HTEPOPAT	$\ln(HPAT_i/pop_i)$	high-tech EPO patent applications per million population; proxy for research activity in high-technology
NHTEPOPAT	$\ln(NHPAT_i/pop_i)$	non high-tech EPO patent applications per million population; proxy for research activity in non high-technology
POPENSITY	$\ln(pop_i/space_i)$	population per square kilometer
CAPITAL	χ_{1i}	regional dummy [0;1]; predominantly capital areas
METRO	χ_{2i}	regional dummy [0;1]; predominantly metropolitan areas
URBAN	χ_{3i}	regional dummy [0;1]; predominantly urban areas (see figure A.48, appendix)
INTERMEDIAT	χ_{4i}	regional dummy [0;1]; predominantly intermediate areas (see figure A.48, appendix)
RURAL	χ_{5i}	regional dummy [0;1]; predominantly rural areas (see figure A.48, appendix)
EUBORDER	κ_{1i}	regional dummy [0;1]; regions sharing an extra-EU border
NATBORDER	κ_{2i}	regional dummy [0;1]; regions sharing a national border
CTRYDUMMY	ψ_i	national control variable [0;1], AT, BE, CY, CZ, DE, DK, EE, ES, FI, FR, GR, HU, IE, IT, LT, LU, LV, MT, NL, PL, PT, SE, SI, SK, UK (see also table B.3, appendix)

Table 5.5. Expected signs of explanatory variables

$\beta(URBAN) > 0$	$\beta(INTERMEDIAT) > 0$	$\beta(\rho) > 0$
$\beta(CAPITAL) > 0$	$\beta(METRO) > 0$	$\beta(POPENSITY) > 0$
$\beta(INDUSTRY) > 0$	$\beta(SERVICES) > 0$	$\beta(GDPLEVEL) < 0$
$\beta(EPOPAT) > 0$	$\beta(HTEPOPAT) > 0$	$\beta(NHTEPOPAT) < 0$
$\beta(NATBORDER) < 0$	$\beta(EUBORDER) < 0$	

error structure, or (iii) by introducing spatial effects from GDP per capita (PPP) of neighboring regions, or (iv) by allowing other spatially lagging covariates in the regression (Arbia *et al.*, 2005; OECD, 2009a). However, it has been argued that spatial interdependence vanishes due to the incorporation of national dummy variables and other region-specific controls (regional typology) (Bräuninger and Niebuhr, 2005). The majority of spatial autocorrelation is assumed to originate from national characteristics and thus represents country-specific effects (Fingleton, 2003). This approach has also been proposed by, e.g., Bräuninger and Niebuhr (2005), Frenken and Hoekman (2006), Paas and Schlitte (2007, 2008) and Falk and Sinabell (2008). Accordingly, the major fraction of spatial spillovers is considered to stop at national borders, meaning that intra-national interdependence and macroeconomic factors appear to be more influential.

The most distinct feature of the spatial regressions (section 5.4.4) is that spatial LM tests turn out to be insignificant and the hypothesis of no spatial dependence cannot be rejected as soon as national dummy variables (CTRYDUMMY) and regional controls (METRO, URBAN, CAPITAL) are introduced as they capture country-specific and region-specific effects.⁵⁰⁶ Moreover, it seems that the OECD TL3 classification reduces spatial interdependence (OECD, 2010). In opposition, higher spatial aggregates are considered to generally induce an averaging process which reduces variance (Arbia *et al.*, 2005; Dewhurst and McCann, 2007; Arbia and Petrarca, 2010).⁵⁰⁷

5.4.3.2. Regional Growth in the EU-15

Table 5.6 summarizes regression models for the EU-15 group (645 observations), which include different covariates/ dummy variables (models 18-24). The results are quite similar to Frenken and Hoekman (2006), although they studied NUTS3 regions.⁵⁰⁸

In the first EU-15 regression, (model 18, OLS-R), the initial GDP per capita level is significant and negative (i.e., indicating convergence tendencies). The urbanization dummy (URBAN) is significant and positive in almost all regression alternatives (models 18-21). This is also the case with the alternative regional classifications, i.e., metro regions (METRO) (see model 20). Moreover, industry employment (INDUSTRY) is significant and negative, meaning that regions with high employment shares in the industry sector have lower growth rates (models 18-24).⁵⁰⁹ This may be explained by the fact that production (and industry employment) is generally located in industry areas and neighboring regions but not in the highly populated centers, which represents a sort of urban hierarchy (Fujita and Ishii, 1999). Nevertheless, the results are generally in line with recent OECD studies at the higher TL2 regional level (1995-2005) (OECD, 2009b,a,f). An always significant covariate

⁵⁰⁶ Regional time-invariant dummy variables are considered to introduce additional spatial heterogeneity and to make spatial dependence vanishing as similarity between observations is decreasing.

⁵⁰⁷ To put it differently, the correlations between observations are assumed to increase with the size of the region, which leads to a severe loss in variation due to aggregation and averaging (i.e., the MAUP).

⁵⁰⁸ Refer also to similar results presented in Geppert and Stephan (2008) and OECD (2009a). Nevertheless, the subsequent regressions differ significantly as they are done at the TL3 level and include differing covariates, e.g., a regional typology, EPO patent applications densities and employment controls.

⁵⁰⁹ This result is identical to the reported negative coefficient of manufacturing concentration in OECD (2009a).

in the EU-15 regressions is the number of EPO patent applications per million inhabitants in high-technology (HTEPOPAT, models 18-22 and model 24). Non-high-technology EPO patenting (NHTEPOPAT), however, is insignificant in the EU-15 regressions (models 18-24). The regressions also include overall EPO-patenting activity (EPOPAT). It is significant and positive (model 23), which is in line with results reported in (OECD, 2009a).⁵¹⁰ Regional employment in services (SERVICES) is insignificant. Moreover, the internal border dummy (NATBORDER) and the external border dummy (EUBORDER) are not significant, although they show the expected negative sign.⁵¹¹ Similarly, neither the capital region dummy (CAPITAL) nor the intermediate region dummy (INTERMEDIAT) are significant in the EU-15 regressions. The insignificance of the capital region dummy in the EU-15 group may be explained by the fact that non-capital EU-15 regions are, on average, on a similar level of development compared to capital regions but on a higher level of development compared to their NMS counterparts (see also the results reported in chapters 3 and 4). Moreover, the inequality decomposition and descriptive statistics have pointed to the possibility that EU-15 regions show lower variation in growth rates compared to the group of NMS countries. In regression model 19, which is again a regression with White heteroscedasticity-consistent standard errors, the regional typology (dummy for urban and intermediate areas) is replaced by a new covariate, i.e., population density (POPDENSITY), which is significant and positive. Industry employment and the initial GDP per capita level remain significant with similar point estimates and signs. In regression model 20, population density (POPDENSITY) is replaced by the metro region dummy (METRO), which is significant and positive. The intermediate region dummy (INTERMEDIAT) is significant and negative in almost all regressions (or at least insignificant), meaning that intermediate regions do not show higher growth rates. Finally, in model 24, high-technology patenting (HTEPOPAT) and the urban dummy (URBAN) are significant and positive.

It can be concluded from the different regression models, i.e., (i) Huber-White robust-sandwich estimator, (ii) robust HC3 regressions, (iii) cluster-robust regression with intra-group correlations, that population density, the regional typology and EPO patent applications are in most cases significant and positive.⁵¹² On the other hand, the initial level of regions' GDP and the share of regions' industry employment are both significant but negative in all EU-15 regressions.⁵¹³ Moreover, the EU-15 regressions demonstrate that the capital region dummy (CAPITAL) is in all cases insignificant (models 18-24), meaning that capital regions in the EU-15 do not grow faster - at least according to the presented regressions. The negative sign of the GDP per capita level in the EU-15 regressions supports the widely accepted opinion that EU-15 regions are generally converging (Frenken and Hoekman, 2006; Paas and Schlitte, 2008). Although the regressions have not explicitly controlled for human capital, i.e., secondary and tertiary education, it may be the

⁵¹⁰ Even the point estimate is quite similar in OECD (2009a), although the regressions are not directly comparable due to a different spatial classification system.

⁵¹¹ Döring *et al.* (2008) discussed similar results for growth regressions in Germany.

⁵¹² Results of (ii) and (iii) are available upon request.

⁵¹³ The results at the TL3 level seem to be generally in line with findings of other studies at the NUTS3, TL2 and NUTS2 level. Refer to Niebuhr and Schlitte (2004), Bräuning and Niebuhr (2005), Frenken and Hoekman (2006), Döring *et al.* (2008), Geppert and Stephan (2008), Paas and Schlitte (2008), Petrakos and Artelaris (2009) and Crespo Cuaresma *et al.* (2009b).

case that the regional typology (urban, metro) and EPO patenting activity have implicitly controlled for these factors. Furthermore, even if the assumption of independence of the observations is relaxed and observations are allowed to be correlated (e.g., intragroup-cluster correlations), the covariates show the same signs and similar significance levels.⁵¹⁴ Finally, concerning the significance of country dummy variables, the regressions clearly demonstrate that most EU-15 countries (and their regions) show stable development (growth) paths relative to the reference nation which is the United Kingdom (exceptions are Greece and Portugal).⁵¹⁵

5.4.3.3. Regional Growth in the New Member States

After the presentation of the EU-15 regressions in the previous section, emphasis is now placed on the NMS.⁵¹⁶ The capital region dummy is assumed to be significant and positive, as growth is assumed to take place predominantly in metropolises and capital regions (see also chapter 5, section 5.3). The urban region dummy (URBAN) is assumed to be significant and positive. Table 5.7 summarizes the estimations for the NMS group and covers several covariates (models 25-31). The first NMS regression (model 25) shows a significant and positive capital region dummy (CAPITAL), meaning that capital regions in the NMS regions are generally equipped with higher growth rates. The initial GDP per capita level (GDPLEVEL) is, on average, not significant in these regressions (models 25-31), which points to missing convergence within the NMS group. Moreover, in opposition to the previously presented EU-15 regressions, the regional industry employment share (INDUSTRY) is significant and positive. Interestingly, the level of EPO patent applications per million inhabitants in non-high-technology fields (NHTEPOPAT) is significant and positive, which is in contrast to the EU-15 regression results. The next regression (model 26) replaces the standard regional typology (URBAN, INTERMEDIAT, RURAL) with population density (POPDENSITY), which ranges from low values in rural areas to very high values in metropolises and capital regions. Again, this density control is significant and positive (models 26 and 28). Besides that, the other covariates remain significant with similar coefficients as in the previous estimations. In the following regression (model 27), the population density control is replaced by the metro region dummy (METRO). METRO is significant and positive, which means that metro regions show on average higher annual regional growth rates. The regressions confirm that highly populated areas (CAPITAL, METRO) show, on average, higher growth rates. Finally, the subsequent regression (model 28) contains the metro region dummy (METRO) and the population density (POPDENSITY). Both coefficients are significant and positive, meaning that highly populated regions exhibit higher growth rates.⁵¹⁷ The other covariates remain significant with the same sign. Again, the capital region control dummy (CAPITAL) is significant at the 1% level (as it is the case with all alternative NMS regressions).

⁵¹⁴ The clustering assumption (OLS-C) relaxes the necessity of independence of observations as it only requires that the observations have to be independent across the clusters (groups), which are national units (CTRYDUMMY).

⁵¹⁵ Refer also to Geppert and Stephan (2008), although their study was conducted at the NUTS1/2 level (only 160-200 regions). See also Frenken and Hoekman (2006) for NUTS3 regressions.

⁵¹⁶ Malta is excluded due to data constraints regarding covariates.

⁵¹⁷ However, the two seem to be partially correlated.

Table 5.6. Robust regression for EU-15 regions

Model	(18)	(19)	(20)	(21)	(22)	(23)	(24)
	OLS-R	OLS-R	OLS-R	OLS-R	OLS-C	OLS-C	OLS-C
	EU-15	EU-15	EU-15	EU-15	EU-15	EU-15	EU-15
<i>dep. var.:</i> $1/T\ln(y_{i,T}/y_{i,t})$							
GDPLEVEL	-0,0091*** (0,0021)	-0,0092*** (0,0021)	-0,0079*** (0,0018)	-0,0081*** (0,0017)	-0,0083*** (0,0023)	-0,0086*** (0,0024)	-0,0089*** (0,0027)
NATBORDER	-0,0008 (0,0006)	-0,0007 (0,0006)	-0,0006 (0,0006)				
EUBORDER	-0,0008 (0,0018)	-0,0008 (0,0013)	-0,0004 (0,0013)				
INDUSTRY	-0,0051** (0,0021)	-0,0054** (0,0021)	-0,0067*** (0,0015)	-0,0070*** (0,0013)	-0,0068** (0,0031)	-0,0073** (0,0033)	-0,0051 (0,0037)
SERVICES	0,0057 (0,0043)	0,0048 (0,0043)					0,0050 (0,0056)
CAPITAL	0,0011 (0,0018)	0,0008 (0,0018)	0,0014 (0,0019)			0,0014 (0,0014)	0,0013 (0,0014)
URBAN	0,0020* (0,0010)			0,0026*** (0,0008)			0,0023** (0,0008)
INTERMEDIAT	-0,0004 (0,0008)		-0,0014** (0,0006)				
METRO			0,0015** (0,0007)				
POPDENSITY		0,0008** (0,0004)			0,0010*** (0,0003)	0,0010*** (0,0002)	
HTEPOPAT	0,0010** (0,0005)	0,0010* (0,0004)	0,0010** (0,0005)	0,0011*** (0,0004)	0,0010* (0,0005)		0,0010* (0,0005)
NHTEPOPAT	0,0001 (0,0005)	0,0001 (0,0005)	0,0002 (0,0005)				
EPOPAT						0,0007* (0,0003)	
AT	-0,0021 (0,0018)	-0,0021 (0,0018)	-0,0041** (0,0015)	-0,0032** (0,0015)	-0,0030*** (0,0008)	-0,0037*** (0,0006)	-0,0025 (0,0015)
BE	-0,0076*** (0,0016)	-0,0072*** (0,0017)	-0,0078*** (0,0016)	-0,0079*** (0,0016)	-0,0074*** (0,0004)	-0,0077*** (0,0004)	-0,0079*** (0,0005)
DE	-0,0060*** (0,0013)	-0,0060*** (0,0013)	-0,0069*** (0,0013)	-0,0063*** (0,0012)	-0,0062*** (0,0007)	-0,0061*** (0,0007)	-0,0061*** (0,0008)
DK	-0,0030* (0,0017)	-0,0030* (0,0017)	-0,0043*** (0,0015)	-0,0035** (0,0015)	-0,0034*** (0,0004)	-0,0038*** (0,0002)	-0,0035*** (0,0004)
ES	0,0122*** (0,0016)	0,0126*** (0,0016)	0,0111*** (0,0015)	0,01151*** (0,0011)	0,0121*** (0,0014)	0,0121*** (0,0015)	0,0118*** (0,0015)
FI	0,0051*** (0,0019)	0,0067*** (0,0020)	0,0037** (0,0017)	0,0045*** (0,0016)	0,0062*** (0,0010)	0,0061*** (0,0009)	0,0048*** (0,0010)
FR	-0,0050*** (0,0011)	-0,0048*** (0,0016)	-0,0057*** (0,0010)	-0,0050*** (0,0011)	-0,0048*** (0,0006)	-0,0051*** (0,0004)	-0,0050*** (0,0007)
GR	-0,0004 (0,0050)	-0,0003 (0,0050)	-0,0032 (0,0044)	-0,0030 (0,0042)	-0,0027** (0,0011)	-0,0025* (0,0013)	-0,0014 (0,0022)
IE	0,0292*** (0,0292)	0,0300*** (0,0040)	0,0273*** (0,0039)	0,02874*** (0,0039)	0,0294*** (0,0011)	0,0292*** (0,0013)	0,0291*** (0,0016)
IT	-0,0108*** (0,0014)	-0,0110*** (0,0014)	-0,0115*** (0,0012)	-0,0117*** (0,0012)	-0,01165*** (0,0008)	-0,0117*** (0,0008)	-0,0112*** (0,0011)
LU	0,02513*** (0,0025)	0,0247*** (0,0025)	0,0227*** (0,0023)	0,0252*** (0,0018)	0,0247*** (0,0016)	0,0227*** (0,0011)	0,0241*** (0,0010)
NL	0,0034*** (0,0034)	0,0035*** (0,0013)	0,0029*** (0,0011)	0,0029** (0,0012)	0,0031*** (0,0006)	0,0032*** (0,0006)	0,0031*** (0,0007)
PT	0,0049 (0,0030)	0,0048 (0,0030)	0,0030 (0,0022)	0,0029 (0,0029)	0,0031 (0,0020)	0,0037 (0,0025)	0,0044 (0,0029)
SE	-0,0056*** (0,0015)	-0,0042** (0,0016)	-0,0066*** (0,0013)	-0,0059*** (0,0013)	-0,0042*** (0,0008)	-0,0044*** (0,0006)	-0,0058*** (0,0006)
N	645	645	645	645	645	645	645
R-squared	0,5592	0,5583	0,5562	0,5551	0,5554	0,5556	0,5576

Source: own estimations. *Notes:* EU-15 growth regressions for period 1995-2006 w/ CTRYDUMMY; standard errors in parentheses; OLS-R represents the Huber and White robust-sandwich estimator/robust estimator of variance; OLS-C represents cluster-robust regression with intragroup correlation; constant not reported; significance levels of coefficients: *** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.10 level. Reference country is UK and RURAL for settlement type dummy.

To conclude, the conditional convergence regressions for the NMS group support several of the proposed hypotheses: (i) the capital region dummy (CAPITAL) is significant and positive; (ii) the metro region dummy (METRO) and population density (POPDENSITY) are significant and positive; (iii) industry employment (INDUSTRY) is significant and positive in the NMS group, which is different to the EU-15 regressions; (iv) the control for non-high-technology EPO patent applications (NHTEPOPAT) is significant and positive; (v) the initial level of GDP per capita (GDPLEVEL) is not significant, meaning that the NMS group shows divergence, which is in strong contradiction to the EU-15 case.⁵¹⁸ Population density seems to be positively related but urban and metro regions in particular exhibit higher growth rates in the EU-15 group. This finding could be explained by the fact that densely populated areas have on average higher levels and growth rates of productivity, a larger stock of human capital and a higher technology level, which has been demonstrated in terms of EPO patenting activity (see chapter 3, section 3.5); cities and metropolises can be regarded as the pivotal growth poles and centers of the creation and diffusion of knowledge and new ideas.⁵¹⁹ That being the case, the aforementioned results can be interpreted as preliminary evidence for higher growth rates in urban regions, metropolises and capital regions in the NMS. In the EU-15, the capital dummy is not significant, which could be explained by the fact that core-periphery structures in the EU-15 are less pronounced.

A serious shortcoming of the presented empirical analysis is the lack of an exploration and test of the working channels of agglomeration economies and missing research results on causalities, endogeneity and additional covariates. Moreover, time-invariant covariates, persistent data constraints and potential spatial autocorrelation have prevented the application of standard panel estimators.

5.4.4. European Regional Growth and Spatial Spillovers

5.4.4.1. A General Spatial Model

Capturing spatial interdependence between observations in regression analysis avoids severe statistical problems, e.g., unstable parameters, unreliable inference. Moreover, it provides information on spatial relationships between observations (e.g., regions). Depending on the specific technique, spatial relationships can be implemented into regression models in various forms; i.e., as a relationship between a dependent and independent variable, between the dependent variable and a spatial lag of itself, or via the error term (Anselin, 2006; OECD, 2009a; Andersson and Gräsjö, 2009).⁵²⁰

⁵¹⁸ This result has also been confirmed by the studies of Bräuninger and Niebuhr (2005, 2008), Paas and Schlitte (2008), Petrakos and Artelaris (2009) and Crespo Cuaresma *et al.* (2009b), although the studies have been conducted at a different spatial level of aggregation.

⁵¹⁹ For similar results refer to Williamson (1965), Florida (1995), Fujita and Thisse (1996), Duranton and Puga (2001), Szörfi (2007) and Crespo Cuaresma *et al.* (2010).

⁵²⁰ See also Anselin (1988a), Anselin (1992), Anselin and Florax (1995), Anselin and Bera (1998) and Anselin (1999).

Table 5.7. Robust regression for NMS

Model	(25)	(26)	(27)	(28)	(29)	(30)	(31)
	OLS-R	OLS-R	OLS-R	OLS-R	OLS-C	OLS-C	OLS-C
	NMS	NMS	NMS	NMS	NMS	NMS	NMS
<i>dep. var.:</i> $1/T \ln(y_{i,T}/y_{i,t})$							
GDPLEVEL	-0,0052 (0,0066)	-0,0078 (0,0060)	0,0020 (0,0042)	-0,0059 (0,0062)	-0,0052 (0,0076)	0,0020 (0,0039)	-0,0002 (0,0069)
NATBORDER	-0,0037* (0,0021)	-0,0036* (0,0021)	-0,0034* (0,0019)	-0,0037* (0,0020)	-0,0037 (0,0036)	-0,0034 (0,0029)	
EUBORDER	-0,0031 (0,0021)	-0,0021 (0,0020)	-0,0024 (0,0020)	-0,0018 (0,0020)	-0,0031 (0,0019)	-0,0024 (0,0019)	
INDUSTRY	0,0114** (0,0056)	0,0119** (0,0060)	0,0103* (0,0055)	0,0106* (0,0058)	0,0114* (0,0059)	0,0103 (0,0061)	0,0131** (0,0056)
SERVICES	0,0075 (0,0080)	0,0050 (0,0072)		0,0020 (0,0074)	0,0075 (0,0089)		
CAPITAL	0,0225*** (0,0034)	0,0119*** (0,0060)	0,0194** (0,0036)	0,0199*** (0,0033)	0,0225*** (0,0026)	0,0195*** (0,0035)	0,0248*** (0,0029)
URBAN	0,0065 (0,0050)				0,0065 (0,0037)		0,0064 (0,0029)
INTERMEDIAT	0,0006 (0,0022)		-0,0015 (0,0020)		0,0006 (0,0028)	-0,0015 (0,0029)	
METRO			0,0058*** (0,0019)	0,0036* (0,0020)		0,0058*** (0,0013)	
POPENSITY		0,0037*** (0,0010)		0,0032** (0,0011)			
HTEPOPAT	-0,0087 (0,0056)	-0,0079* (0,0055)	-0,0097* (0,0056)	-0,0084 (0,0055)	-0,0087 (0,0049)	-0,0097 (0,0059)	
NHTEPOPAT	0,0047** (0,0021)	0,0038* (0,0021)	0,0050** (0,0022)	0,0038* (0,0021)	0,0047** (0,0018)	0,0050** (0,0019)	
CY	-0,0262*** (0,0072)	-0,0228*** (0,0066)	-0,0313*** (0,0061)	-0,0254*** (0,0068)	-0,0262*** (0,0053)	-0,0313*** (0,0042)	-0,0318*** (0,0048)
CZ	-0,0255*** (0,0044)	-0,0251*** (0,0039)	-0,0290*** (0,0037)	-0,0261*** (0,0039)	-0,0255*** (0,0032)	-0,0290*** (0,0019)	-0,0255*** (0,0031)
EE	0,0278*** (0,0055)	0,0314*** (0,0055)	0,0315*** (0,0056)	0,0316*** (0,0055)	0,0278*** (0,0030)	0,0315*** (0,0017)	0,0272*** (0,0035)
HU	-0,0105** (0,0043)	-0,0104*** (0,0039)	-0,0103*** (0,0038)	-0,0102** (0,0039)	-0,0104*** (0,0030)	-0,0102*** (0,0022)	-0,0084*** (0,0009)
LT	0,0094* (0,0049)	0,0109** (0,0047)	0,0098** (0,0049)	0,0102** (0,0047)	0,0094** (0,0029)	0,0098** (0,0030)	0,010*** (0,0030)
LV	0,0134* (0,0077)	0,0149** (0,0070)	0,0174** (0,0068)	0,0154** (0,0070)	0,0134** (0,0055)	0,0174*** (0,0042)	0,0163** (0,0051)
PL	-0,0093** (0,0040)	-0,0109*** (0,0038)	-0,0111*** (0,0039)	-0,0125*** (0,0037)	-0,0093* (0,0042)	-0,0111** (0,0042)	-0,0069** (0,0021)
SI	-0,010* (0,0060)	-0,0090* (0,0054)	-0,0155*** (0,0047)	-0,0098* (0,0052)	-0,0105*** (0,0029)	-0,0155*** (0,0024)	-0,0092** (0,0048)
N	121	121	121	121	121	121	121
R-squared	0,7549	0,7661	0,7601	0,7713	0,7549	0,7601	0,7248

Source: own estimations. *Notes:* NMS growth regressions for period 1995-2006 w/ CTRYDUMMY; standard errors in parentheses; OLS-R represents the Huber-White robust-sandwich estimator/robust estimator of variance; OLS-C represents cluster-robust regression with intragroup correlation; constant not reported; significance levels of coefficients: *** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.10 level. Reference country is SK and RURAL regions for settlement type dummy.

A “general” spatial model that incorporates several spatially lagged variables but also spatially correlated error terms can be expressed as in 5.4.3:

$$\begin{aligned}
 y &= \underbrace{\rho W_y y}_a + \underbrace{\beta X}_b + \underbrace{\varphi W_X X}_c + \varepsilon, \\
 \varepsilon &= \underbrace{\lambda W_\xi \xi}_d + u, \\
 u &\sim N(0, \sigma_u^2 I).
 \end{aligned}
 \tag{5.4.3}$$

W represents a spatial weight matrix for the autoregressive process $\rho W_y y$, the cross-regressive process $\varphi W_X X$ and the error term process $\lambda W_\xi \xi$. y represents a $(n \times 1)$ vector of observations of a dependent variable; $W y$ is a $(n \times 1)$ vector of observations of a spatially lagged dependent variable for a $(n \times n)$ spatial weight matrix W ; ρ represents the $(k \times 1)$ spatial auto-regressive parameter/coefficient; X is the $(n \times k)$ vector of exogenous explanatory variables; β is a $(k \times 1)$ vector of corresponding coefficients; $\varphi W_X X$ represents a $(n \times 1)$ vector of a spatially lagged independent variable. ε finally represents a $(n \times 1)$ vector of independent disturbances, which can be implemented as a spatially lagged process. u is a $(n \times 1)$ vector of errors assumed to be independently and normally distributed with $u \sim N(0, \sigma_u^2 I)$. The generalized spatial model can also be reduced to several sub-mechanisms a, b, c, d . Note that a represents an autoregressive process of the dependent variable, whereas c represents a cross-regressive process. d is a spatially weighted process of the error term; b is just a standard vector of exogenous explanatory variables (Freund, 2008; Richter and Freund, 2008; Andersson and Gråsjö, 2009). Thus, alternative implementations $[0; 1]$ of weights (W_y, W_X, W_ξ) will provide differing model structures that account for alternative forms of spatial interdependence. Simple spatial lags are obtained by setting $W_\xi = 0$, so that the error term satisfies classical assumptions (Freund, 2008; Richter and Freund, 2008; Andersson and Gråsjö, 2009).

5.4.4.2. Regional Growth Models and Spatial Interdependence

The previous section stressed general methodological issues of spatial dependence with respect to regional regressions. Potential issues in cross-sectional regional data and regressions can be addressed by spatial models, e.g., commuting effects, trade flows, input-output structures, diffusion of knowledge and technology across regional borders (Bräuning and Niebuhr, 2005; Arbia *et al.*, 2008; Patuelli *et al.*, 2010).⁵²¹ However, allowing for spatial spillovers in growth regressions could lead to decreasing effects of the initial GDP level on the growth rate and thus on the speed of convergence (Abreu *et al.*, 2005; Paas and Schlitte, 2008; Geppert and Stephan, 2008). If spatial spillovers are significant, then European regions are considered to influence neighboring regions’ growth rates in a meaningful and positive (or negative) way (and vice versa). Moreover, the presence of spatial growth spillovers could be interpreted in the following way: exogenous shocks in one region, e.g., supply and/or demand shocks, or knowledge accumulation, induce positive (negative) effects on neighboring regions and some kind of feed-back effects as spatial dependence is

⁵²¹ See also Rey and Montouri (1999) and Baumont *et al.* (2000).

bi-directional.⁵²² In the same vein, policy instruments with local focus would also be determined by a sincere spatial crowding-out effect to neighboring units (Abreu *et al.*, 2005; Freund, 2008; Harris, 2008).

The incorporation of spatially lagged dependent variables or errors leads to endogeneity issues. Anselin (1988a), among others, proposed a spatial maximum-likelihood approach.⁵²³ Accordingly, the first methodological line of research implements spatial interaction via the dependent variable by modeling the spatial processes of interest (see model 5.4.3) (Anselin, 1988a, 2002, 2006). Otherwise, OLS estimates would be biased, if substantial spatial dependence is present. A second approach identifies spatial dependence between ignored variables, which is reflected by the error term (see model 5.4.3). Such nuisance spatial dependence yields unbiased but inefficient OLS regression results (Anselin, 1988a, 2002, 2006; Fingleton and López-Bazo, 2006).⁵²⁴ To repeat a point made earlier, spatial growth models that explicitly account for spatial autocorrelation (see section 4.2.1.4) show in most cases slower catching-up processes because the point estimates of the initial income variable (GDPLEVEL) decrease due to the implementation of a spatially lagged dependent variable (Rey and Montouri, 1999; Harris, 2008; Arbia *et al.*, 2008).⁵²⁵

Regarding regional heterogeneity, the applied spatial typology (i.e., capital, urban, rural regions) and the implementation of national dummy variables control for a large fraction of spatial interdependence between areas, but may, nevertheless, leave considerable variation in the data. Under this hypothesis, the majority of spatial spillovers are unlikely to reach beyond regions' borders (Bräuninger and Niebuhr, 2005; Andersson and Gråsjö, 2009; Patuelli *et al.*, 2010).⁵²⁶ However, in order to test for remaining neighborhood effects, the growth models have to test for nuisance and substantive spatial dependence by inclusion of (i) an endogenous ($n \times n$) spatially lagged ($k \times 1$) vector of dependent variables ($\rho W y$), or (ii) by a ($n \times n$) spatially lagged ($k \times 1$) vector of exogenous variables ($\phi W X$), or (iii) by inclusion of potential spatial interaction in the error term ($\lambda W \varepsilon$) (Anselin, 2006; Andersson and Gråsjö, 2009), or (iv) by inclusion of additional covariates that minimize spatial dependence (regional typology or spatial filter) (Anselin, 2006; Andersson and Gråsjö, 2009).⁵²⁷

⁵²² It is incorrect to compare the β -coefficient of a spatial lag model (direct marginal effect) with the β -coefficient of an OLS regression (total marginal effects). The column sum of the matrix of the spatial multiplier $\beta(1 - \rho W)^{-1}$ then captures the total effect of an exogenous shock from region i on all neighboring regions j , whereas the row sum of the matrix represents the total effect on region i from a simultaneous shock in all neighboring regions j (Abreu *et al.*, 2005).

⁵²³ Spatial ML-regressions allows for endogeneity and heteroscedasticity. For more details see, e.g., Anselin (1992), Anselin and Getis (1992), Rey and Montouri (1999), Anselin (1999), Smirnov and Anselin (2001), Abreu *et al.* (2005), van Oort and Raspe (2007), Anselin (2007) and Arbia *et al.* (2008).

⁵²⁴ The Moran's I test offers results for alternative forms of ignored spatial dependence, whereas the LM test supplies detailed information about the kind of spatial dependence (Anselin and Rey, 1991; Anselin and Bera, 1998; Anselin and Florax, 1995). It is clear that the choice of spatial weights and the modeled distance decay effects are highly dependent on the assumed spatial process.

⁵²⁵ See also Abreu *et al.* (2005) and Fingleton and López-Bazo (2006).

⁵²⁶ The inclusion of spatial spillovers do not at all give any theoretic indication about the microeconomic or regional origin of the spillover. The spatial control variable is simply considered to be a necessary econometric correction.

⁵²⁷ Spatial dependence is of nuisance form if the LM-test for spatial error dependence (LM_{err}) is more significant than the test for spatial lag dependence (LM_{lag}) and the robust LM test for the error (RLM_{err}) is significant and the one for the robust spatial lag is not (RLM_{lag}). Contrary, when the

In this respect, the regional typology can be interpreted to reduce spatial dependence between observations.⁵²⁸

A first possible treatment of spatial effects that might affect inter-regional growth rates is accomplished by incorporating a $k \times 1$ vector of spatially weighted exogenous variables, $WX_{i,t}$, with

$$W = \begin{cases} w_{ij} = 1, & \text{if } d_{ij} \leq d \\ w_{ij} = 0, & \text{otherwise.} \end{cases} \quad (5.4.4)$$

w_{ij} defines the interaction between regions i and j ; W is a spatial $n \times n$ weight matrix. The weight matrix combines a spatial structure (distance band with $d_{ij} \leq d$) with a $k \times 1$ vector of regional factors ($X_{i,t}$) of neighboring regions with a parameter vector ϕ (see section 4.2.1.3 for more details). Therefore, the original growth regression model (5.4.2), which represents a log-linear approximation of a conditional convergence equation, can be extended by incorporating spatial spillover effects from neighboring regions, i.e., $W \ln(X_{i,t})$, which transforms the initial a-spatial conditional convergence model to a cross-regressive spatial convergence model (SCR). Thus, spatially lagged income levels attribute importance to spatial relations (Abreu *et al.*, 2005; Anselin, 2006; Andersson and Gräsjö, 2009).⁵²⁹

$$\begin{aligned} \frac{1}{T} \ln \left(\frac{y_{t+T}}{y_t} \right) &= \beta_0 + \beta_1 \ln(y_t) + \beta_2 \ln(X_t) + \phi [W \ln(X_t)] + \varepsilon \\ \varepsilon &\sim N(0, \sigma_\varepsilon^2 I) \end{aligned} \quad (5.4.5)$$

The spatial (mixed-regressive-) autoregressive model (SAR) with inter-regional spillovers effects represents an alternative (5.4.6). It is different to the previous model (5.4.5) as it includes a spatial lag of the dependent variable ($\sum_{j=1}^N w_{ij} \frac{1}{T} \ln \left(\frac{y_{j,t+T}}{y_{j,t}} \right)$). However, the problem arises that the spatial lag is endogenous to the dependent variable, which requires 2SLS- or ML-technique (Anselin and Rey, 1991; Anselin, 2006; Andersson and Gräsjö, 2009).

$$\begin{aligned} \frac{1}{T} \ln \left(\frac{y_{t+T}}{y_t} \right) &= \beta_0 + \beta_1 \ln(y_t) + \beta_3 \ln(X_t) + \rho \left[\frac{1}{T} W \ln \left(\frac{y_{t+T}}{y_t} \right) \right] + \varepsilon \\ \varepsilon &\sim N(0, \sigma_\varepsilon^2 I) \end{aligned} \quad (5.4.6)$$

W represents the spatial weight matrix for the autoregressive process. In general, $\sum_{j=1}^N w_{ij} y_j$ is a $(n \times 1)$ vector of a spatially lagged dependent variable, here $\frac{1}{T} \ln \left(\frac{y_{j,t+T}}{y_{j,t}} \right)$ for a $n \times n$ spatial weight matrix; ρ represents the parameter vector of the spatial auto-regressive process

robust spatial lag LM-test (RLM_{lag}) is significant, inference goes in favor of a spatial autocorrelated lag variable. Alternative treatment of spatial weights will provide differing model structures that account for alternative spatial mechanisms (Anselin and Florax, 1995; Andersson and Gräsjö, 2009).

⁵²⁸ See Rey and Montouri (1999), Baumont *et al.* (2001, 2003), Le Gallo *et al.* (2003), Anselin (2006) and Patuelli *et al.* (2010), among others.

⁵²⁹ This specification can still be estimated with an OLS estimator as $\sum_{j=1}^N w_{ij} X_{j,t}$ is exogenous to the covariates as long as the errors and the dependent variables are independent.

(Anselin, 2006; Andersson and Gråsjö, 2009).⁵³⁰ If the spatially lagged (weighted) dependent variable is positive and significant, it would mean that (i) spatial spillovers exist and (ii) that spillovers are determining the growth process of neighboring regions.

As an alternative to the above presented SAR model, the so-called spatial error model (SER) is adequate when nuisance spatial dependence originates from omitted variables (Andersson and Gråsjö, 2009).⁵³¹ When the errors follow a first order process, the conditional convergence/growth model can be written as in 5.4.7:

$$\begin{aligned} \frac{1}{T} \ln \left(\frac{y_{t+T}}{y_t} \right) &= \beta_0 + \beta_1 \ln(y_t) + \beta_3 \ln(X_t) + \varepsilon & (5.4.7) \\ \varepsilon &= \lambda W \xi + u \\ u &\sim N(0, \sigma_u^2 I) \end{aligned}$$

Thus, the SER model includes spatial dependence in the error term.⁵³²

A technical consideration concerns the choice between the above illustrated regression approaches. Following the arguments of, e.g., Fingleton (2003), growth spillovers are likely to cross regions' administrative borders and might influence neighboring regions' growth process (Bräuninger and Niebuhr, 2005). The growth regressions are done for the EU-15 and NMS regions.⁵³³ For illustration and comparison purpose, the SAR estimations are reported for the EU-15 and NMS group.

5.4.4.3. Estimation Results

With regard to the methodological issues discussed in the previous section, tables 5.8 and 5.9 (and B.11, appendix) highlight the regression results for the EU-15 group (models 32-40). The regression results for the NMS group (models 40-53) are illustrated in table 5.10 (and B.12, appendix).

It can be concluded from the highlighted EU-15 regressions (models 32-45) that regional spillovers (of average annual regional GDP growth rates) are only statistically significant when country dummy variables (CTRYDUMMY) are excluded from the regressions (see table B.11, appendix, models 41-45). As soon as country dummy variables are included (models 32-40), the spatial multipliers cannot reject the hypothesis of no spatial dependence. Rook contiguity distance matrices (rook1, rook12) and a large number of alternative

⁵³⁰ It represents the spatially weighted average growth rate of neighboring observations that influences region i . See also Anselin and Bera (1998) and Rey and Montouri (1999).

⁵³¹ The issue is treated by the error process with errors from different neighboring regions (displaying spatial covariance).

⁵³² λ is a scalar spatial error coefficient expressing the intensity of spatial correlation between regression residuals ε . $u_{t,1}, u_{t,2}, \dots, u_{t,n}$ is assumed to be independently and normally distributed. SER and SAR are in general estimated in a maximum likelihood (ML) or generalized method of moments (GMM) framework (Anselin, 1988a, 2006; Andersson and Gråsjö, 2009).

⁵³³ The robust LM-lag and robust LM-error test have been applied to choose between the SER and SAR concept. It turns out that LM-lag is always larger than LM-error. However, all LM-tests remain insignificant when country dummy variables are included.

distance band weight matrices (e.g., 100, 200, 250, 300, 350, 400, 500 kilometers) have been tested.⁵³⁴

According to the theoretical remarks on knowledge diffusion and inter-regional effects (chapter 2, section 2.1) and the empirical evidence of existing studies (chapter 2, section 2.2), spatial interdependence with significant and positive influence (lag or error interdependence) is expected to occur within a distance band of maximum 200-400 kilometers as has been observed in several regional studies (Moreno *et al.*, 2005c; Greunz, 2005).⁵³⁵ Spatial spillovers are most likely to happen in close neighborhoods or between primary and secondary growth poles at a proximate distance. However, the spatial LM-tests cannot confirm remaining spatial autocorrelation when national dummy variables (as well as regional typology dummy variables) are included (models 32-40). Therefore, national dummy variables are interpreted as a crucial factor in these models as they indicate that inter-regional spillovers seem to decrease (and vanish) at national borders.⁵³⁶ Regional and national characteristics seem to play a dominant role compared to spatial spillovers; at least in the methodological approach used in this study. Thus, in the presented regressions (models 32-40), the effects of spatial spillovers seem to be sufficiently captured by national controls (and the implementation of a regional typology), which eliminate spatial autocorrelation as indicated by insignificant spatial lags in the spatial maximum likelihood set-up and insignificant spatial LM-tests (see also Eckey *et al.*, 2003; Fingleton, 2003; Bräuninger and Niebuhr, 2005). Concerning the covariates in the presented spatial model alternatives, GDPLEVEL is always significant and negative in the EU-15 group (tables 5.8 and 5.9, models 32-40), which can be interpreted as evidence for convergence of EU-15 regions. This finding is also supported by the work of Bräuninger and Niebuhr (2005, 2008) at the NUTS1/2 level. Moreover, similar to the previous OLS regressions (see section 5.4.3.2), the regional industry employment share (INDUSTRY) is significant and negative. URBAN and HTEPOPAT are again significant and positive. The spatial spillover, ρ , turns out to be statistically significant and positive, dominating other covariates, when national controls (CTRYDUMMY) are excluded (see table B.11, appendix, models 41-45). In this case (models 41-45), the capital region control (CAPITAL) becomes also significant and positive, whereas other covariates become insignificant.

The spatial regressions for NMS regions (models 46-53) are presented in the following (table 5.10 and table B.12, appendix). First and foremost, the results are quite similar compared to the a-spatial approach in the previous section 5.4.3.3. It can be concluded from the ML-estimations (models 46-50) that capital regions (CAPITAL) exhibit higher growth rates (table 5.10). Moreover, industry employment (INDUSTRY) is significant and positive. The initial level of GDP per capita (GDPLEVEL) is insignificant when country dummy variables are included. However, when country dummy variables are excluded, the spatial lag becomes significant and positive, dominating other covariates (table B.12, models 51-53, appendix), meaning that spatial autocorrelation is present (i.e., spillovers).

⁵³⁴ A fraction of all tested weight matrices is presented in the tables. Further information is available from the author upon request. For similar results at the NUTS1/2 level see Bräuninger and Niebuhr (2005).

⁵³⁵ See also chapter 2, section 2.2.

⁵³⁶ This idea has been proposed by Bräuninger and Niebuhr (2005) and Feldkircher (2006). Refer also to Geppert *et al.* (2005), Geppert and Stephan (2008) and Paas and Schlitte (2007, 2008) for similar conclusions with respect to national controls.

To conclude, regional industry employment (INDUSTRY), the urban dummy (URBAN) and capital dummy (CAPITAL) remain significant and positive in spatial NMS regressions. Interestingly, the GDP level (GDPLEVEL) becomes significant and negative when country dummy variables are excluded, which could be interpreted as convergence tendencies in case that regressions do not control for national characteristics.

To conclude, the presented simple regressions demonstrate that the EU-15 and NMS TL3 regions show differing growth structures. Moreover, the significance of covariates/ dummy variables in the regional growth regressions is not identical. The regional typology can be considered to implement additional information into the regional regressions. Furthermore, patenting activity, measured via EPO patent application densities, adds additional information regarding inventive activity into the regressions.⁵³⁷ The reported results, although preliminary and limited in detail, seem to confirm the existence of structural differences between the NMS and EU-15 concerning the growth process of regions. Nevertheless, additional empirical analysis is needed in order to analyze the structural features and differences of the European regions. A necessary step would be to improve the availability of regional data at the TL3 level for the EU-25, Switzerland and Norway; e.g., employment data at the 2-3 digit-level, data on human resources and skill-levels, spatially disaggregated R&D data at the TL3 level (governmental R&D, higher-educational R&D, business R&D). Furthermore, the provision of longer time series on GDP and productivity at the TL3 level should improve the possibilities for future descriptive and econometric studies.

⁵³⁷ Unfortunately, the causality remains unchallenged. Does patenting activity affect regional growth or vice versa? This issue needs additional research.

Table 5.8. Spatial regression (ML-SAR) for EU-15 regions

Model	(32) EU-15	(33) EU-15	(34) EU-15	(35) EU-15	(36) EU-15
<i>dep. var.:</i> $1/T\ln(y_{i,T}/y_{i,t})$					
GDPLEVEL	-0,0095*** (0,0016)	-0,0088*** (0,0015)	-0,0088*** (0,0016)	-0,0089*** (0,0016)	-0,0091*** (0,0016)
NATBORDER	-0,0008 (0,0006)	-0,0008 (0,0006)	-0,0007 (0,0006)	-0,0008 (0,0006)	-0,0008 (0,0006)
EUBORDER	-0,0008 (0,0013)	-0,0007 (0,0013)	-0,0003 (0,0013)	-0,0003 (0,0013)	-0,0003 (0,0013)
INDUSTRY	-0,0053** (0,0017)	-0,0050*** (0,0016)	-0,0056*** (0,0017)	-0,0056*** (0,0017)	-0,0058*** (0,0017)
SERVICES	0,0050 (0,0034)	0,0062* (0,0033)	0,0046 (0,0033)	0,0045 (0,0033)	0,0044 (0,0033)
CAPITAL	0,0012 (0,0014)	0,0010 (0,0014)	0,0013 (0,0013)	0,0013 (0,0013)	0,0012 (0,0013)
URBAN	0,0020* (0,0010)	0,0019* (0,0010)	0,0017* (0,0010)	0,0017* (0,0010)	0,0017* (0,0010)
INTERMEDIAT	-0,0004 (0,0008)	-0,0004 (0,0008)	-0,0004 (0,0008)	-0,0004 (0,0008)	-0,0004 (0,0008)
HTEPOPAT	0,0010** (0,0005)	0,0010** (0,0004)	0,0010* (0,0005)	0,0010** (0,0005)	0,0010** (0,0005)
NHTEPOPAT	0,0001 (0,0005)	0,0002 (0,0005)	0,0002 (0,0005)	0,0001 (0,0005)	0,0001 (0,0005)
AT	-0,0022 (0,0014)	-0,0018 (0,0017)	-0,0023 (0,0018)	-0,0030 (0,0018)	-0,0039** (0,0019)
BE	-0,0077*** (0,0020)	-0,0070*** (0,0024)	-0,0074*** (0,0023)	-0,0079*** (0,0023)	-0,0086*** (0,0023)
DE	-0,0061*** (0,0092)	-0,0056*** (0,0011)	-0,0058*** (0,0012)	-0,0065*** (0,0013)	-0,0074*** (0,0013)
DK	-0,0028 (0,0018)	-0,0026 (0,0021)	-0,0029 (0,0021)	-0,0036* (0,0022)	-0,0046** (0,0013)
ES	0,0124*** (0,0013)	0,0117*** (0,0014)	0,0121*** (0,0016)	0,0127*** (0,0015)	0,0135*** (0,0016)
FI	0,0046*** (0,0016)	0,0051*** (0,0019)	0,0046** (0,0019)	0,0047** (0,0019)	0,0051*** (0,0019)
FR	-0,0050*** (0,0008)	-0,0047*** (0,0010)	-0,0049*** (0,0012)	-0,0055*** (0,0012)	-0,0061*** (0,0013)
GR	-0,0050 (0,0025)	0,0004 (0,0027)	-0,0010 (0,0028)	-0,0016 (0,0027)	-0,0021 (0,0027)
IE	0,0281*** (0,0023)	0,0284*** (0,0029)	0,0282*** (0,0032)	0,0295*** (0,0031)	0,0306*** (0,0030)
IT	-0,0110*** (0,0010)	-0,0103*** (0,0012)	-0,0105*** (0,0017)	-0,0117*** (0,0018)	-0,0132*** (0,0019)
LU	0,0242*** (0,0079)	0,0254*** (0,0076)	0,0248*** (0,0075)	0,0242*** (0,0075)	0,0236*** (0,0071)
NL	0,0032* (0,0019)	0,0035 (0,0022)	0,0036 (0,0022)	0,0029 (0,0022)	0,0021 (0,0022)
PT	0,0044** (0,0020)	0,0048** (0,0021)	0,0031 (0,0022)	0,0033 (0,0022)	0,0037* (0,0022)
SE	-0,0059*** (0,0016)	-0,0051*** (0,0019)	-0,0056*** (0,0019)	-0,0062*** (0,0019)	-0,0068*** (0,0019)
ρ	-0,0517 (0,0317)	0,0393 (0,0342)	0,0412 (0,0915)	-0,0519 (0,1026)	-0,1727 (0,1129)
N	640	640	640	640	640
W-matrix	ϑ : rook1	ϑ : rook12	ϑ : 250km	ϑ : 300km	ϑ : 350km
LR-test	0,0006	1,2752	0,1893	0,2521	-71,2431
AIC	-4460,3	-4463,53	-4446,52	-4443,82	-4372,33
log likelihood	2256,15	2256,76	2248,2581	2247,91	2212,16
R-squared	0,5540	0,5601	0,5634	0,5635	0,5652

Source: own estimations. *Notes:* Growth regressions for period 1995-2006 w/ CTRYDUMMY; standard errors in parentheses; SAR-maximum likelihood estimation with spatial lagged dependent variable (ρ); standard errors in parentheses; spatial lags insignificant for tested threshold distances ϑ (contiguity, kilometers); constant not reported; significance levels of coefficients: *** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.10 level. Reference country is UK and rural regions for settlement type. Projected shapefile and matrix generated in ArcGIS 9.3.1. environment.

Table 5.9. Spatial regression (ML-SAR) for EU-15 regions (cont'd)

Model	(37)	(38)	(39)	(40)
	EU-15	EU-15	EU-15	EU-15
<i>dep. var.:</i> $1/T\ln(y_{i,T}/y_{i,t})$				
GDPLEVEL	-0,0089*** (0,0016)	-0,0082*** (0,0015)	-0,0091*** (0,0016)	-0,0084*** (0,0015)
NATBORDER	-0,0007 (0,0006)		-0,0007 (0,0006)	
EUBORDER	-0,0003 (0,0013)		-0,0003 (0,0013)	
INDUSTRY	-0,0060*** (0,0016)	-0,0069*** (0,0011)	-0,0060*** (0,0016)	-0,0070*** (0,0011)
SERVICES	0,0036 (0,0033)		0,0035 (0,0033)	
CAPITAL	0,0009 (0,0014)		0,0009 (0,0014)	
POPDENSITY	0,0010*** (0,0003)	0,0010*** (0,0003)	0,0009*** (0,0003)	0,0010*** (0,0003)
HTEPOPAT	0,0009* (0,0005)	0,0009*** (0,0004)	0,0009* (0,0005)	0,0009*** (0,0004)
NHTEPOPAT	0,0002 (0,0005)		0,0001 (0,0005)	
AT	-0,0021 (0,0017)	-0,0028* (0,0016)	-0,0027 (0,0018)	-0,0034** (0,0017)
BE	-0,0070*** (0,0023)	-0,0072*** (0,0023)	-0,0075*** (0,0023)	-0,0077*** (0,0023)
DE	-0,0056*** (0,0012)	-0,0059*** (0,0012)	-0,0063*** (0,0013)	-0,0066*** (0,0013)
DK	-0,0027 (0,0021)	-0,0032 (0,0020)	-0,0035 (0,0021)	-0,0039 (0,0021)
ES	0,0128*** (0,0016)	0,0125*** (0,0015)	0,0133*** (0,0016)	0,0130*** (0,0015)
FI	0,0063*** (0,0020)	0,0061*** (0,0019)	0,0065*** (0,0020)	0,0064*** (0,0019)
FR	-0,0046*** (0,0012)	-0,0046*** (0,0012)	-0,0052*** (0,0012)	-0,0051*** (0,0012)
GR	-0,0009 (0,0027)	-0,0026 (0,0022)	-0,0014 (0,0028)	-0,0030 (0,0022)
IE	0,0292*** (0,0031)	0,0289*** (0,0031)	0,0301*** (0,0030)	0,0300*** (0,0029)
IT	-0,0106*** (0,0017)	-0,0112*** (0,0016)	-0,0110*** (0,0018)	-0,0123*** (0,0017)
LU	0,0246*** (0,0075)	0,0248*** (0,0073)	0,0241*** (0,0075)	0,0242*** (0,0074)
NL	0,0036 (0,0022)	0,0033 (0,0022)	0,0030 (0,0022)	0,0027 (0,0022)
PT	0,0031 (0,0022)	0,0016 (0,0016)	0,0033 (0,0022)	0,0019 (0,0017)
SE	-0,0040** (0,0020)	-0,0041** (0,0020)	-0,0045** (0,0020)	-0,0046** (0,0020)
ρ	0,0002 (0,0005)	0,0266 (0,0909)	-0,0530 (0,1020)	-0,0576 (0,1014)
N	640	640	640	640
W-matrix	$\vartheta : 250km$	$\vartheta : 250km$	$\vartheta : 300km$	$\vartheta : 300km$
LR-test	0,1360	0,0813	0,2626	0,3188
AIC	-4446,46	-4453,39	-4446,59	-4453,63
log likelihood	2248,23	2246,69	2248,29	2246,81
R-squared	0,5639	0,5618	0,5640	0,5620

Source: own estimations. *Notes:* Growth regressions for period 1995-2006 w/ CTRYDUMMY; standard errors in parentheses; SAR-maximum likelihood estimation with spatial lagged dependent variable (ρ); standard errors in parentheses; spatial lags insignificant for tested threshold distances ϑ (contiguity, kilometers); constant not reported; significance levels of coefficients: *** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.10 level. Reference country is UK and rural regions for settlement type. Projected shapefile and matrix generated in ArcGIS 9.3.1. environment.

Table 5.10. Spatial regression (ML-SAR) for NMS regions

Model	(46) NMS	(47) NMS	(48) NMS	(49) NMS	(50) NMS
<i>dep. var.:</i> $1/T\ln(y_{i,T}/y_{i,t})$					
GDPLEVEL	-0,0055 (0,0055)	-0,0051 (0,0056)	-0,0049 (0,0055)	-0,0078 (0,0054)	-0,0085 (0,0053)
NATBORDER	-0,0037* (0,0019)	-0,0037* (0,0019)	-0,0035* (0,0019)	-0,0037* (0,0019)	-0,0036** (0,0018)
EUBORDER	-0,0022 (0,0022)	-0,0032 (0,0022)	-0,0030 (0,0021)	-0,0021 (0,0020)	-0,0012 (0,0020)
INDUSTRY	0,0116** (0,0048)	0,0114** (0,0048)	0,0106** (0,0048)	0,0119** (0,0046)	0,0122** (0,0046)
SERVICES	0,0089 (0,0074)	0,0071 (0,0075)	0,0059 (0,0074)	0,0049 (0,0072)	0,0069 (0,0071)
CAPITAL	0,0225*** (0,0034)	0,0224*** (0,0035)	0,0217*** (0,0034)	0,0220*** (0,0034)	0,0219*** (0,0033)
URBAN	0,0068* (0,0040)	0,0065 (0,0041)	0,0065 (0,0040)		
INTERMEDIAT	0,0010 (0,0020)	0,0006 (0,0020)	0,0007 (0,0020)		
POPENSITY				0,0037*** (0,0012)	0,0039*** (0,0012)
HTEPOPAT	-0,0079** (0,0040)	-0,0087** (0,0040)	-0,0094** (0,0039)	-0,0079** (0,0039)	-0,0071* (0,0039)
NHTEPOPAT	0,0044** (0,0019)	0,0047** (0,0019)	0,0051*** (0,0019)	0,0038** (0,0019)	0,0035* (0,0018)
CZ	-0,0234*** (0,0046)	-0,0260*** (0,0047)	-0,0282*** (0,0046)	-0,0252*** (0,0046)	-0,0224*** (0,0044)
EE	0,0206*** (0,0071)	0,0297*** (0,0086)	0,0434*** (0,0096)	0,0318*** (0,0082)	0,0231*** (0,0067)
HU	-0,0102*** (0,0037)	-0,0104*** (0,0037)	-0,0098*** (0,0037)	-0,0105*** (0,0036)	-0,0103*** (0,0035)
LT	0,0070 (0,0049)	0,0100* (0,0052)	0,0147*** (0,0053)	0,0111** (0,0048)	0,0082* (0,0046)
LV	0,0091 (0,0066)	0,0146** (0,0073)	0,0233*** (0,0077)	0,0152** (0,0069)	0,0097 (0,0062)
PL	-0,0085** (0,0038)	-0,0094** (0,0039)	-0,0094** (0,0038)	-0,0109*** (0,0038)	-0,0102*** (0,0038)
SI	-0,0099* (0,0057)	-0,0107* (0,0058)	-0,0110* (0,0057)	-0,0090 (0,0056)	-0,0082 (0,0055)
ρ	0,1764 (0,1170)	-0,0475 (0,1767)	-0,4041* (0,2166)	-0,0109 (0,1697)	0,2056* (0,1116)
W-matrix	$\vartheta : 150km$	$\vartheta : 200km$	$\vartheta : 250km$	$\vartheta : 200km$	$\vartheta : 150km$
LR-test	2,0262	0,0623	3,1547*	0,0034	2,9094
AIC	-769,9170	-767,9530	-771,0460	-775,5010	-778,4070
log likelihood	403,9590	402,9770	404,5230	405,7500	407,2030
N	120	120	120	120	120
R-squared	0,7595	0,7543	0,7625	0,7653	0,7726

Source: own estimations. *Notes:* NMS growth regressions for period 1995-2006 w/ CTRYDUMMY; standard errors in parentheses; SAR-maximum likelihood estimation with spatial lagged dependent variable (ρ); standard errors in parentheses; spatial lags insignificant for tested threshold distances ϑ (contiguity, kilometers); constant not reported; significance levels of coefficients: *** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.10 level. Reference country is SK and rural regions for settlement type. Projected shapefile and matrix generated in ArcGIS 9.3.1. environment.

6. Summary, Conclusions and Future Research

This chapter summarizes the main findings and empirical results of this study. Concluding remarks, shortcomings and limitations of the conducted empirical analyses as well as suggestions for future research will be given.

The main objective of this study was to offer insights into the spatial distribution of research and inventorship activity (i.e., EPO patenting activity), core-periphery structures and co-patenting networks across European TL3 regions in the 1980s, 1990s and 2000s. In chapter 3, a special emphasis was placed on the spatial distribution and structural development of research clustering in different technology fields at the level of European TL3 regions. Furthermore, this study introduced a quantitative multidimensional measure of research clustering in a pan-European context. In addition to global clustering statistics, the quantitative cluster analysis identified leading European regions for a comprehensive number of technology fields. Furthermore, the strength of the identified research clusters was analyzed relating to the regional typology. Another major objective of this study was to identify and analyze the structure and development of technology field-specific inter-regional co-patenting (co-inventor) networks in Europe. For this reason, chapter 4 emphasized inter-regional co-patenting network linkages between European TL3 regions and countries for the periods 1990-1994 and 2000-2004. The analysis of inter-regional co-patenting linkages at the European TL3 level enabled global and local technology field-specific comparisons and conclusions. Finally, chapter 5 placed emphasis on the development of European regional income disparities and the determinants of regional growth between the 1990s and 2000s, with a special focus on regional patenting activity and the regional typology.

6.1. The Literature Review

Chapter 2 offered a theoretical and empirical literature review regarding core-periphery structures, agglomeration economies and research clustering.

The theoretical literature review (section 2.1) offered a review and discussion of a remarkable number of causes, working channels and stylized facts relating to location, co-location, agglomeration and co-agglomeration of industries, whereas special emphasis was placed on R&D clustering, research networks and the distribution of knowledge-intensive tasks. Research clustering, a.k.a. the geography of innovation, is challenged by several epistemic communities and approached in different strands of empirical research. Some researchers have particularly emphasized pecuniary externalities, linkages and formal networks at the firm-level in dense markets and industry agglomerations, whereas others have primarily devoted their attention to technological externalities, social networks, the nature of knowledge and the process of knowledge transmission. Nevertheless, both lines of research offered

pivotal explanations for the observed skewed distribution of R&D activity, the emergence and disappearance of industry agglomerations and research clusters.

The theoretical approaches and concepts presented in the review differ with regard to the weight given to the different dimensions of agglomeration economies, the micro-foundations of knowledge transmission and the attention devoted to the spatial distribution of innovative activity in general (i.e., the “industrial” dimension, the “technological” dimension, the “geographic” dimension, the “socio-cultural” dimension, the “cognitive” dimension of clustering). The theoretical review demonstrated that the literature on clusters and agglomerations is manifold and that the different streams of research have co-evolved for decades with and without moments of cross-fertilization. In summary, almost all lines of research give support to the existence of pecuniary externalities, localized and inter-regional knowledge spillovers and flows. The theoretical review was elementary to identify pivotal indicators regarding knowledge-intensive industries and core-periphery structures. It was demonstrated that the spatial distribution of researchers, high-skilled workers, blueprints (i.e., patents) and GVA in knowledge-intensive industries is considered to be an essential indicator for innovative capacity and research clustering. Besides physical geography (i.e., first-nature), second-nature agglomeration economies generally emerge from sharing, matching, and learning mechanisms in industry agglomerations, metropolises and research clusters.

Accordingly, the theoretical review demonstrated that the origins of core-periphery structures are indeed multifaceted: (i) intra-market externalities (pecuniary externalities) that work via prices, (ii) quasi-market externalities (externalities from network transactions) and (iii) extra-market externalities (technological externalities) that occur without (complete) monetary compensation. Moreover, a general taxonomy was introduced, which was built upon the following pillars: (i) the spatial dimension of externalities (proximity/agglomeration vs. network link externalities); (ii) the effects of externalities (efficiency vs. innovation externalities); and (iii) the nature of externalities (pecuniary vs. non-pecuniary externalities). Regarding pecuniary externalities, the concepts of urbanization and localization economies were integrated (section 2.1.5). With regard to dynamic effects in agglomerations, the origins and effects of innovation (development) externalities (section 2.1.6) were addressed and special emphasis was placed on the concepts of Marshall-Arrow-Romer externalities (section 2.1.6.2), Jacobs externalities (section 2.1.6.3) and Porter externalities (section 2.1.6.4). Finally, special attention was given to knowledge generation and its transmission via anonymous market transactions, via (routine) network link transactions and via intentional and unintentional knowledge flows in networks at a proximate distance (section 2.1.7).

In conclusion, the intensity and overall effect of centripetal and centrifugal forces is largely dependent on economic integration, scale and scope economies, the spatial range of inter- and intra-industry knowledge spillovers, factor mobility and the presence of informal and formal networks. Although spatial proximity is generally beneficial for research activities and knowledge transmission, long-distance research networks and informal social networks also have the potential to overcome long distances and to enforce regional innovative capacities. Regarding these theoretical conclusions, the recent activities of the European institutions, the aim of which is to support and intensify inter-regional and cross-border research collaborations, can be considered to be a suitable step forward.

The empirical literature review in chapter 2 (section 2.2) has demonstrated that the research agendas of economists and geographers, regarding patenting activity, agglomeration economies and research clustering, mainly consist of the following lines of research: (i) the analysis of the spatial distribution of research activity and innovative capacities; (ii) the identification and in-depth analysis of clusters; (iii) the analysis of the different types of (R&D) knowledge spillovers and flows; (iv) the analysis of the spatial range of externalities and flows; (v) the identification and analysis of informal networks between firms and researchers; (vi) the analysis of researchers' mobility in a spatial context; and (vii) the identification and analysis of knowledge flows and externalities in formal R&D networks. Accordingly, the research lines can be divided into several dimensions: an "industrial" and "technological" dimension; a "geographic" dimension; a "socio-cultural" dimension and a "cognitive" dimension. The existing research lines represent combinations of these dimensions. Therefore, the empirical review summarized the main research results regarding these different approaches in the European context and discussed their advantages, disadvantages, major shortcomings and technical issues.

In reviewing studies relating to the distribution of research and patenting activity (section 2.2.2), the empirical review confirmed the lack of a pan-European empirical study on the spatial distribution of research and patenting activity. Empirical studies on the distribution and clustering of research and patenting activity have, unfortunately, occupied a rather minor position on research agendas. Most cross-country studies and national and regional studies focused on regional employment, GVA and production structures. Furthermore, most studies have directly challenged the effects and economic consequences of clustering and industry agglomeration with regard to employment, production and growth, but not the distribution itself. Accordingly, the trans-regional structures and dynamics of clustering remained unexplored in most studies, especially the global distribution and core-periphery structures of knowledge-intensive tasks, i.e. research and patenting activity. A comprehensive, harmonized and quantitative pan-European study, which analyzes the distribution of patenting activity over a large (nearly complete) number of technology field aggregates and all 819 European regions, and which covers the 1980s, 1990s and 2000s, did not previously exist to the author's knowledge. Moreover, the empirical literature was missing a harmonized, technology field-specific, quantitative research cluster study, which is built upon a balanced spatial classification system, and which identifies European research clusters in the entire population of 819 regions. Regarding the last three decades, it was rather unclear whether or not the whole population of the European regions in question was determined by a decrease, increase or a lack of change in the regional disparities in technology field-specific patenting activity and clustering. Therefore, chapter 3 in this study examined the distributional characteristics of patenting activity and identified European research clustering.

The empirical review also showed that the regional knowledge production function represents a pivotal empirical approach which combines the industrial, geographic and technological dimensions of agglomeration economies and knowledge production (section 2.2.3). Evidence regarding R&D spillovers and the relative ease of knowledge diffusion across agents' production functions and more aggregated spatial units is less ambiguous. The majority of European KPF studies affirms the presence of positive regional spillovers of R&D activity over up to 300-600 kilometers. The influence of neighboring regions' R&D

expenditures on other regions' patenting output is significant and positive in most European studies, but the working channels of spillovers remain a "black box" and are highly dependent on the implemented spatial classification system, i.e., the level of aggregation (MAUP), and the spatial weight matrix for constructing lagged covariates. Moreover, the empirical review also demonstrated that the differentiation between knowledge externalities and flows is extremely fuzzy in contemporary studies, as researchers use the terms "flows," "spillovers" and "externalities" interchangeably. Regarding this issue, the review also summarized the criticisms relating to the knowledge production function approach. The review essentially criticized the fatuous interpretation of significant spatial dependence (i.e., significant lagged covariates) in knowledge production function estimations as evidence for the presence of unintentional knowledge spillovers. From a methodological point of view, spatial dependence of regional patenting activity can be considered to originate from fractional counting of patent data at the regional level. Accordingly, spatial dependence could emerge as a by-product of meaningful co-patenting activities between neighboring regions. This idea has been challenged empirically in chapter 4.

Another debate which appeared in the literature on clusters is related to the relationship between local scale and industry specialization/diversity and its effects on regional productivity, innovative capacities and employment growth (section 2.2.4). Taking an "industrial" perspective, Marshall-Arrow-Romer externalities and Jacobs externalities (localization and urbanization economies respectively) are considered to affect intra-regional innovative capacities, employment growth and productivity gains. Regarding the innumerable quantity of studies, both types of agglomeration economies, localization and urbanization, showed positive coefficients as often as negative coefficients. Thus, it was argued that evidence on the dominance of one specific externality is not extensive enough to be compelling, and that studies have hit fairly rapidly decreasing returns. To conclude, regional studies on districts, milieus and clusters generally explain the incentives, causes and effects of agglomeration on the basis of the aforementioned different agglomeration economies, regardless of whether or not these effects are of an inter- or intra-industry type. Regarding this issue, regional specialization and diversity was challenged empirically in this study through an examination of technology field-specific research clusters across the 819 European regions with regard to their regional typology. Differences regarding research clustering between urban and rural regions were empirically challenged in chapter 3 (section 3.5).

With respect to the channels of knowledge transmission, it was demonstrated in the empirical review that the patent citation approach (section 2.2.5) can be regarded as the answer to elementary critiques regarding the existence and importance of knowledge spillovers. This approach combines an industrial, technological and geographic dimension of knowledge production and diffusion. Researchers have attempted to measure the existence and strength of knowledge flows directly by using patent citation data. The reviewed patent citation studies showed similar evidence, namely that knowledge, in terms of patents and their cited-citing ratio, is highly concentrated in space. Moreover, spatial distance exhibits negative effects on knowledge spillovers, although the negative effects of national borders seem to have vanished. However, the review also revealed problems and technical issues. It was demonstrated that inter-regional citation studies in most cases applied the standard NUTS classification, which generally leads to a severe bias in citation networks. This is a crucial concern, as the underlying spatial classification system is generally biased in

terms of the absolute size of the regions. Furthermore, the citation approach ignores the major fraction of knowledge that is frequently transmitted via the market process and within intra- and inter-regional co-patenting networks. Moreover, the citation approach is problematic, because it is not clear whether or not knowledge spillovers, by means of documented patent citations, have really been realized. Almost 90% of all citations are traced by patent examiners, which raises severe doubts regarding the realized knowledge transmission between researchers. Due to the methodological disadvantages, drawbacks and technical issues discussed above, the patent citation approach was not applied in this study and a co-inventor network analysis was conducted instead (see chapter 4).

Regarding inter-regional linkages and networks, knowledge-intensive industries in clusters and regions are said to increasingly benefit from formal and informal network linkages between researchers. It was argued in section 2.2.6 that (informal) social network ties between researchers and their (former) colleagues are considered to be essential channels for tacit knowledge transmission. Spatial and social proximity both simplify the creation and extension of networks through which knowledge is transmitted. Therefore, empirical studies started to interpret and analyze cities and regions as interlinked places in a “space of flows.” It is generally argued in the literature that tacit knowledge is mainly transmitted within networks, and that knowledge transmission at a proximate distance is highly dependent on the existence of localized networks between individuals. Accordingly, the review demonstrated that recent studies on social networks, inventor mobility, innovative milieus and epistemic communities place a special emphasis on the micro-foundations of knowledge transmission and the capacity of agents (and regions) to absorb appropriate tacit knowledge. Recent studies argued that regions are hosting technology-specific epistemic communities, which differ in terms of their group-specific technological specialization but also in their formal and informal institutions (e.g., skills, language, codifiability of knowledge, trust, norms) and diaspora. Accordingly, researchers have argued that the assumption that knowledge is a public good is a conscious exaggeration in growth models from the 1980s and 1990s, as knowledge is only partially non-rival and non-excludable (e.g., varying codifiability, property rights). Finally, the review summarized recent studies on social networks and researcher mobility, which confirmed the existence of highly localized researchers, and which indicated that (implicit) knowledge transmission is localized to the extent that networks are localized. A comprehensive analysis of social inventor networks in Europe is, however, limited due to severe data constraints regarding micro data on researchers’ mobility.

In a final step, the analysis of inter-regional co-patenting networks was identified as the promising line of research in a pan-European context (section 2.2.7). In contrast to citation analysis, co-patenting studies make direct use of information on research collaborations between agents and regions. The linkages between regions can be directly interpreted as knowledge flows between agents (and regions). The empirical literature survey reviewed co-patenting and co-inventor studies, which are generally used in order to analyze the structures and dynamics of R&D collaboration activities in a regional and firm-level context. Firms, clusters and regions are considered to be increasingly benefiting from inflows of external forefront knowledge via network linkages to innovative neighborhoods, to global knowledge hot spots and centers of research excellence. The inflow of forefront knowledge is considered to depend increasingly upon long-distance research linkages between clusters

and regions, but also on network transaction linkages at a proximate distance, i.e. within larger spatial aggregates (see chapter 2, sections 2.1.7.3 and 2.1.7.4). As inter-regional formal research collaboration networks are considered to enforce regional innovative capacities, knowledge transmission, cluster connectedness and regional interdependence, the analysis in chapter 4 placed special emphasis on co-patenting linkages. In conclusion, the review of co-patenting studies showed that there is still a relatively small body of studies on European inter-regional co-patenting activity. The review depicted the severe lack of a pan-European study on technology field-specific inter-regional co-patenting linkages.

To conclude, the review of the different strands of empirical studies on research clustering, research networks and regional disparities identified severe research gaps in a pan-European context. These gaps were challenged in chapters 3, 4 and 5.

6.2. Research Clustering in Europe

In chapter 3, the empirical analysis of the distribution of European regional research activity proceeded in two steps. In section 3.4, global distributional statistics on research activity across the entire population of the 819 regions in the ERA were presented. The study placed a special emphasis on the regional distribution of EPO patent application activity and EPO inventors since the 1980s in 51 technology field aggregates. Moreover, a harmonized, multidimensional research clustering index was introduced and the co-location of technology field-specific research clustering was explored in section 3.5. In addition to global statistics on research clustering, the section offered a comprehensive list of the leading European research cluster regions for 50 technology field aggregates. The empirical analysis of the distribution of patenting activity in Europe in chapter 3 was a first essential objective of this study and aimed to sharpen the cognition and to enrich the understanding of spatial structures, regional disparities and ongoing dynamics of research and patenting activities in Europe.

In a first step, the empirical analysis in section 3.4 contributed empirical findings on the structural dynamics of European inventorship activity in several ways. This analysis has to be recognized as exemplifying a purely quantitative “top-down” approach in the regional disparity and geographic concentration analysis tradition. The presented calculations are based on data extractions from the OECD RegPAT (January 2009) patent database and the OECD regional database. The implemented spatial classification covered 819 European regions, i.e., the TL3 regions of the EU-25, Switzerland and Norway. From a technology field point of view, the matching of IPC codes with 43 technology fields was accomplished through the application of the ISI-SPRU-OST-concordance (Schmoch *et al.*, 2003). In addition, the spatial characteristics of 6 high-technology fields (EUROSTAT, 2009) and 2 larger technology field aggregates were included in the analysis. The empirical analysis of regional disparity and the concentration of inventorship activity was enriched through the calculation of standard descriptives, e.g., patent densities (patents per million population, patents per square kilometer), kurtosis, skewness and percentiles of the distributions. The study demonstrated that the 819 European regions are increasingly filing patent applications at the EPO, which has led to an increasing number of less developed European regions with small numbers of EPO patent applications. Accordingly, the big picture is one

of dispersion. In addition, revealed technological advantage (RTA) indices and Herfindahl-Hirschman indices (HHI) were computed, with the latter being an alternative measure of spatial concentration. Moreover, the analysis incorporated the computation of technology field-specific weighted Gini coefficients as population densities and areal surface characteristics differ tremendously across the 819 European TL3 regions. In this respect, the empirical analysis applied Gini computations at the regional level that explicitly accounted for spatial heterogeneity of observations in terms of regional population and area size. Furthermore, the analysis demonstrated that the distribution of EPO inventors (full counting) represents an acceptable proxy for EPO patent applications (fractional counting) across all technology fields. Several conclusions with regard to the technology fields which were analyzed and their spatial characteristics could be drawn from the quantitative analysis in section 3.4. First and foremost, the analysis identified highly skewed distributions of patenting activity across all technology fields, although the technology fields differ remarkably in terms of their development (dynamics) between the 1980s and 2000s. The analysis demonstrated that the 51 technology fields (including two larger aggregates) differed in terms of their geographic concentration across the 819 European TL3 regions. Technology-specific EPO patent applications and EPO inventors are, by and large, similarly concentrated across the 819 European regions. The average level of EPO patenting and research activity has increased since the 1980s in almost all technology fields. Accordingly, geographic dispersion has increased in the majority of technology fields since the 1980s. Nevertheless, even today, the majority of regions only account for small fractions of EPO patent applications and EPO inventors. The absolute number of specialized European regions ($RTA > 1$) has increased within the population of the 819 European TL3 regions. However, a larger share of European regions are involved in EPO patenting today compared to the 1980s and 1990s. Consequently, the share of specialized regions ($RTA > 1$), within the group of European regions that have at least a minimum level of patent application activity ($n > 0$) in a specific technology field, has decreased. Accordingly, Europe is determined by a process of ongoing dispersion, and decreasing relative concentration and specialization. High-technology fields show, on average, higher levels of regional disparity and thus geographic concentration compared to less R&D-intensive technology fields. Several high-technology fields are characterized by strong dispersion tendencies, e.g., *HT5 Communication technology*, *HT4 Semiconductors*, *HT2 Computer & office machines*, whereas patenting activity in *HT1 Aviation* and *HT3 Laser* remains relatively localized in a few European regions. Regarding weighted global disparity measures, and depending on the technology field under analysis, the computed locational Gini coefficients revealed more significant changes than their spatial alternatives. Regional disparity in terms of the spatial Gini was extraordinarily high in the 1980s. Both weighted Gini alternatives revealed a remarkable decline in spatial disparities in almost all technology fields. Nevertheless, it was demonstrated that the overall decline in regional disparities within the group of all 819 regions was accompanied by an increase in regional disparities within a small number of European member states. To conclude, the overall picture in a pan-European context is one of dispersion, which corresponds to the targets of the ERA.

In a second step, the cluster analysis in section 3.5 placed the emphasis on the identification and analysis of the spatial distribution of research clusters in the EU-25, Switzerland and Norway, i.e., the ERA. The empirical analysis of regional research clustering focused on 50 technology field aggregates, 819 TL3 regions and the periods 1990-1994 and 2000-2004.

A major contribution made by this analysis was the development of a multidimensional composite index at the regional level, the so-called “research cluster index” (RCI), which combined several coefficients relating to EPO patent applications, EPO inventors, regional population, areal size and research density. Based upon the computed RCI for each of the 819 European regions for all technology fields, the cluster analysis demonstrated that the majority of research clusters are located in leading European countries of the EU-15 and their core regions, predominantly in Germany, France, the Netherlands, Italy, the United Kingdom and Switzerland. The analysis also worked out that only a few EU-15 and Swiss regions exhibit high RCI values and that the 10 NMS still show weak research clustering. Furthermore, a list of the leading TOP20 European research cluster regions was reported, which gave support to the picture of skewed distributions relating to strong research clusters. Moreover, the RCI calculations demonstrated statistical evidence for co-agglomeration of patenting activity in a small number of leading locations.

Regarding regional specialization and diversity, the empirical analysis challenged the question of whether or not urban and metropolitan regions show, on average, more diversified research clustering structures compared to their rural counterparts. The cluster analysis unveiled that metropolitan areas and urban and capital regions exhibit a remarkably diversified research clustering structure compared to rural and intermediate regions. The analysis also identified persistent “north-south” and “east-west” gradients of strong research clustering, which is very similar to the results which were found with regard to regional growth and convergence (see chapter 5). It can be concluded from the cluster analysis that research clustering and diversified technology structures in the ERA are mainly restricted to capital regions and urban and metropolitan regions in the EU-15. Moreover, the analysis showed that rural regions are defined by a more specialized technology structure, as clustering (i.e., $RCI > 16$) can be only observed in a small number of technology fields (a few rural regions are exceptions). Thus, it is rather impossible to find technologically diversified research clusters in rural European regions, which represents a pivotal fact of the geography of innovation for policy programs. Furthermore, the analysis of research clustering at the regional level indicated that technological diversity in research activity can be found first and foremost in European capital regions, metro regions and their closest urban neighborhoods, e.g., Paris, London, Vienna, Berlin, Copenhagen, Stockholm, Nord-Holland, Bern, Oslo, Dublin, Budapest, Rome and Prague, which supports the theory of an urban hierarchy and distributional regularity of economic activity as has been proposed in urban economics (Duranton and Puga, 2001; Capello, 2007; Henderson, 2010). Regarding the former CEE-10 countries, several capital regions still showed only weak clustering in the 2000s, e.g., Budapest, Warsaw, Bratislava and Vilnius; moreover, a similar picture was presented for several EU-15 capital regions in Southern Europe, e.g., Athens, Cyprus (city), Malta (city). In southern European countries and the NMS, only Madrid, Rome, Lisbon and Riga show meaningful RCI values, but only in a small number of technology fields. Accordingly, the “east-west” and “north-south” gradients are still present in Europe, although meaningful dispersion across the hundreds of regions can be observed, especially since the 1990s. To conclude, the measure of research clustering for all 819 European TL3 regions across a comprehensive number of technology fields and its combination with the regional typology generated rich information on the “specialization-diversity” debate, although the analysis was restricted to a quantitative identification of co-agglomeration of clusters.

A clear shortcoming of the applied empirical approaches in sections 3.4 and 3.5 is their sole focus on quantitative measures and patent statistics. Unfortunately, all research activities which are not registered (and identified) via patent applications are completely ignored in the global disparity measures (section 3.4) and the research cluster analysis (section 3.5). Furthermore, the analysis completely ignored industry clustering (i.e., clustering of industry production, services and employment) due to its sole focus on the outcome of knowledge-intensive tasks. Moreover, pivotal aspects of clustering and the innovation process were completely excluded from the analyses, e.g., place-specific factors, history, regional institutions, regional policy. However, these shortcomings notwithstanding, the application of patent statistics represents the only possible way to construct a comprehensive quantitative pan-European measure with regard to hundreds of European regions. An alternative approach would have been to conduct more than 800 harmonized regional case studies, which was clearly beyond the scope of this study.

6.3. Inter-Regional Co-Patenting Linkages in Europe

Chapter 4 contributed to the research on relational patent statistics in several ways. In addition to spatial statistics on the geographical interdependence of research activity in Europe, the study provided specific empirical results relating to co-patenting activity in Europe. According to the empirical literature survey, and to the best of the author's knowledge, the empirical literature at the time of this study was missing a comprehensive study of the structures and dynamics of inter-regional co-patenting networks between the 819 European TL3 regions for a meaningful number of technology fields. Regarding this deficit in empirical studies, this study examined the structures and dynamics of inter-regional co-inventor networks and research collaborations between European regions (chapter 4). Special emphasis was placed on the structural development of inter-regional co-patenting linkages within larger TL2 regions, between larger TL2 regions but within national borders and inter-regional linkages between European countries. The results are the following:

In the first part of the chapter, section 4.2 offered statistical results regarding the existence and strength of spatial autocorrelation of patent densities by technology field at the regional level. It was demonstrated that the majority of technology fields are characterized by positive spatial autocorrelation for spatial distances up to 300-600 kilometers at the TL3 level, meaning that fractionally counted patent statistics exhibit spatial interdependence. The results confirmed the presence of strong spatial autocorrelation between neighboring regions, although the origin of spatial interdependence remained a "black box." Therefore, chapter 4 also introduced a complementary approach with which to address the issue of regional interdependence. The significance of spatial autocorrelation in patent statistics was challenged by explicitly taking into account the inter-regional "connectedness" of European regions and the presence of inter-regional research collaborations at a proximate distance between European regions, i.e., co-patenting activity. Accordingly, the empirical analyses in sections 4.3.4 and 4.3.5 aimed to directly address the existence of positive spatial autocorrelation in (fractionally counted) patent statistics at the regional level.

The second part of chapter 4 offered a descriptive analysis of European co-patenting activity with foreign co-inventors at the national level. Section 4.3.4 picked up recent debates on

the internationalization of R&D, the emergence of international research collaborations and the integration of European countries into an expanding ERA. The empirical results of the cross-country co-patenting analysis pointed to meaningful tendencies towards an increase in international and European research collaborations (in terms of numbers and shares of co-patents with foreign co-inventors) since the 1990s, especially in the second half of the 1990s and the 2000s. That being the case, the average share of EPO patents with foreign co-inventors has increased considerably since the 1980s. It was demonstrated in the first part of the analysis that the group of co-patenting countries, in absolute (and relative) terms, is still predominantly dominated by a few countries, e.g., Germany, Switzerland, Belgium, the Netherlands, the United Kingdom, Sweden, Austria and Italy. The NMS are still determined by a very low level of co-patenting; however, co-patenting activity has increased in terms of absolute numbers and shares. Accordingly, the NMS have experienced a remarkable increase in EPO co-patenting activity with foreign European co-inventors, especially the Czech Republic, Hungary, Poland, Slovenia, the Slovak Republic and Latvia. Moreover, it was demonstrated that the European integration process, with regard to foreign co-patenting activity and R&D collaborations, gained momentum in the second half of the 1990s. Nevertheless, it has already been argued in the empirical review that national studies suffer from severe methodological drawbacks and that cross-country studies have also reached decreasing returns.

The third part, sections 4.3.5 and 4.3.6, offered a calculation of inter-regional linkages and global and local network statistics relating to inter-regional co-patenting activity. Empirical findings on European co-patenting network structures, geographical coincidence/co-location of networks and the centrality characteristics of technology-specific networks were presented in these sections. From a methodological perspective, it has been argued that research activity (i.e., EPO patent applications) generally leaves a paper trail in the form of patent documents, which can be examined when developing relational patent data.

Co-patenting linkages have been extracted for a comprehensive number of technology fields since 1980. In a following step, inter-regional networks were constructed from the extracted linkages, and global and local network statistics were computed which cover the entire population of the 819 European TL3 regions (EU-25, Switzerland and Norway). The reported global co-patenting statistics for each technology field cover: (i) the overall number and shares of interconnected regions; (ii) the number and shares of unique and overall inter-regional co-patenting linkages; (iii) the number and shares of inter- and intra-national linkages between regions. For the purpose of comparison, the study also incorporated additional calculations and analyses of the technology-specific inter-regional TL3 linkages that occur within and between larger European TL2 regions. The calculation and comparison of network linkages and nodes made it possible to depict potential distance decay effects and to combine the geographic and technological dimension of European inter-regional co-patenting activity. Furthermore, the analysis revealed structural changes in research co-operations and knowledge flows between the 1990s and 2000s.

The co-patenting study offered statistical evidence for the presence of highly localized European co-inventorship networks in almost all 43 technology fields. Although the networks are complex and heterogenous, a strong sense of localized connectedness between neighboring regions (TL3 and TL2 regions) in the form of inter-regional patenting activity could be identified. The majority of European co-patenting activity seems to happen at a proximate

distance and has an intra-regional nature, meaning that a large fraction of research collaborations take place via inter-regional TL3 linkages within the administrative borders of larger TL2 regions. In addition, the results of this study confirm that approximately 90% of all European inter-regional co-patenting linkages occur between actors or organizations within the same country, which underlines the local nature of co-inventor activity. Even in the 2000s, a strong concentration of inter-regional research co-operations could be observed within the national borders of the respective European member states, although the overall share of these linkages has decreased in almost all technology fields. At the same time, international co-patenting linkages, i.e., inter-regional TL3 linkages between (TL1) countries, have increased in absolute numbers and shares. Moreover, the computations also covered the numbers and shares of unique inter-regional linkages. These unique linkages have expanded in absolute numbers in almost every technology field between the 1990s and 2000s. The analysis of the spatial range of inter-regional linkages within the two periods unveiled a significant structural change in European co-patenting activity. The calculations presented in this study provide some evidence that international linkages have increasingly replaced intra-national ones. The technology-specific shares of inter-regional-TL3 linkages between larger TL2 regions within the same country (inter-TL2 within country) have decreased, whereas the shares of inter-regional-TL3 linkages within larger TL2 regions (intra-TL2 within country) increased between the 1990s and 2000s. Furthermore, the shares of inter-regional linkages between countries have increased considerably between the 1990s and 2000s (inter-TL1/between country). Accordingly, the pan-European co-patenting analysis identified remarkable core-periphery structures but also meaningful structural changes with regard to long-distance research collaborations as reflected by co-patenting linkages. The presented results point to an ongoing dispersion of research collaborations and growth of the ERA.

Moreover, similar to the national co-patenting results (section 4.3.4), the performed regional analysis pointed to the presence of a European integration process of the NMS with regard to research collaboration activities at the level of the TL3 and TL2 regions. A deeper analysis of the extracted co-patenting linkages offered additional evidence regarding the presence of an ongoing integration of NMS regions into technology field-specific pan-European regional co-patenting networks. The numbers and shares of inter-regional linkages between the EU-15 group and the NMS group were calculated for the 1990s and 2000s. It is obvious from the presented tables and figures that the eastern part of Europe is being increasingly integrated into knowledge-intensive activities, as reflected by the numbers and shares of international co-patenting linkages between the EU-15 and NMS regions. Furthermore, the empirical analysis offered a comparison of the network structures of the 1990s and 2000s, using both global network statistics and network graphs for selected technology fields. The computed network graphs revealed considerable increases in the number of interconnected NMS regions, although the technology fields differed enormously in their spatial structure and overall dispersion. To sum up, the NMS regions, especially the urban, capital and metropolitan regions, have mostly been integrated into pan-European research networks, although these regions are only incorporated into a few technology fields. Regarding the aforementioned points, this study also provided local network statistics that are related to the individual position of regions in order to identify “hub-and-spoke network structures” and to explore the network centrality and connectedness of European regions by technology field. In this respect, some empirical evidence was

reported which indicated that European regions differ in terms of their technology field-specific network centrality. The results confirmed that a few European regions dominate the European technology field-specific co-patenting networks due to their central position, which represents a crucial matter of fact for European regional policy and the European innovation system as a whole. Although co-patenting networks are generally increasing in the number of regions, the ERA is still dominated by a small group of leading research centers in the core regions of the EU-15. Nevertheless, the integration of NMS regions into inter-regional and international networks seems to have gained momentum since the 1990s, which has to be perceived by innovation policy at different spatial levels.

Finally, the analysis in chapter 4 provided preliminary results regarding the spatial coincidence/ co-location of co-patenting networks in regions (section 4.3.6). According to the presented results, technology-specific co-patenting networks seem to co-locate in a small number of European regions, which supports the hypothesis of technological diversification of co-inventorship activity in European regions (especially in capital regions and urban and metro regions). The TOP20 regions are in most cases the same TL3 regions across all analyzed technology fields, indicating that these regions are central nodes in different technology fields. The results obtained are complementary to the ones of the research clustering study (see chapter 3, section 3.5) and highlight a degree of regularity with regard to centrality. For a more detailed analysis of geographic coincidence and co-location, the computed network centrality indices were ranked at the TL2 level and Spearman rank correlation coefficients were calculated for all 43 technology fields. Regarding the obtained coefficients, it has been argued that the rankings of network centrality are similar across the technology fields, meaning that several European technology-specific co-patenting networks co-locate predominantly in the same European regions (i.e., urban areas, metropolises and capital regions), which confirms the hypotheses that (i) European regions are indeed “multi-field” research network nodes and (ii) that co-patenting activities are subject to certain spatial (urban) hierarchies and regularities.

To conclude, co-inventorship activity is increasingly inter-regional and border-crossing, meaning that policy makers have to realize the increasing connectedness and embeddedness of regions. It can be argued that the official statistics should pay much more attention to the relational aspect of patenting activity. Fractional counting of patent data represents an established method of analysis, but it is still possible for meaningful information to be lost. The results highlighted that patterns of inter-regional knowledge exchange and embeddedness differ tremendously across European regions. Regarding supra-national, national and regional innovation policy, policymakers have to take into account both the increasing inter-regional embeddedness of regions into networks and local innovation activities before starting any relevant policy action. Existing regional disparities and the increasing integration of regions into networks also demonstrate that best-practice innovation policies are hard to observe and cannot be implemented in different places without significant modifications. Policy programs and institutional changes could be regarded as a useful instrument when they increase the freedom of inter-regional research co-operation between different research locations. Nevertheless, the inter-regional European networks need additional research and the presented results have to be challenged by alternative methodologies (e.g., estimation of gravity models).

6.4. Regional Growth and Income Disparities in Europe

Finally, the study placed emphasis on regional growth, regional income disparities and core-periphery structures across European regions in chapter 5. Regarding regional growth, convergence and divergence in the European context, it remained an open question as to whether or not research activity (i.e., high-technology and non-high-technology research and patenting activity) and regional typologies (i.e., urban, rural, metro region) are positively related to regional GDP per capita growth at the TL3 level. Chapter 5 approached these deficits in two steps. Section 5.3 analyzed the development of regional income disparities and section 5.4 provided regional growth regressions at the TL3 level.

In the first part of the chapter (section 5.3), the study applied a measure of global income inequality, which clearly demonstrated that European countries exhibit different dynamics with regard to their within-country income disparities at the TL3 level. The analysis depicted different distributional patterns and revealed that not all countries are following the classical inverted U-shaped relationship proposed by Kuznets (1955) and Williamson (1965). The Kuznets curve is based upon the hypothesis that economic inequality increases while a country is developing, and then, after a certain average income is attained, inequality is said to decrease (Capello, 2007; Szörfi, 2007). The results do not support the presence of such an inverted U-shaped relationship for all European countries, but it is possible that the period of analysis was not long enough, as the inequality decomposition analysis only covered 12 years. This is a clear shortcoming of this study, which is, however, based on severe data constraints at the TL3 level stemming from EUROSTAT and the OECD (Combes and Overman, 2004). Nevertheless, the regional income inequality analysis revealed the following developments: (i) a decrease in inequality in Austria and Italy; (ii) a general increase in income inequality in Switzerland, the Czech Republic, Denmark, Estonia, Greece, Hungary, Ireland, Lithuania, the Netherlands, Portugal, Slovenia, Slovakia and the United Kingdom; and (iii) an inverted U-shaped trend in income inequality in Belgium, Germany, Spain, Finland, France and Sweden. That being the case, and based upon the global inequality analysis, it was argued that there is a general decreasing trend in regional disparities across the 819 European regions, whereas European countries revealed differing within-country disparities. However, it was also demonstrated that the decrease in global income disparities is mainly based upon decreasing between-country income disparities. A salient feature of the European regional growth process was elaborated on from the statistical decomposition of overall regional income disparities. Regarding the origins of inequality, it was useful to deconstruct global income disparities into between- and within-subgroup income disparities. In addition to the fact that overall income disparities have decreased across the entire population of the 819 European regions, the empirical analysis illustrated that the share of between-subgroup income disparities has decreased by approximately 15% since the year 1995. At the same time, within-subgroup income disparities have (relatively speaking) increased, meaning that several European countries experienced significant increases in their intra-national regional income disparities. It has been demonstrated that the EU-15 group is determined by a very similar overall trend of decreasing disparities compared to the entire population of the 819 regions, i.e., a meaningful decrease in overall inequality since 1995. Between-subgroup income disparity has decreased in a similar way to within-subgroup inequality. Moreover, it has been shown

that between-subgroup inequality in the EU-15 today is at a very low level compared to within-subgroup inequality. With regard to the NMS, the inequality analysis clearly showed that the decrease in between-subgroup income disparities could not compensate for the observed increase in within-subgroup income disparities, which led to an overall increase in income disparities in the NMS. Therefore, it can be concluded that the group of NMS regions is determined by a strong asymmetric growth process, characterized by emerging core-periphery structures, and by exorbitantly positive GDP per capita growth rates in the capital and metropolitan regions, which supports the “growth poles picture” which was expanded upon by Williamson (1965).

Nevertheless, a severe shortcoming of the European income disparity study is the unavailability of longer time series, i.e., for the 1960s, 1970s and 1980s at the TL3 level. Criticisms made by other researchers regarding this issue have already been presented within the empirical review. Future studies may have the advantage of identifying and de-constructing regional disparities relating to additional economic indicators, i.e., GVA by industry, employment data at the 2-3 digit level and productivity statistics by industry. Generally, the official statistics of the EU need a superior harmonization, an improved data coverage and a stable provision of longer time series. Regarding the latter aspect, frequent changes in the spatial classification system (NUTS) are cumbersome.

In the second part of chapter 5, the regional inequality analysis was complemented by regional growth regressions (section 5.4). For the purpose of contributing to the convergence/divergence debate, this study analyzed a broad range of factors rather than specific growth determinants. Nevertheless, the empirical findings can be considered to contribute to a more realistic assessment of the process of regional development and to contribute with results relating to regional settlement typologies and regional growth. The results of the very general regression models therefore seem to support but also to extend existing regional studies. Unfortunately, due to the restricted set of covariates at the TL3 level, it was impossible to determine whether and to what extent the significant decrease in income disparities and regional convergence in the EU-15 was the result of neoclassical convergence accompanied by capital deepening and factor mobility, or whether it was a result of decreasing transaction costs in a new economic geography tradition, or based upon technological convergence via knowledge diffusion, technology transfer, or the result of disparity-reducing and gap-closing European regional cohesion policy. This aspect represents a serious shortcoming of the analysis which was performed. However, the methodological design could not be extended because of severe constraints regarding regional European data.

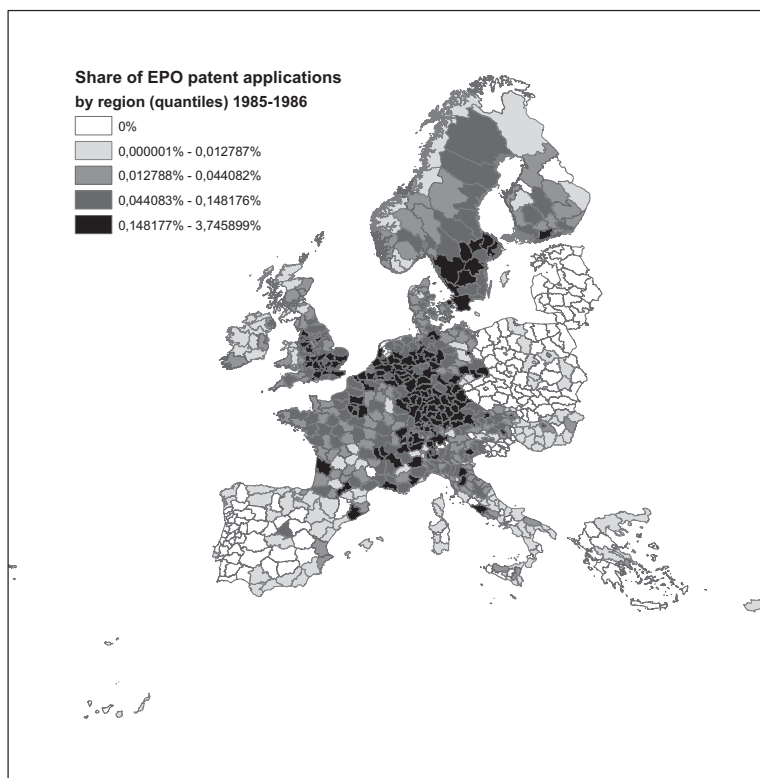
In line with several existing studies that have been conducted at a higher spatial level, the reduction of income disparities since the 1990s is assumed to originate predominantly from income convergence between EU-15 countries at the national level, but not between regions within nation states. Within-subgroup disparities are either constant or increasing. Although there is significant variation at the regional level, national characteristics (e.g., institutions, national networks, infrastructures and nation-specific macro-economic conditions in general) seem to determine the growth path of nations and their regions, as spatial dependence was not an issue when country dummy variables and a regional typology were implemented.

With regard to the regional typology (i.e., the settlement structure), metropolitan regions, urban regions and capital regions generally showed higher GDP per capita growth rates compared to rural and intermediate regions. Regarding the growth process in the NMS, capital regions have improved their position in the upper end of the regional income distribution. Unfortunately, the reasons for higher growth rates in urban areas and metropolitan and capital regions could not be determined or explored, as potential transmission channels were not explicitly modeled due to constraints regarding the data. Nevertheless, the implemented regional typology introduced a control for differences in the regional characteristics into the regression setup, e.g., urbanization, population size, infrastructure. The typology is thus regarded as to control in some way for the level of urbanization and thus agglomeration. Accordingly, the dummy variables for the regional typology may reflect agglomeration economies of an unknown type. Although countries have been generally converging since the 1990s, several factors have affected the average GDP per capita growth rate. The regressions confirmed that both the settlement structure and the regional knowledge/technology base are significant and positive, meaning that urban areas exhibit higher growth rates and that research (patenting) activity is positively related to regional growth. However, the reasons for the significance of the regional typology, i.e., urban regions, metro regions, capital regions, remain unclear. The significance may originate from MAR externalities and/or Jacobs externalities, from intra-regional R&D externalities in knowledge-intensive industries, or from static localization and/or urbanization effects (labor pooling, division of labor). We simply do not know as the regressions did not control for these channels due to severe data constraints. Nevertheless, the study clearly demonstrated that the regional typology and data on regional patenting activity implement meaningful additional information into regional growth regressions.

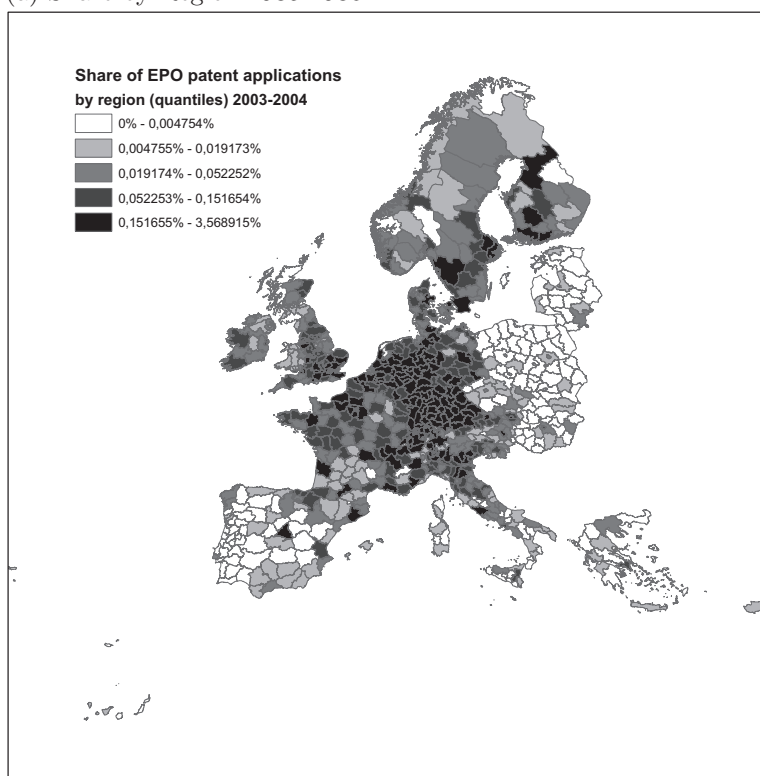
The presented shortcomings can be regarded as a crucial starting point for future research. Data coverage and harmonization are major problems regarding European regional studies. It is desirable that the harmonization and expansion of European regional data will proceed.

Finally, this study comes to the conclusion that place still matters a lot in the 21st century.

A. Appendix: Figures



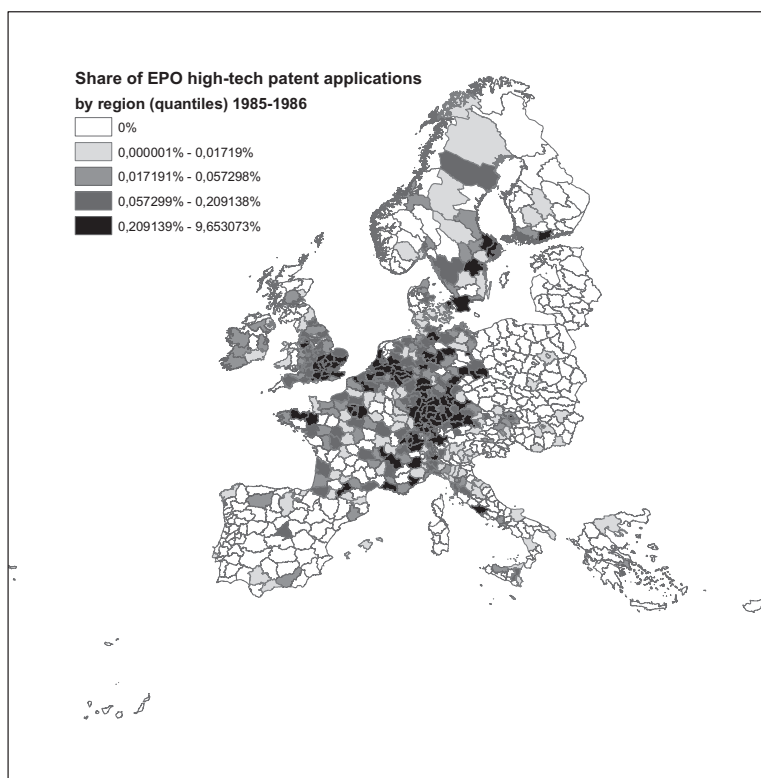
(a) Share by Region 1985-1986



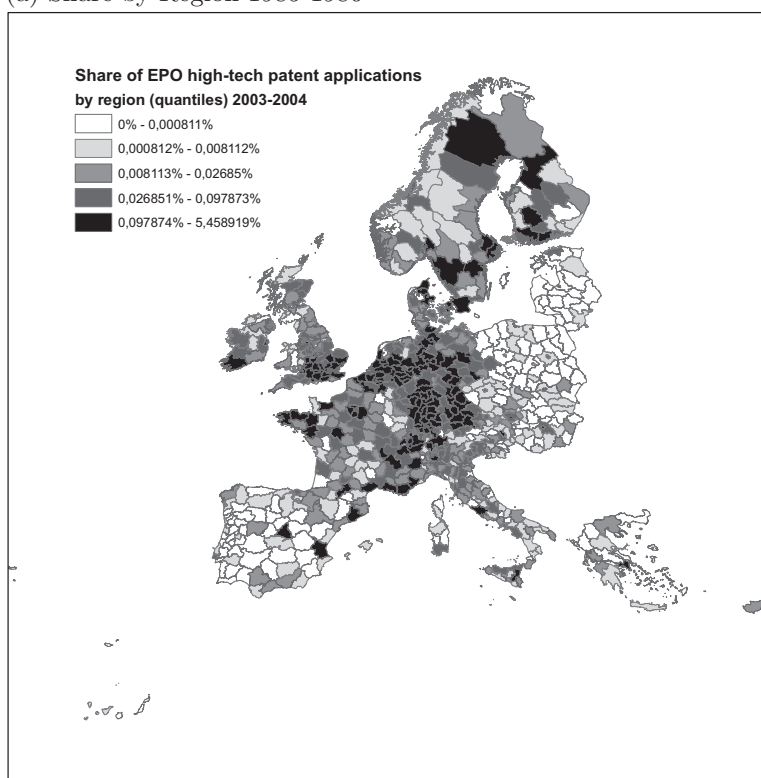
(b) Share by Region 2003-2004

Fig. A.1. EPO Patent Applications: Share by Region and Quantile

Source: own calculations and illustration. Notes: Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.



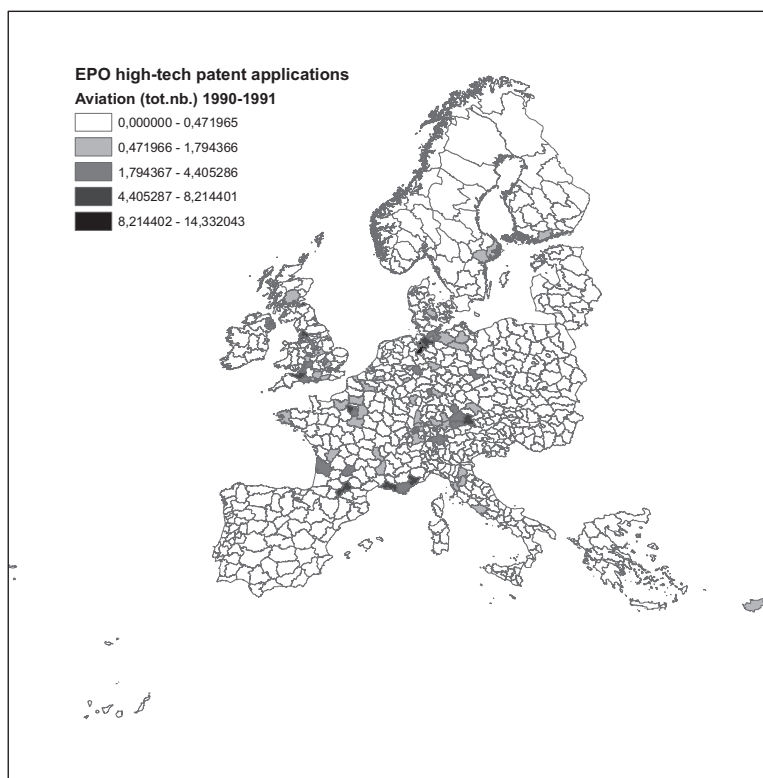
(a) Share by Region 1985-1986



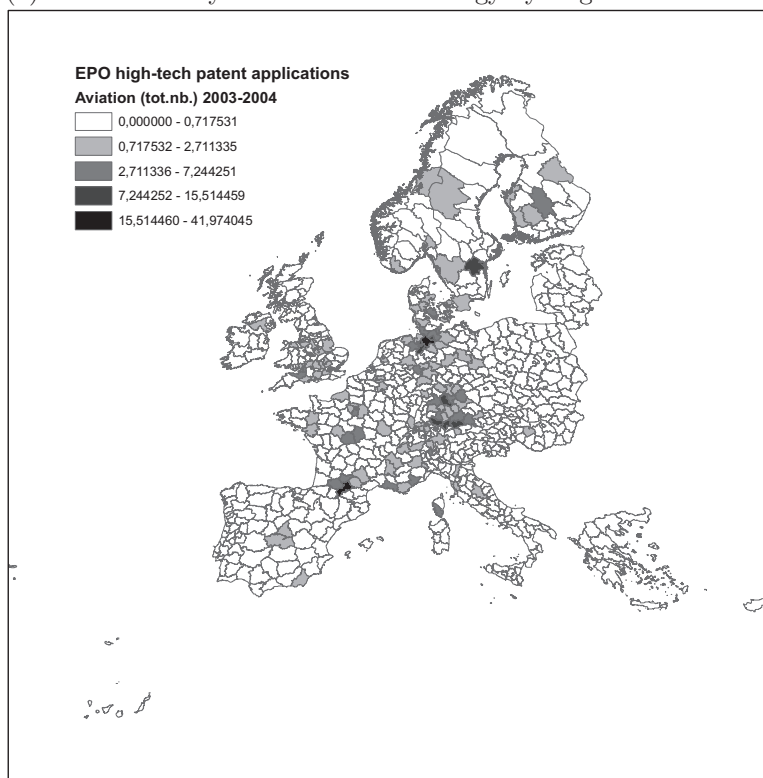
(b) Share by Region 2003-2004

Fig. A.2. High-tech EPO Patent Applications: Share by Region and Quantile

Source: own calculations and illustration. Notes: Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.



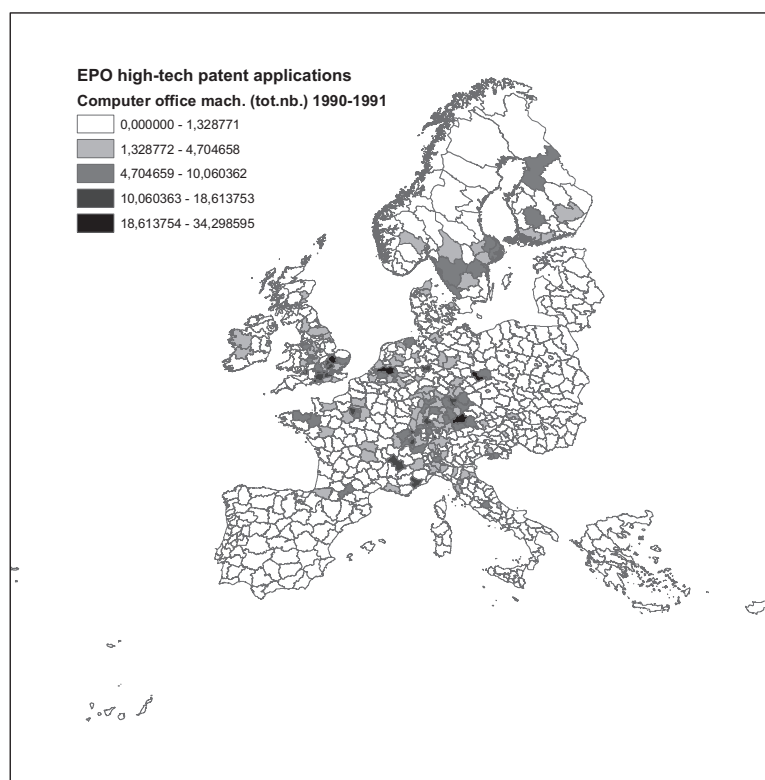
(a) Patent Density in Aviation Technology by Region 1990-1991



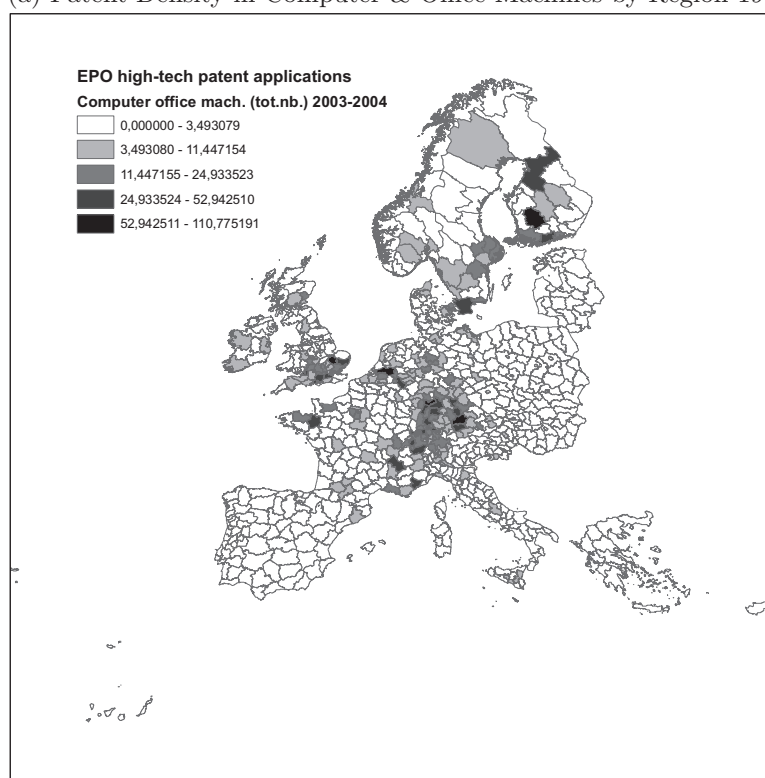
(b) Patent Density in Aviation Technology by Region 2003-2004

Fig. A.3. Aviation Technology: EPO Patent Application Density by Region

Source: own calculations and illustration. Notes: Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.



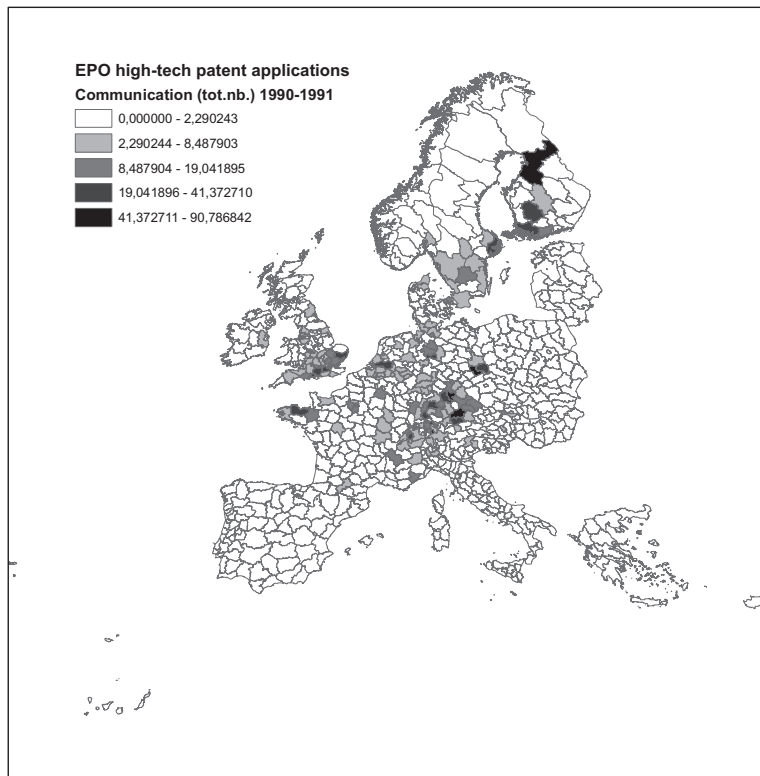
(a) Patent Density in Computer & Office Machines by Region 1990-1991



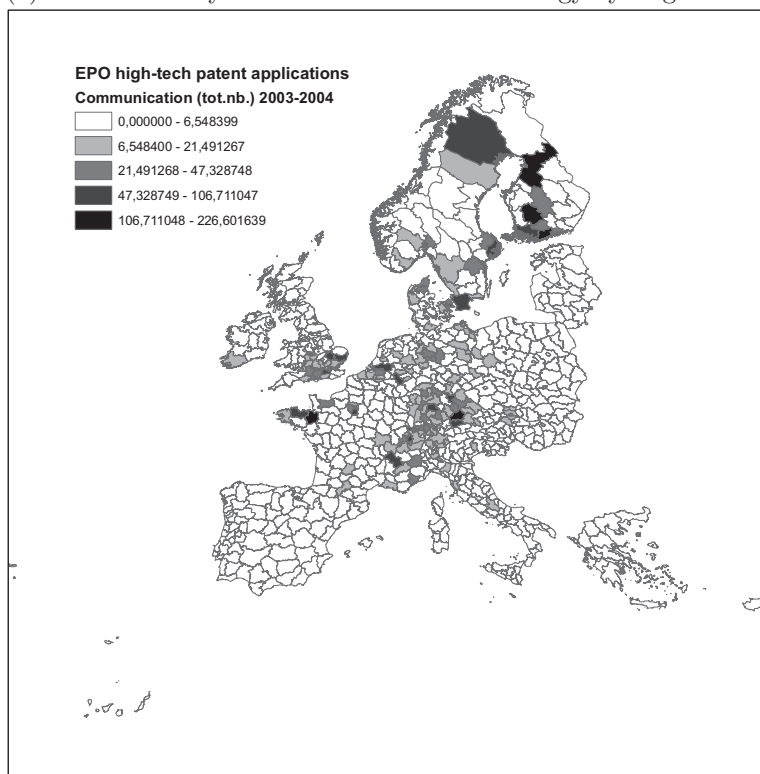
(b) Patent Density in Computer & Office Machines by Region 2003-2004

Fig. A.4. Computer & Office Machines: EPO Patent Application Density by Region

Source: own calculations and illustration. *Notes:* Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.



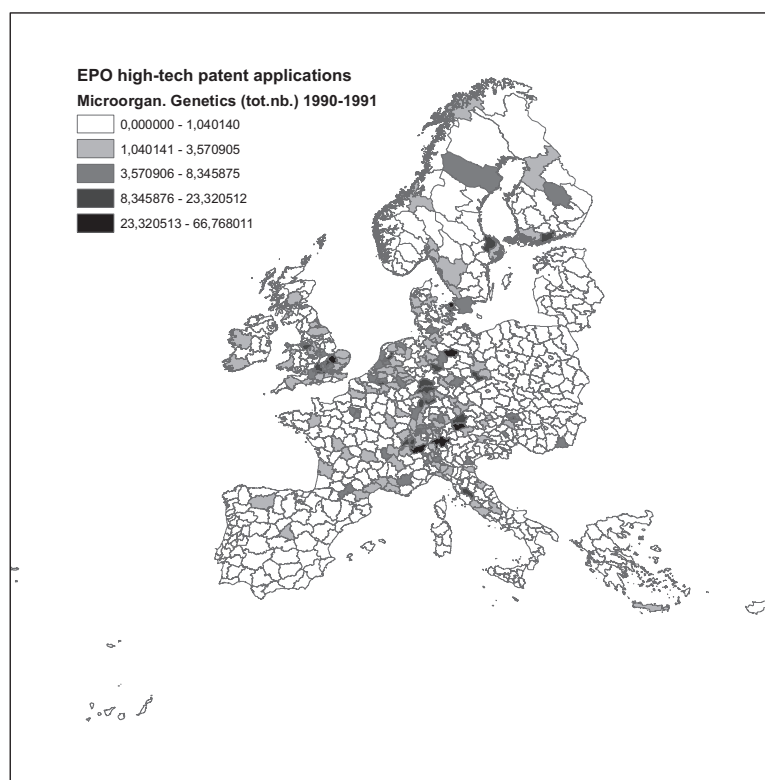
(a) Patent Density in Communication Technology by Region 1990-1991



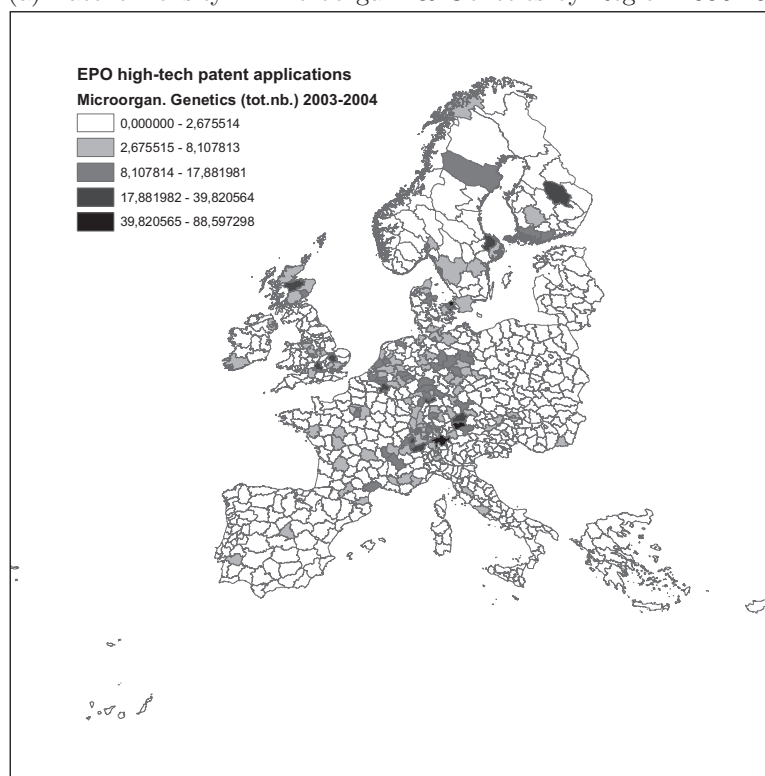
(b) Patent Density in Communication Technology by Region 2003-2004

Fig. A.5. Communication Technology: EPO Patent Application Density by Region

Source: own calculations and illustration. *Notes:* Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.



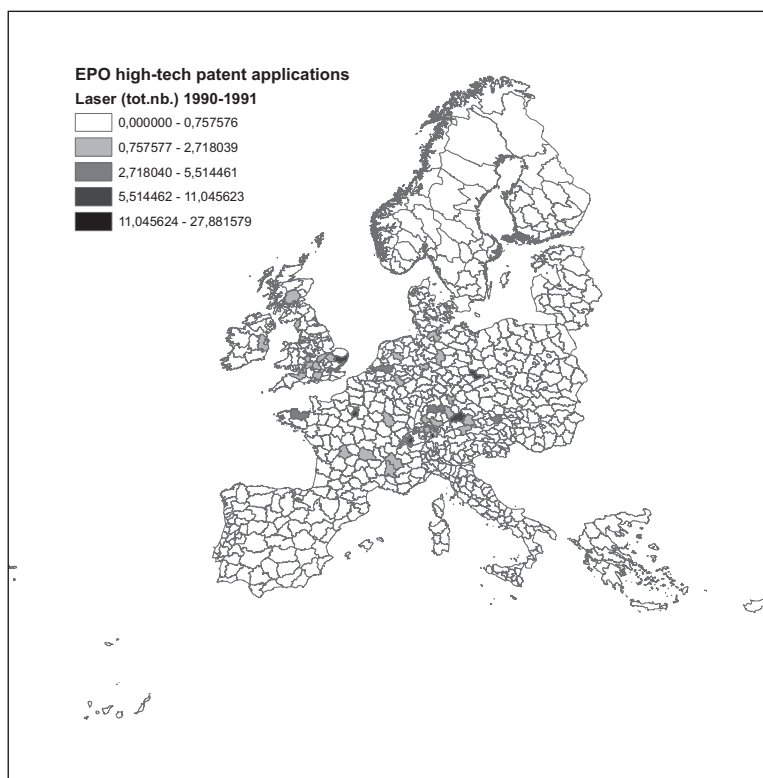
(a) Patent Density in Microorgan. & Genetics by Region 1990-1991



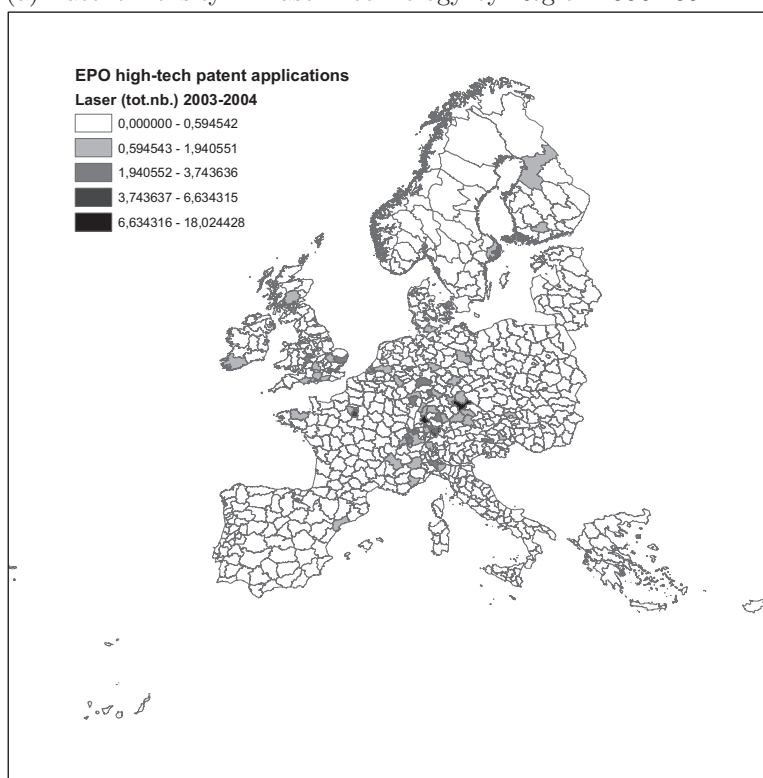
(b) Patent Density in Microorgan. & Genetics by Region 2003-2004

Fig. A.6. Microorgan. & Genetics: EPO Patent Application Density by Region

Source: own calculations and illustration. Notes: Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.



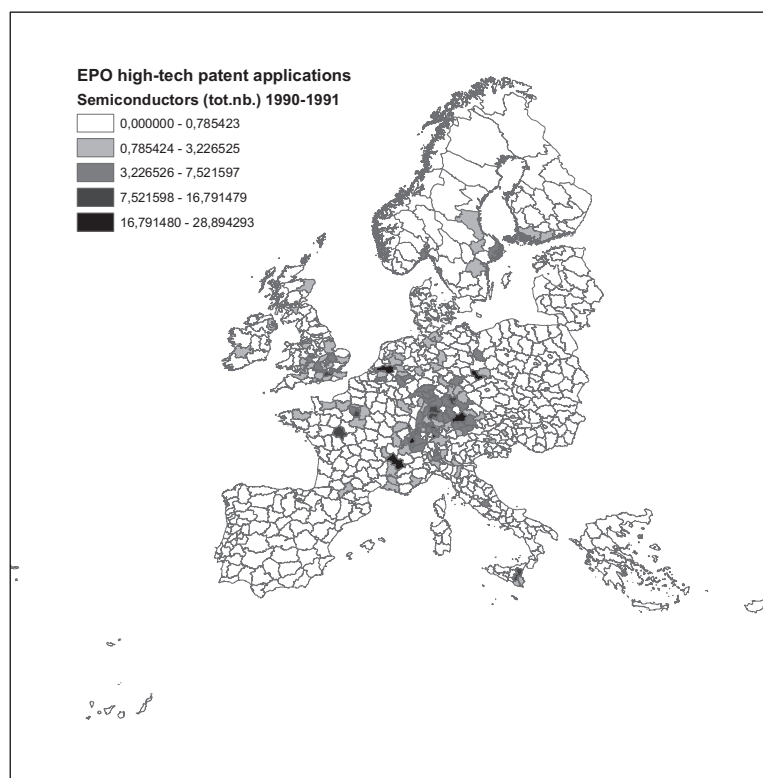
(a) Patent Density in Laser Technology by Region 1990-1991



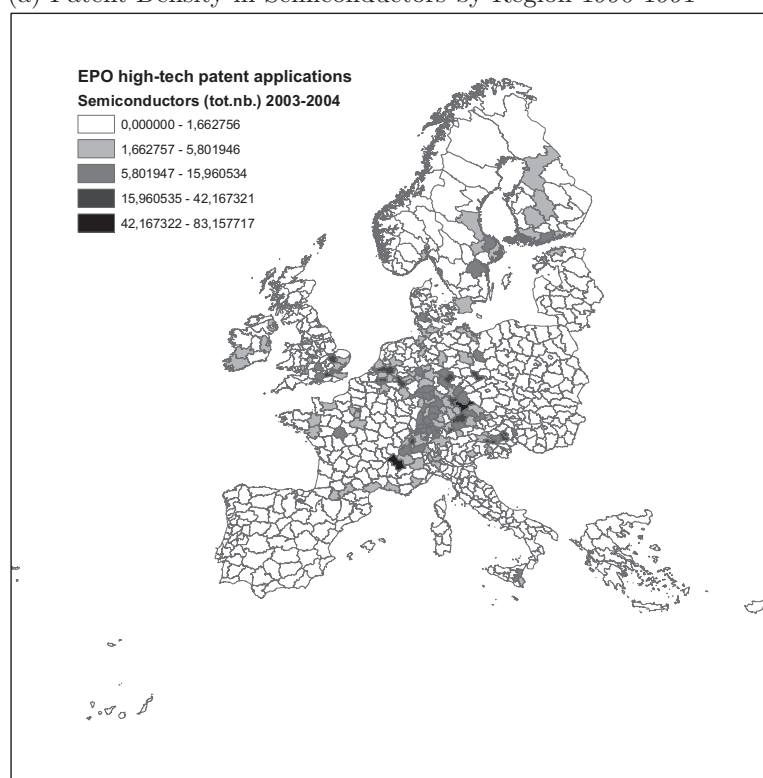
(b) Patent Density in Laser Technology by Region 2003-2004

Fig. A.7. Laser Technology: EPO Patent Application Density by Region

Source: own calculations and illustration. Notes: Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.



(a) Patent Density in Semiconductors by Region 1990-1991



(b) Patent Density in Semiconductors by Region 2003-2004

Fig. A.8. Semiconductors: EPO Patent Application Density by Region

Source: own calculations and illustration. Notes: Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.

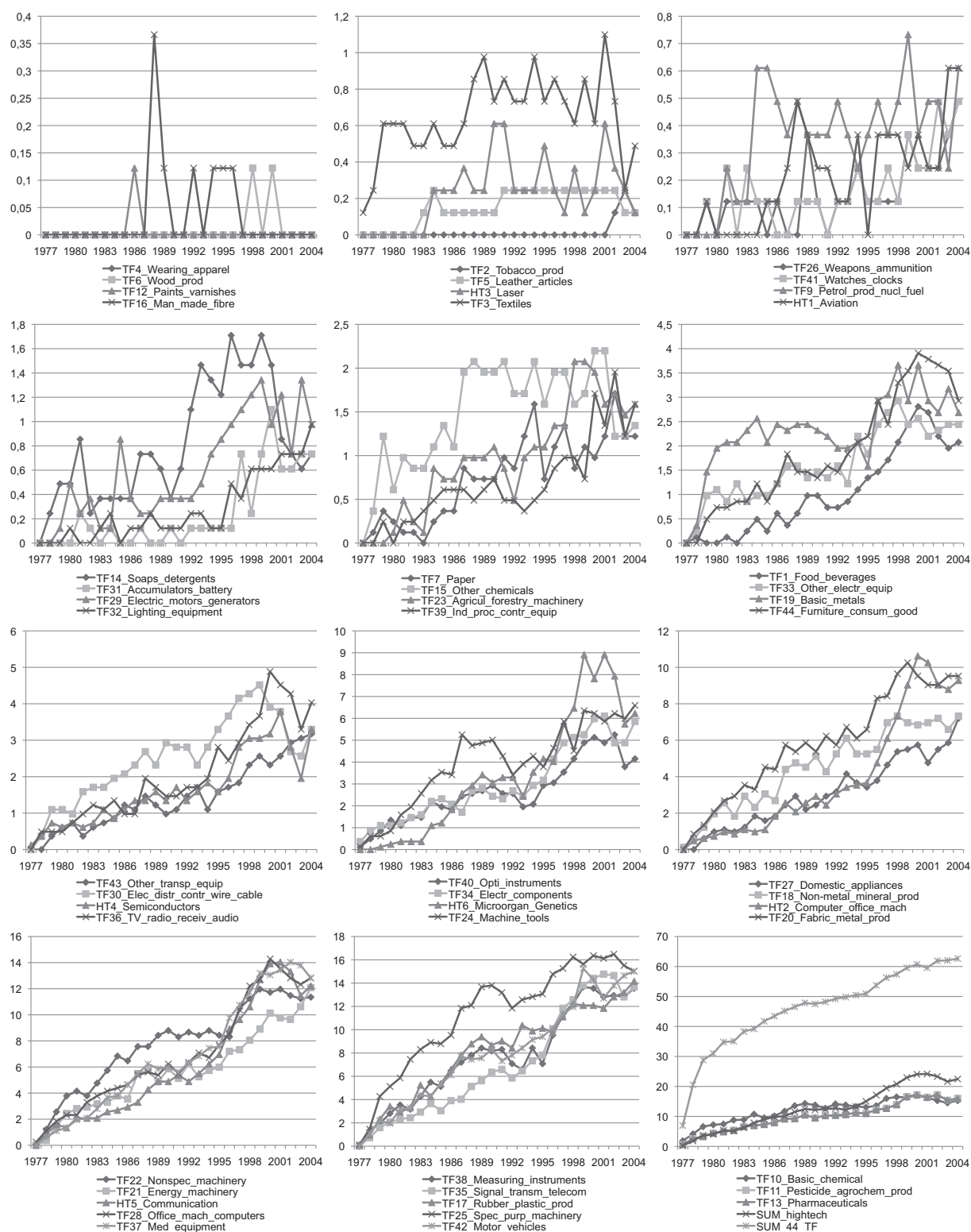


Fig. A.9. Share of European regions with $n > 9$ patent applications by TF

Source: own calculations and illustration. *Notes:* Fractional counting, 1977-2004; the population covers 819 European TL3 regions. Patent data generated by MySQL OECD RegPAT (2009) extractions and application of ISI-SPRU-OST concordance. TL3 population data constructed from EUROSTAT REGIO, OECD, ESPON and BBR data. For Belgium, Greece and the Netherlands, OECD TL3 correspond to EUROSTAT NUTS2. For Germany, 97 "Raumordnungsregionen" are used (OECD, 2003).

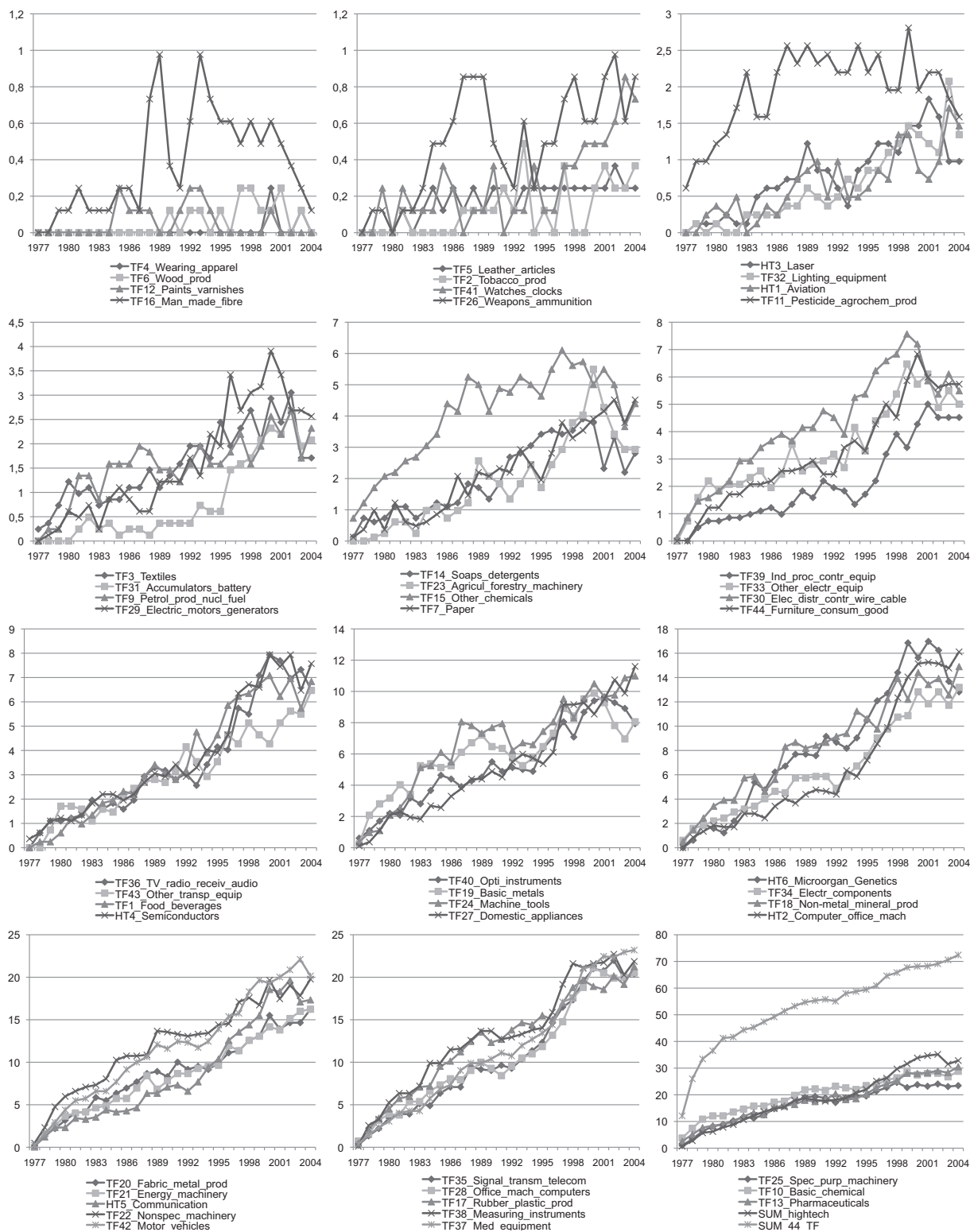


Fig. A.10. Share of European regions with $n > 9$ inventor IDs by TF

Source: own calculations and illustration. *Notes:* Full counting, 1977-2004; the population covers 819 European TL3 regions. Patent data generated by MySQL OECD RegPAT (2009) extractions and application of ISI-SPRU-OST concordance. TL3 population data constructed from EUROSTAT REGIO, OECD, ESPON and BBR data. For Belgium, Greece and the Netherlands, OECD TL3 correspond to EUROSTAT NUTS2. For Germany, 97 “Raumordnungsregionen” are used (OECD, 2003).

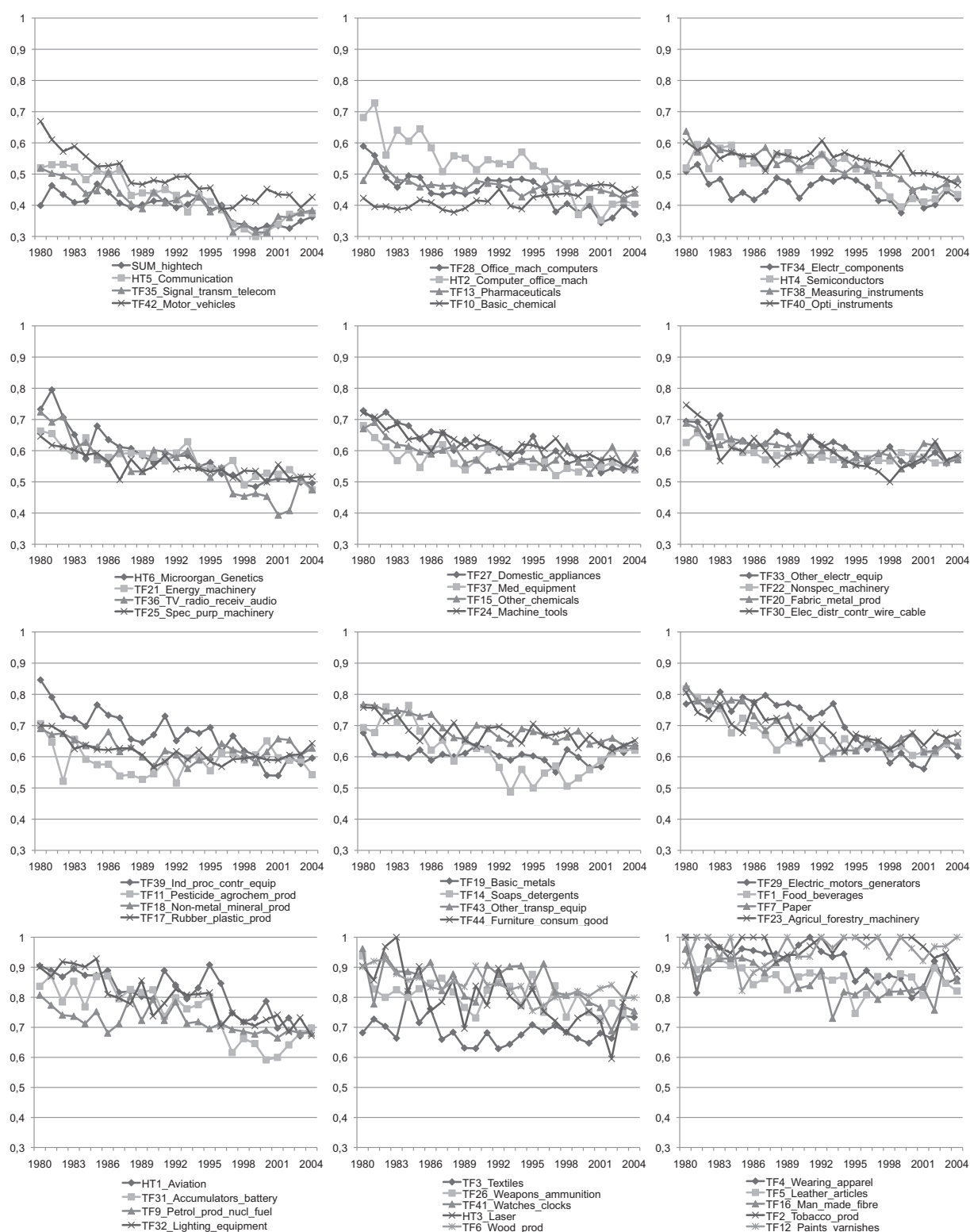


Fig. A.11. Share of European regions w/ $RTA > 1$ of regions w/ $n > 0$ patent applications

Source: own calculations and illustration. *Notes:* Calculations by technology field for period 1988-2004; the population covers 819 European TL3 regions. Patent data generated by mySQL OECD RegPAT (2009) extractions and application of ISI-SPRU-OST concordance. TL3 population data constructed from EUROSTAT REGIO, OECD, ESPON and BBR data. For Belgium, Greece and the Netherlands, OECD TL3 correspond to EUROSTAT NUTS2. For Germany, 97 “Raumordnungsregionen” are used (OECD, 2003).

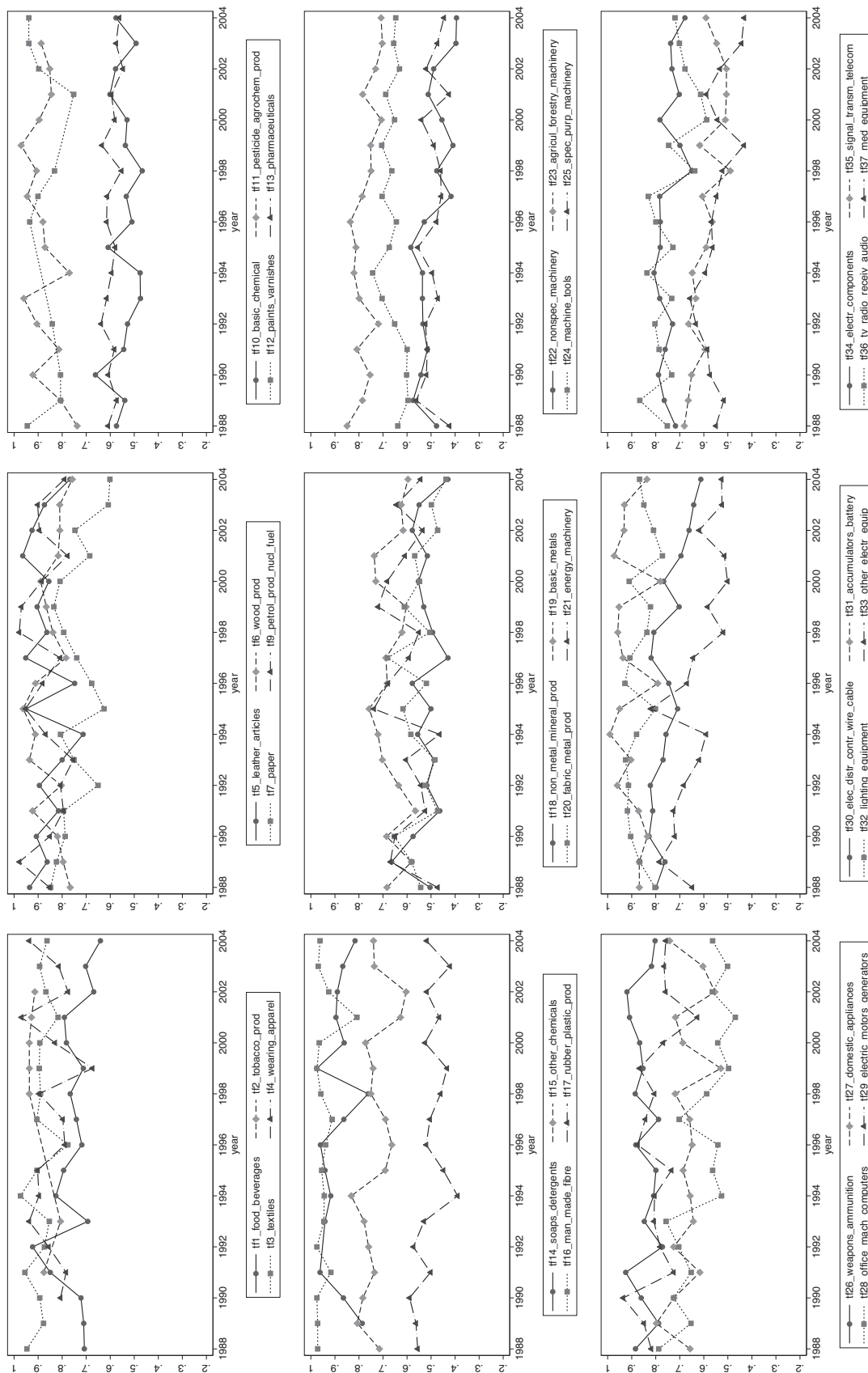


Fig. A.12. Austria: Locational Gini of EPO Patent Applications by TF (a)
 Source: own calculations and illustration. Notes: Gini calculation (G_{LOC}^*) based upon RegPAT (January 2009) data.

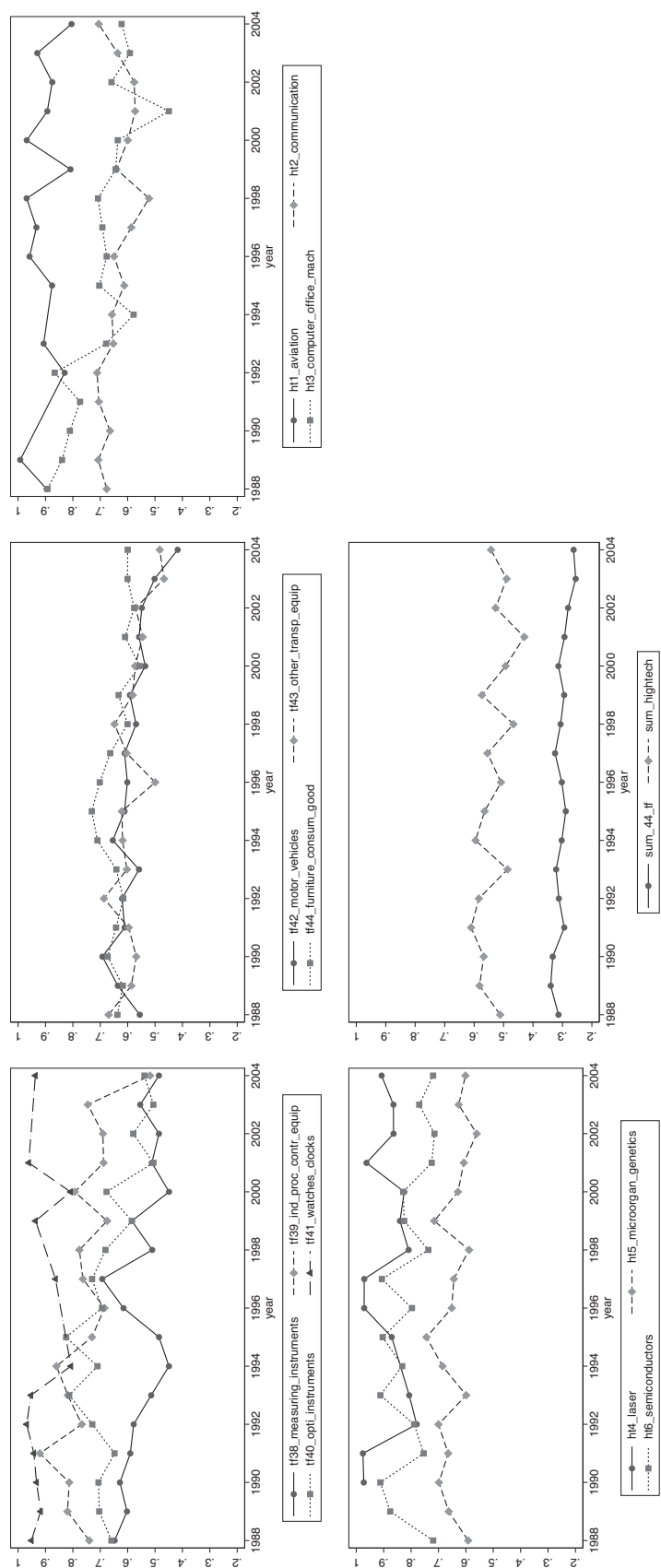


Fig. A.13. Austria: Locational Gini of EPO Patent Applications by TF (b)
Source: own calculations and illustration. *Notes:* Gini calculation (G_{Loc}^*) based upon RegPAT (January 2009) data.

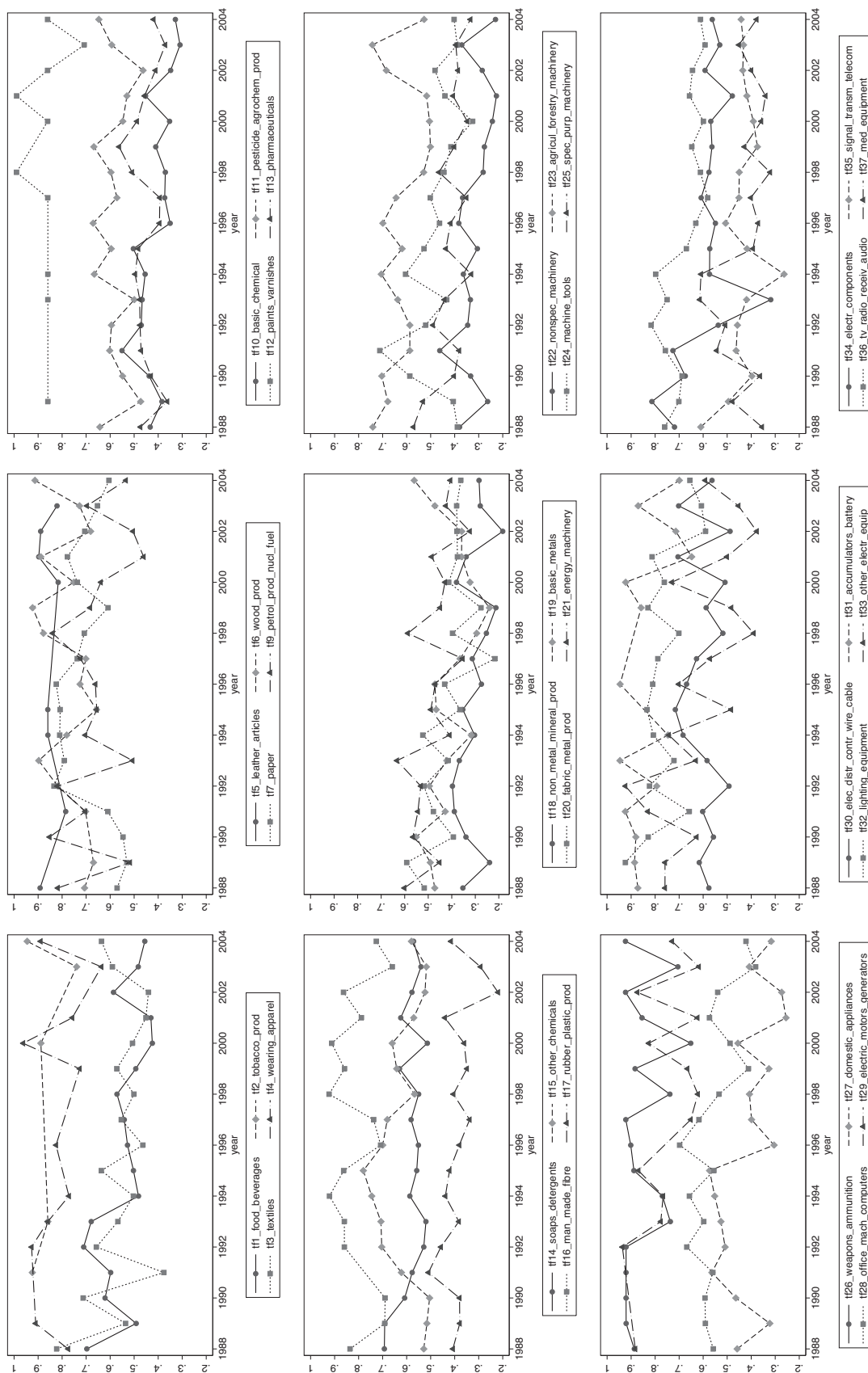


Fig. A.14. Belgium: Locational Gini of EPO Patent Applications by TF (a)
 Source: own calculations and illustration. Notes: Gini calculation (G_{Loc}^*) based upon RegPAT (January 2009) data.

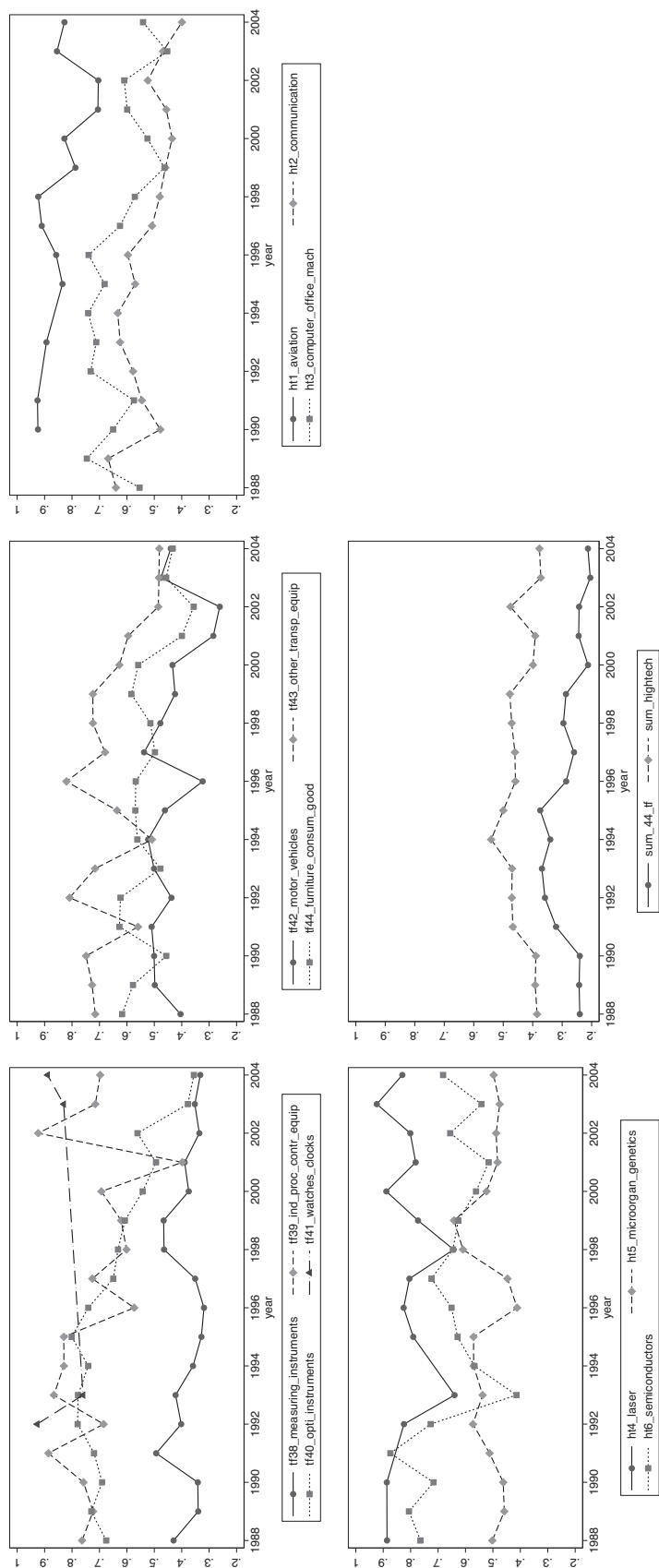


Fig. A.15. Belgium: Locational Gini of EPO Patent Applications by TF (b)
 Source: own calculations and illustration. Notes: Gini calculation (G_{Loc}^*) based upon RegPAT (January 2009) data.

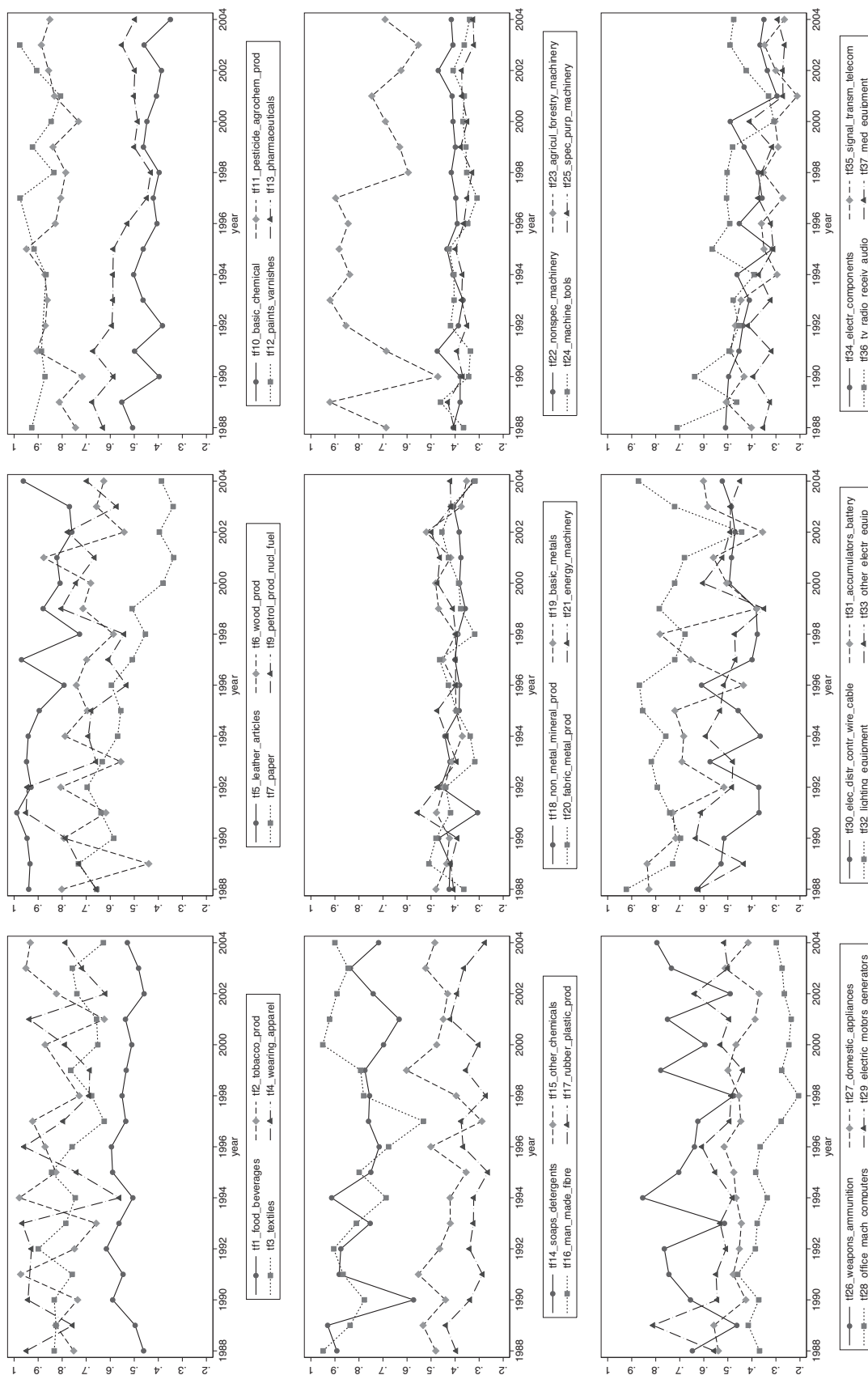


Fig. A.16. Switzerland: Locational Gini of EPO Patent Applications by TF (a)
 Source: own calculations and illustration. Notes: Gini calculation (G_{LOC}^*) based upon RegPAT (January 2009) data.

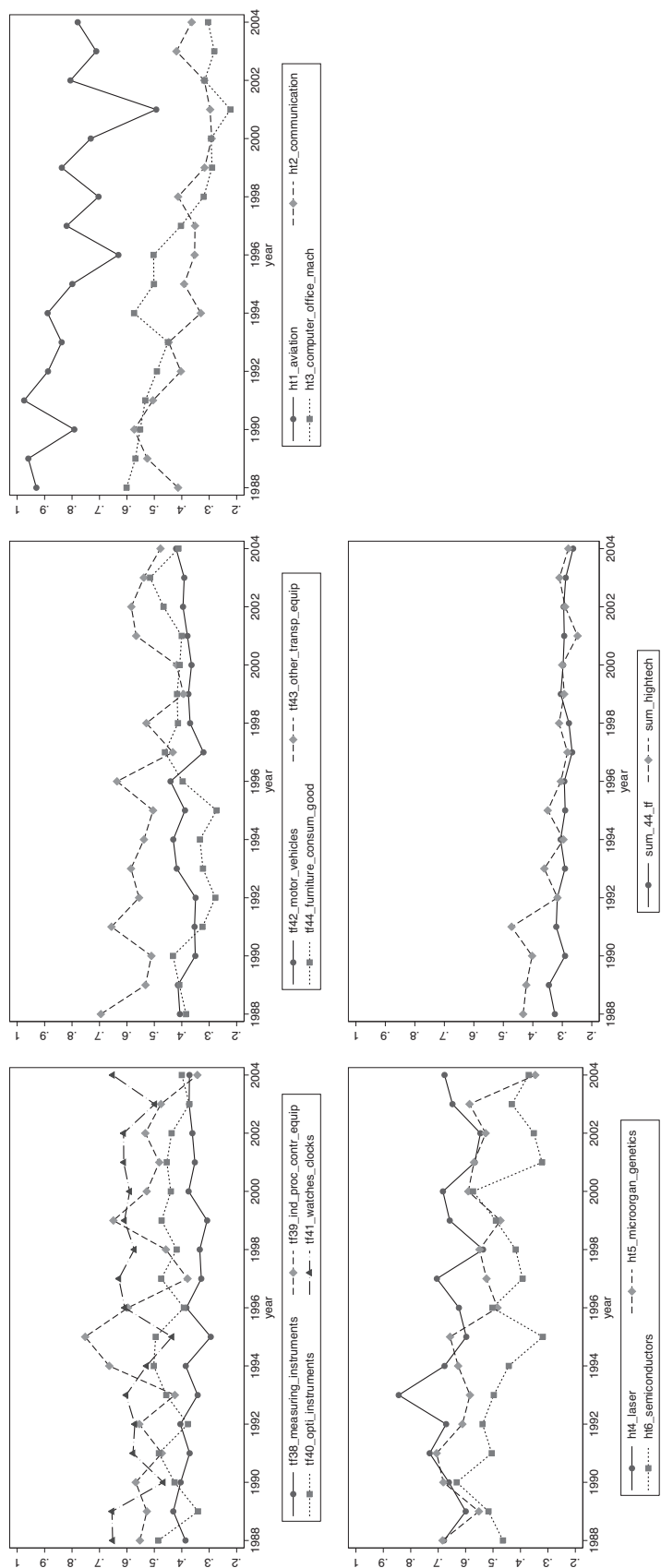


Fig. A.17. Switzerland: Locational Gini of EPO Patent Applications by TF (b)
 Source: own calculations and illustration. Notes: Gini calculation (G_{LOC}^*) based upon RegPAT (January 2009) data.

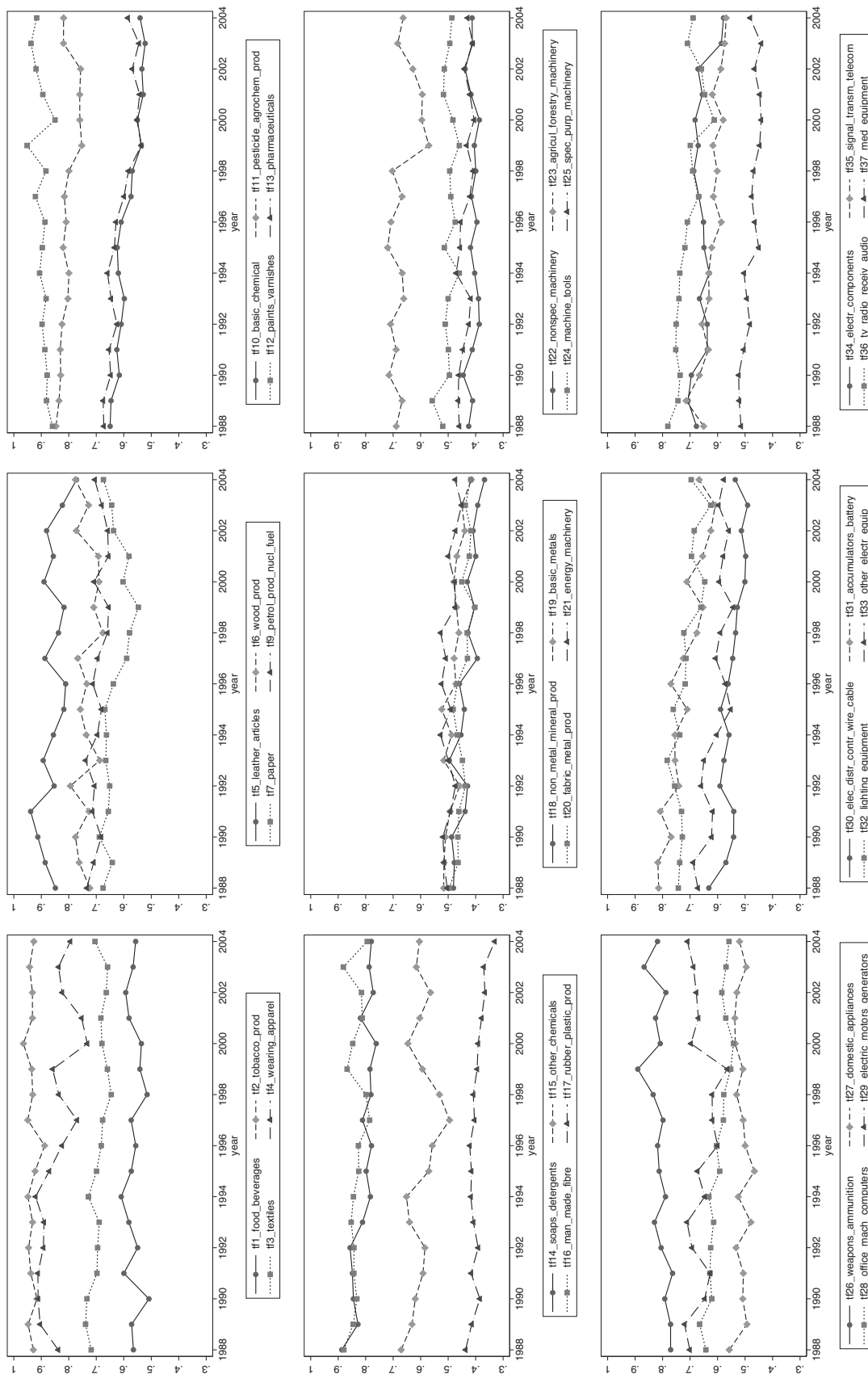


Fig. A.18. Germany: Locational Gini of EPO Patent Applications by TF (a)
 Source: own calculations and illustration. Notes: Gini calculation (G_{LOC}^*) based upon RegPAT (January 2009) data.

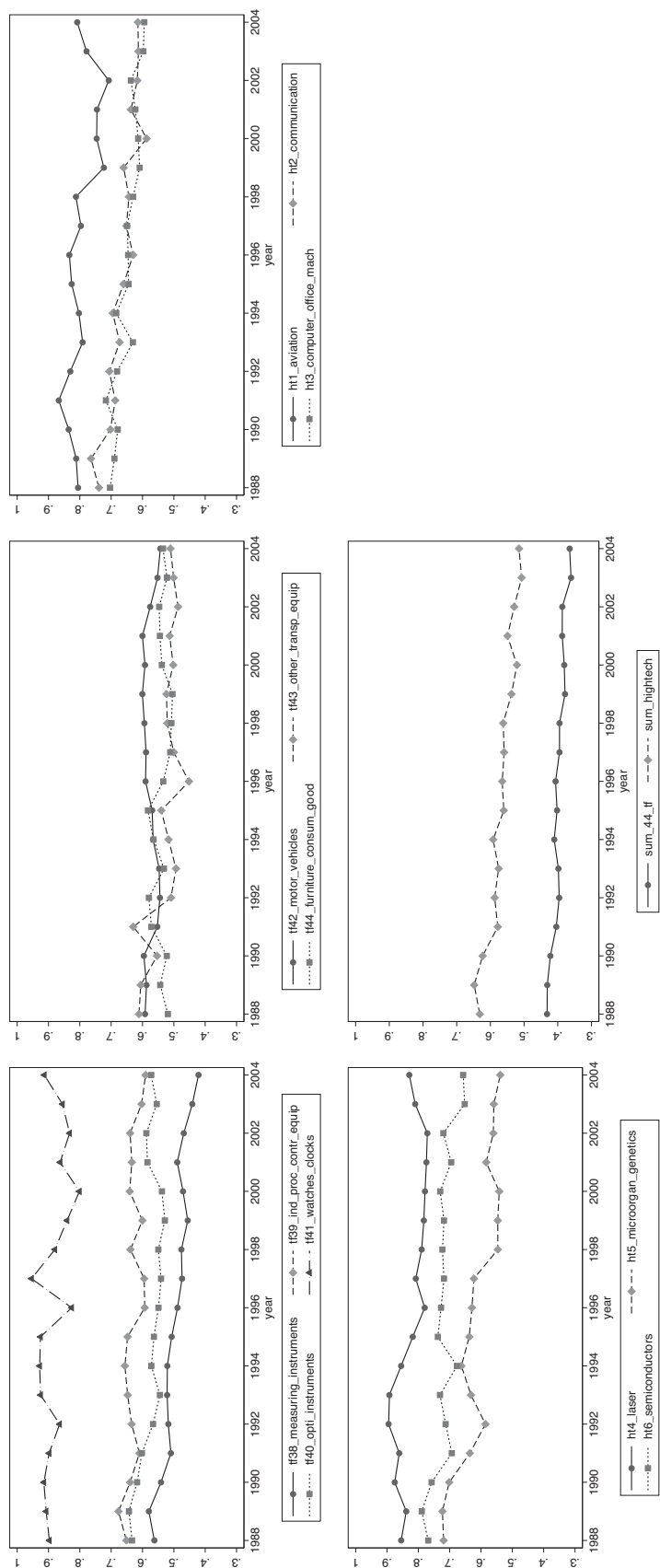


Fig. A.19. Germany: Locational Gini of EPO Patent Applications by TF (b)
 Source: own calculations and illustration. Notes: Gini calculation (G_{LOC}^*) based upon RegPAT (January 2009) data.

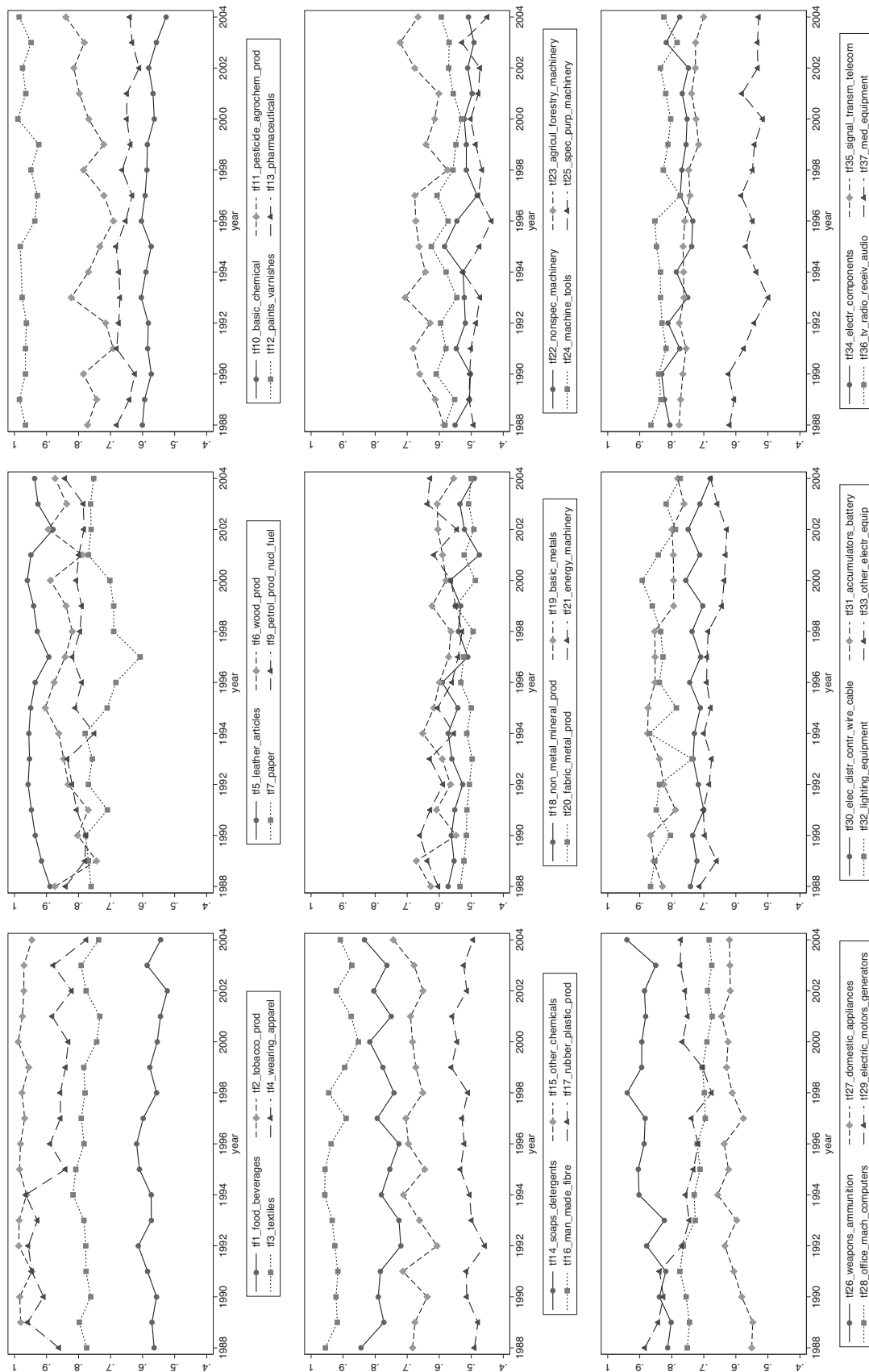


Fig. A.20. France: Locational Gini of EPO Patent Applications by TF (a)
 Source: own calculations and illustration. Notes: Gini calculation (G_{LOC}^*) based upon RegPAT (January 2009) data.

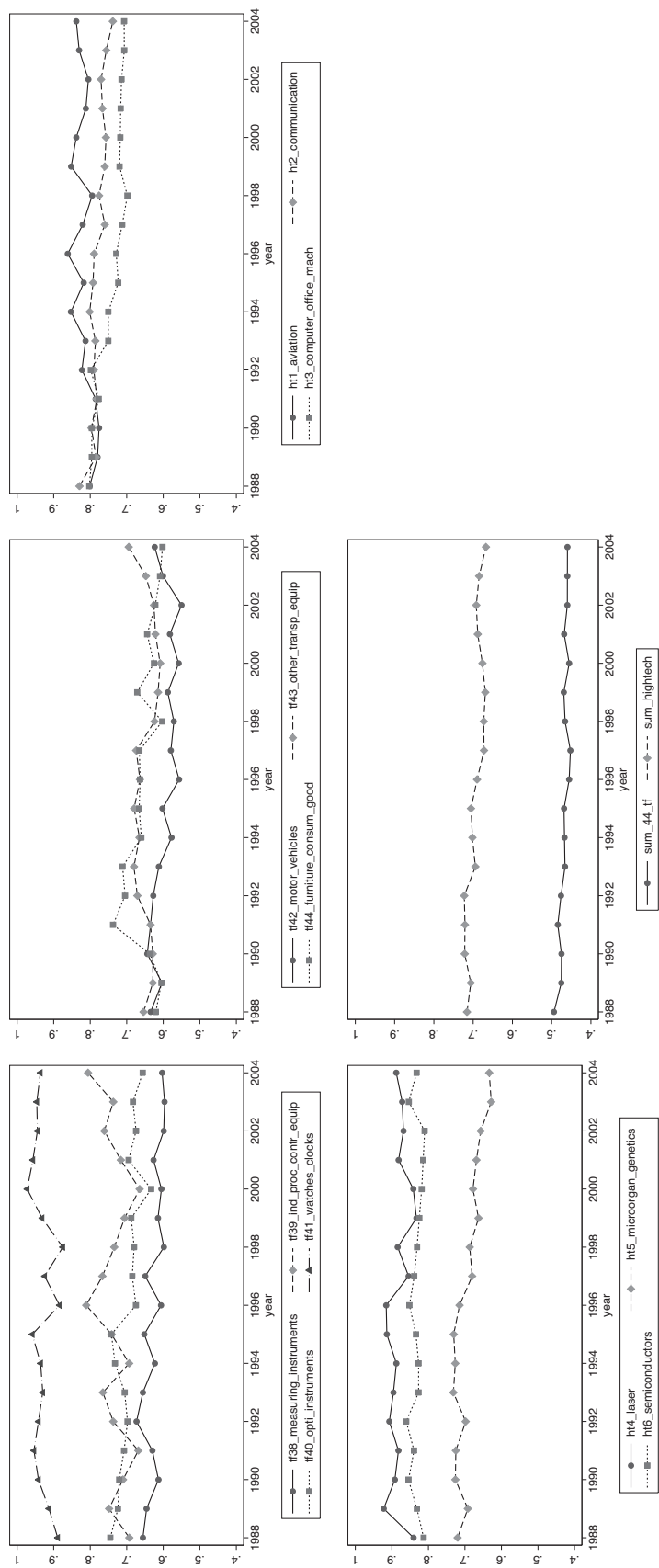


Fig. A.21. France: Locational Gini of EPO Patent Applications by TF (b)
 Source: own calculations and illustration. Notes: Gini calculation (G_{LOC}^*) based upon RegPAT (January 2009) data.

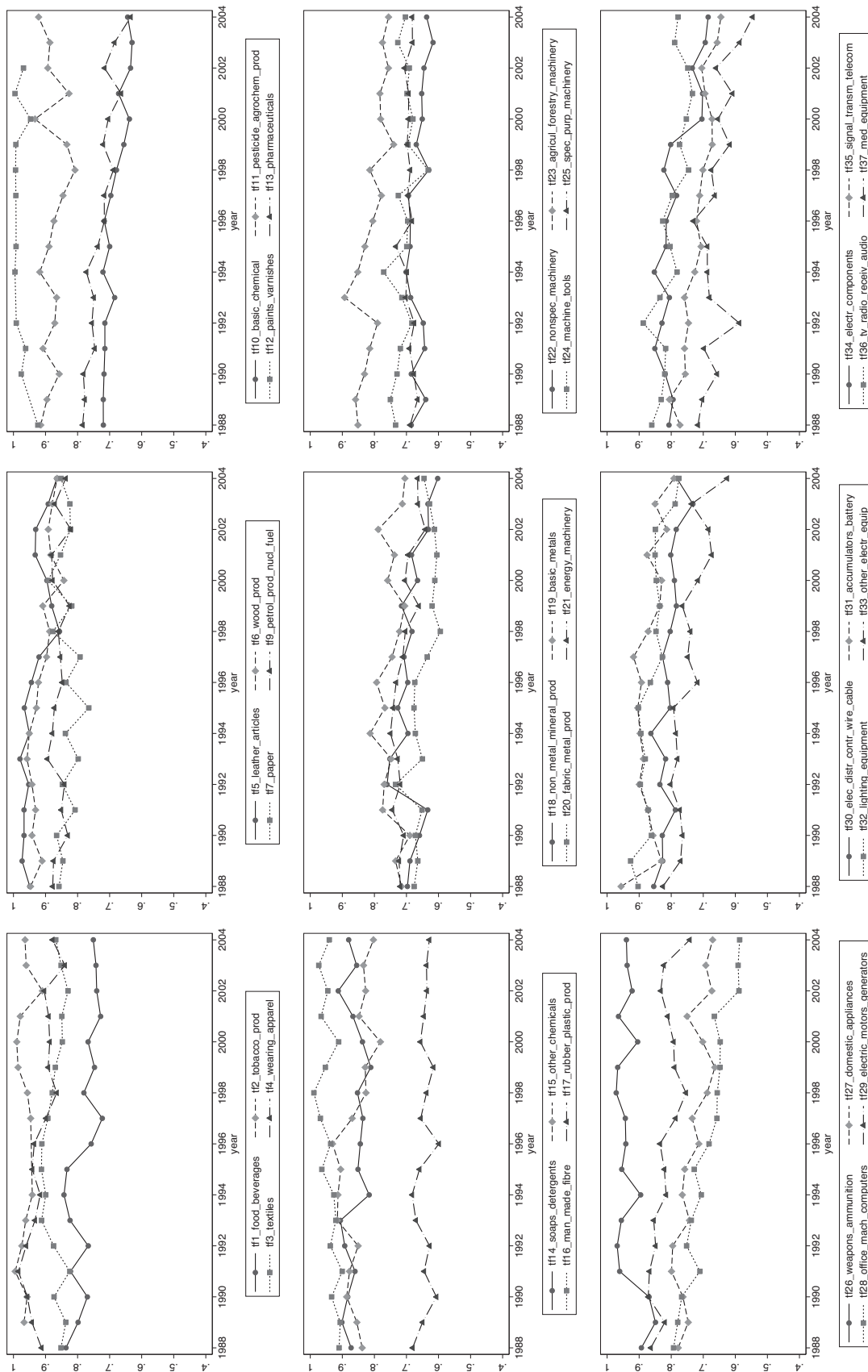


Fig. A.22. Italy: Locational Gini of EPO Patent Applications by TF (a)
 Source: own calculations and illustration. Notes: Gini calculation (G_{LOC}^*) based upon RegPAT (January 2009) data.

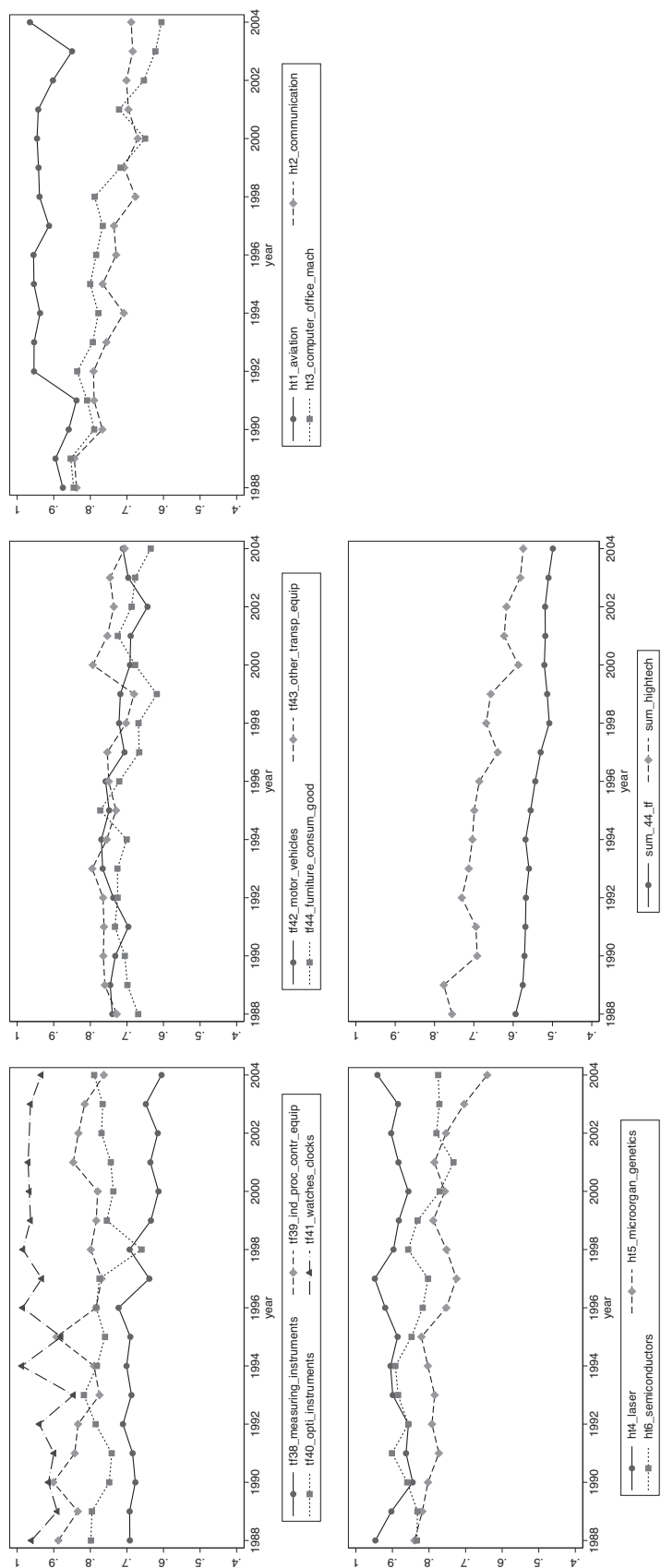


Fig. A.23. Italy: Locational Gini of EPO Patent Applications by TF (b)
 Source: own calculations and illustration. Notes: Gini calculation (G_{Loc}^*) based upon RegPAT (January 2009) data.

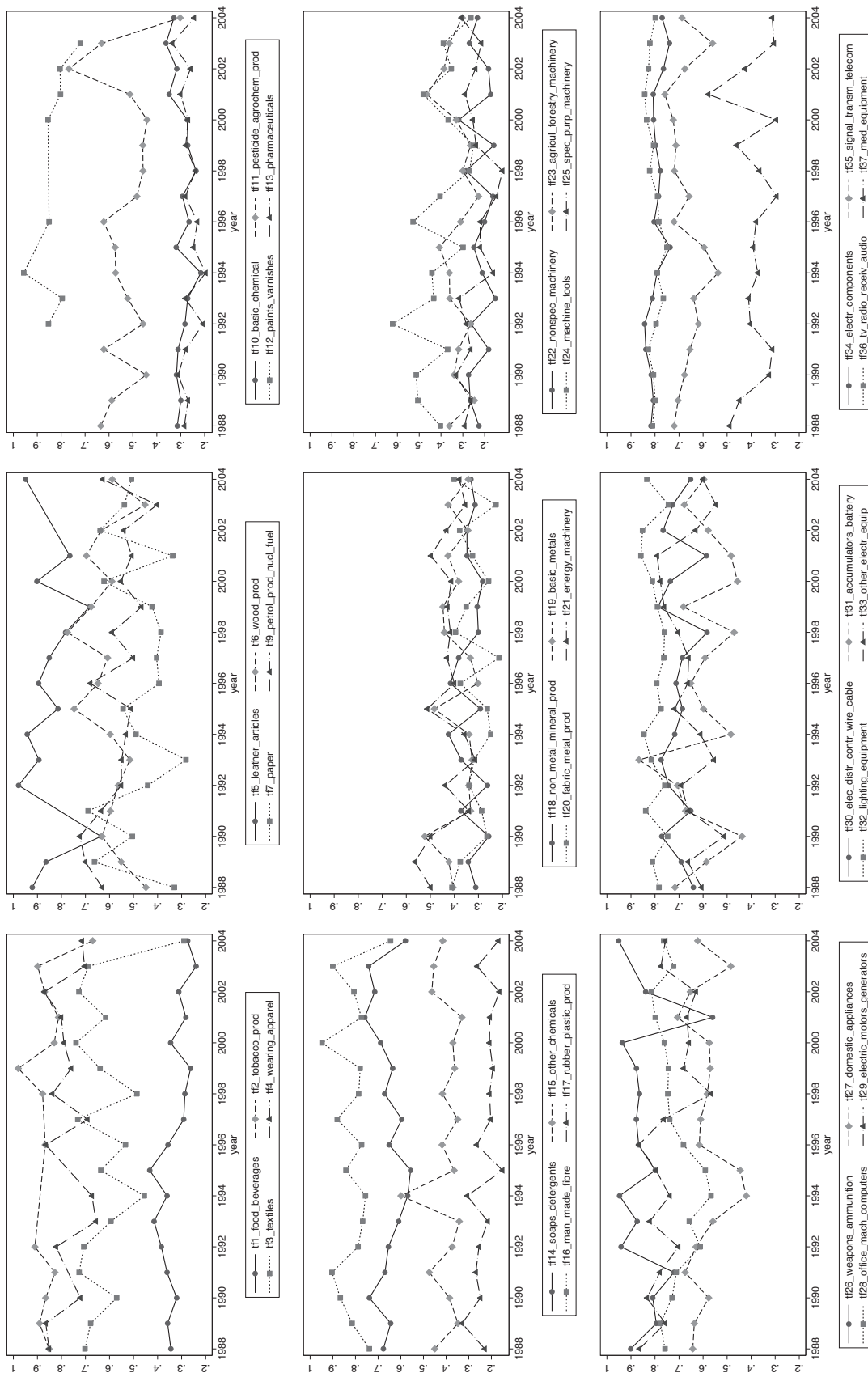


Fig. A.24. Netherlands: Locational Gini of EPO Patent Applications by TF (a)
 Source: own calculations and illustration. Notes: Gini calculation (G_{LOC}^*) based upon RegPAT (January 2009) data.

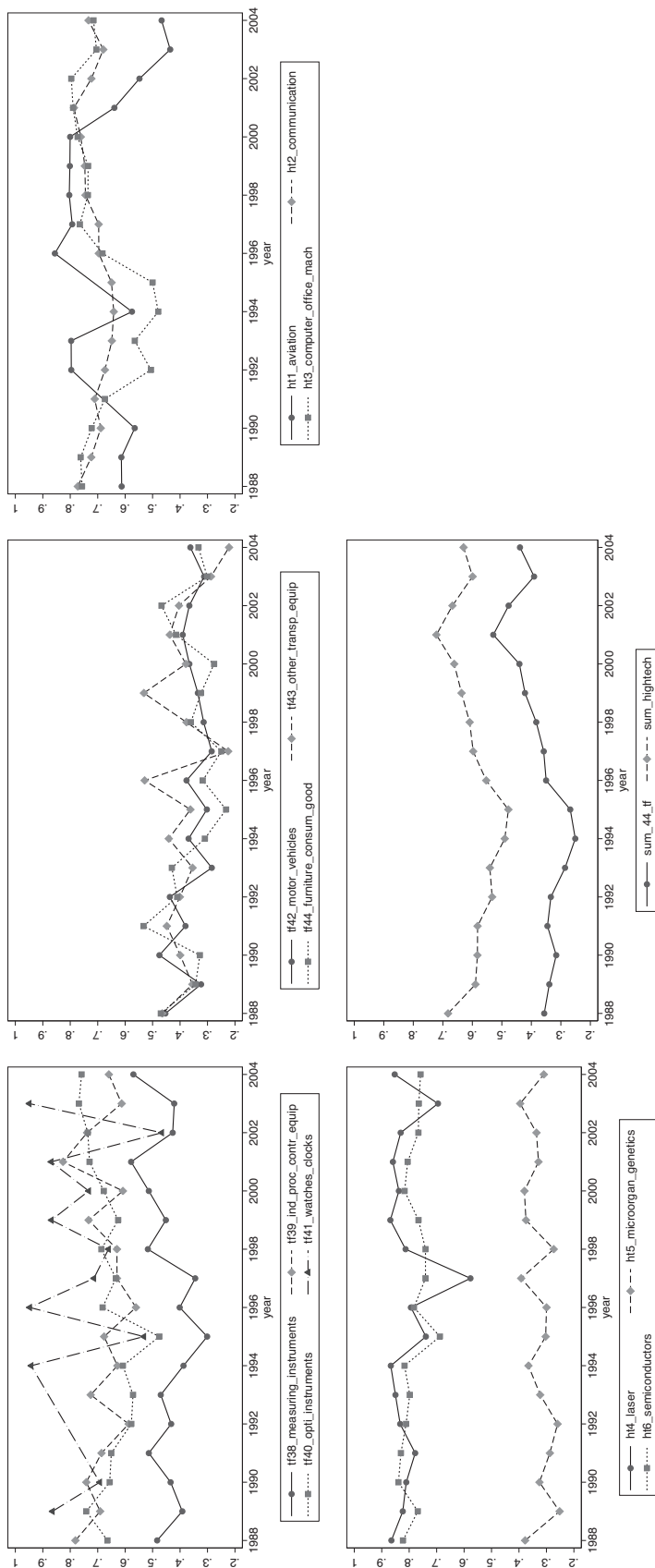


Fig. A.25. Netherlands: Locational Gini of EPO Patent Applications by TF (b)
Source: own calculations and illustration. *Notes:* Gini calculation (G_{LOC}^*) based upon RegPAT (January 2009) data.

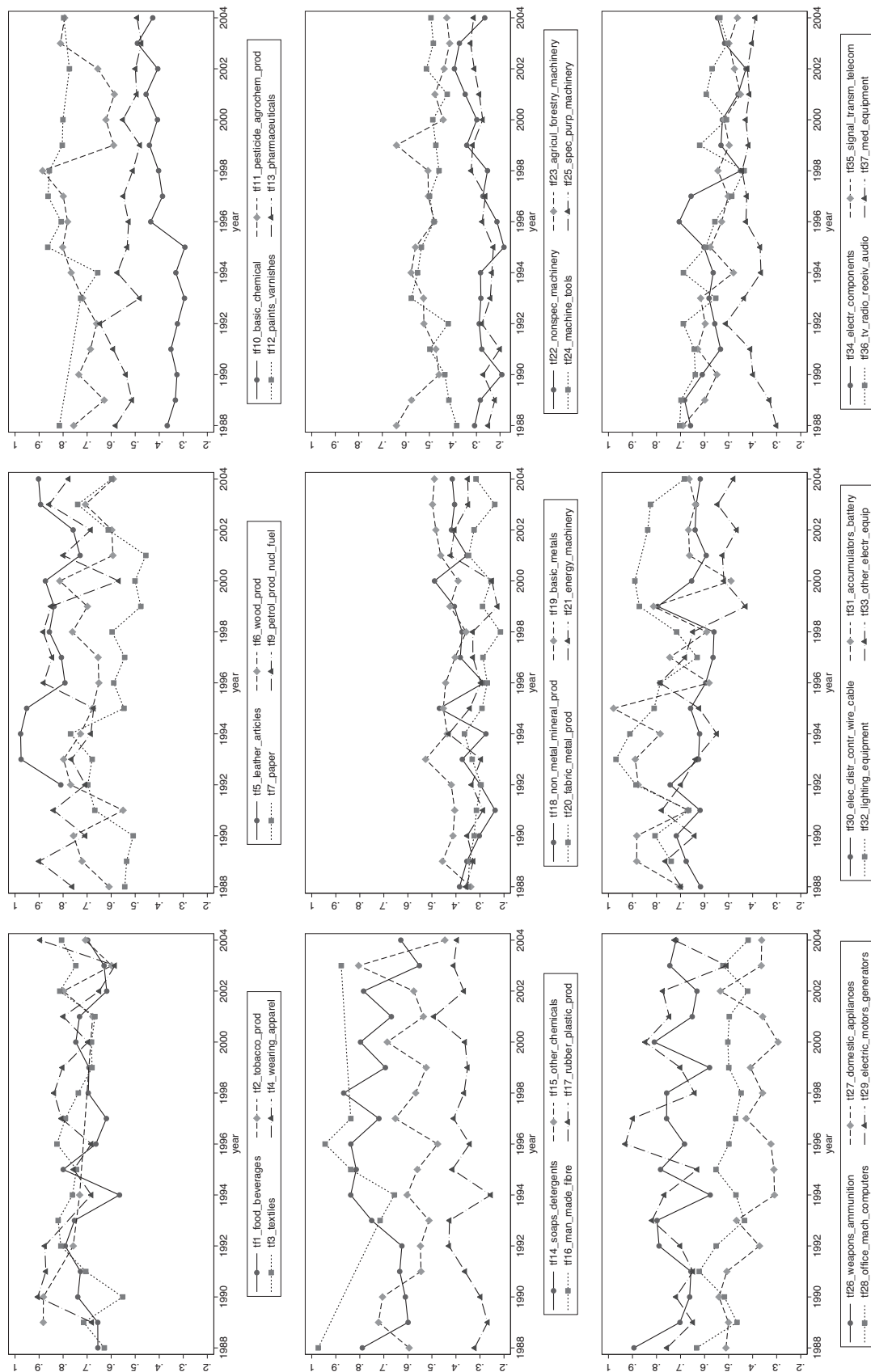


Fig. A.26. Sweden: Locational Gini of EPO Patent Applications by TF (a)
 Source: own calculations and illustration. Notes: Gini calculation (G_{LOC}^*) based upon RegPAT (January 2009) data.

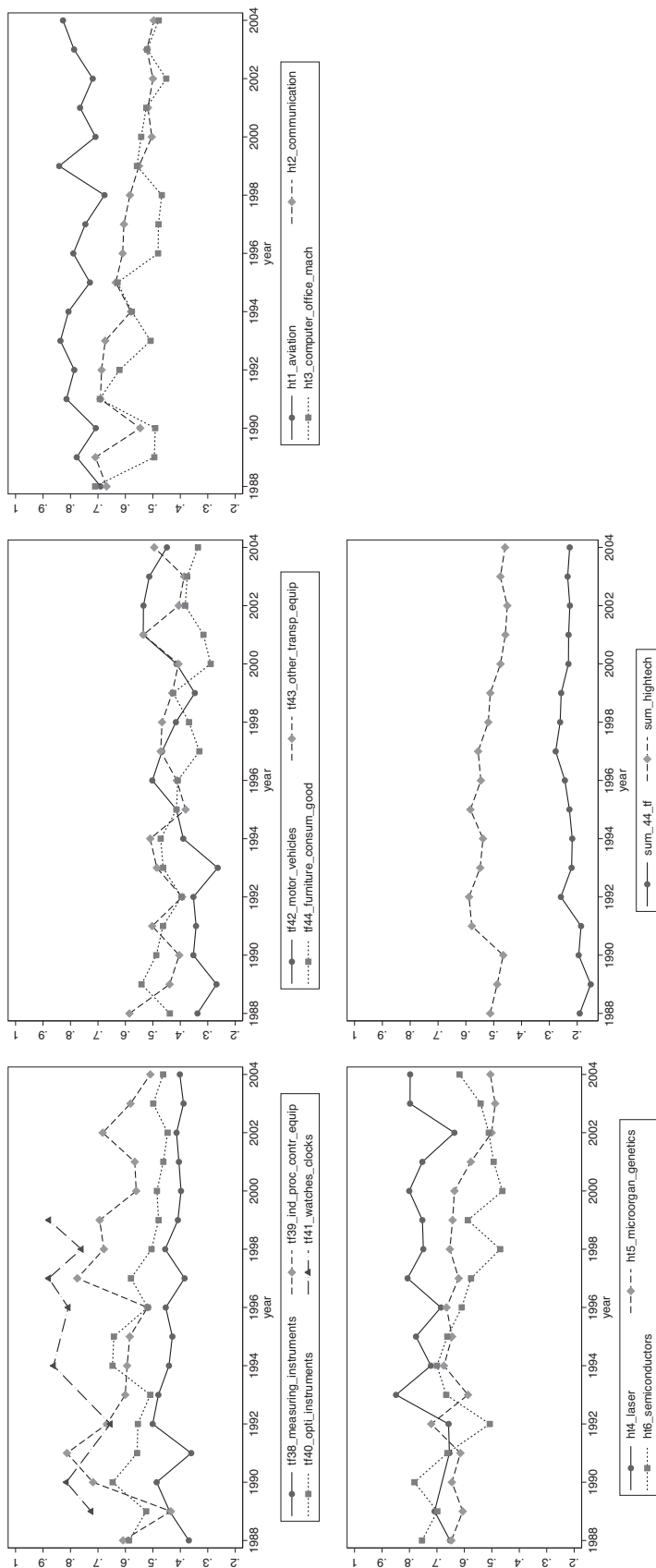


Fig. A.27. Sweden: Locational Gini of EPO Patent Applications by TF (b)
Source: own calculations and illustration. *Notes:* Gini calculation (G_{LOC}^*) based upon RegPAT (January 2009) data.

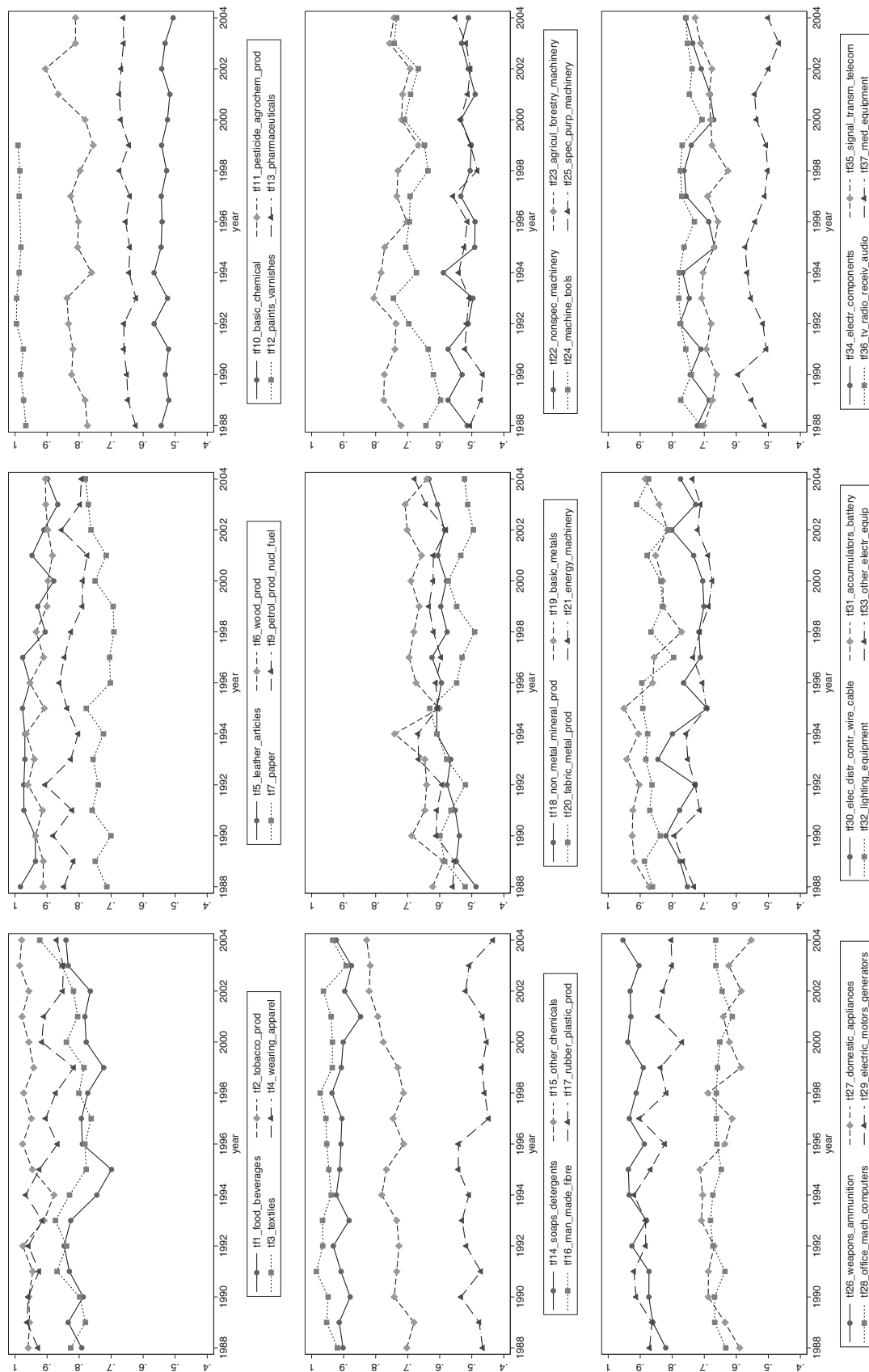


Fig. A.28. United Kingdom: Locational Gini of EPO Patent Applications by TF (a)
 Source: own calculations and illustration. Notes: Gini calculation (G_{Loc}^*) based upon RegPAT (January 2009) data.

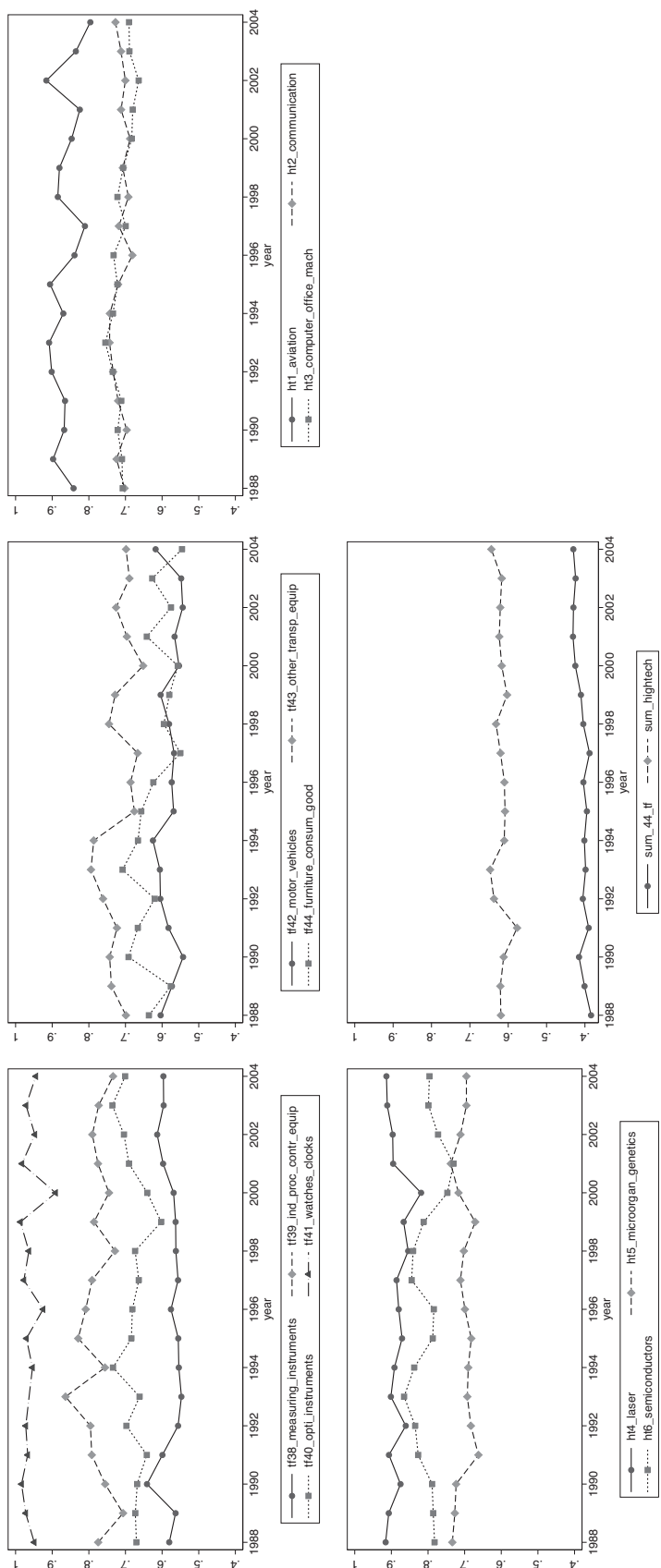


Fig. A.29. United Kingdom: Locational Gini of EPO Patent Applications by TF (b)
 Source: own calculations and illustration. Notes: Gini calculation (G_{LOC}^*) based upon RegPAT (January 2009) data.

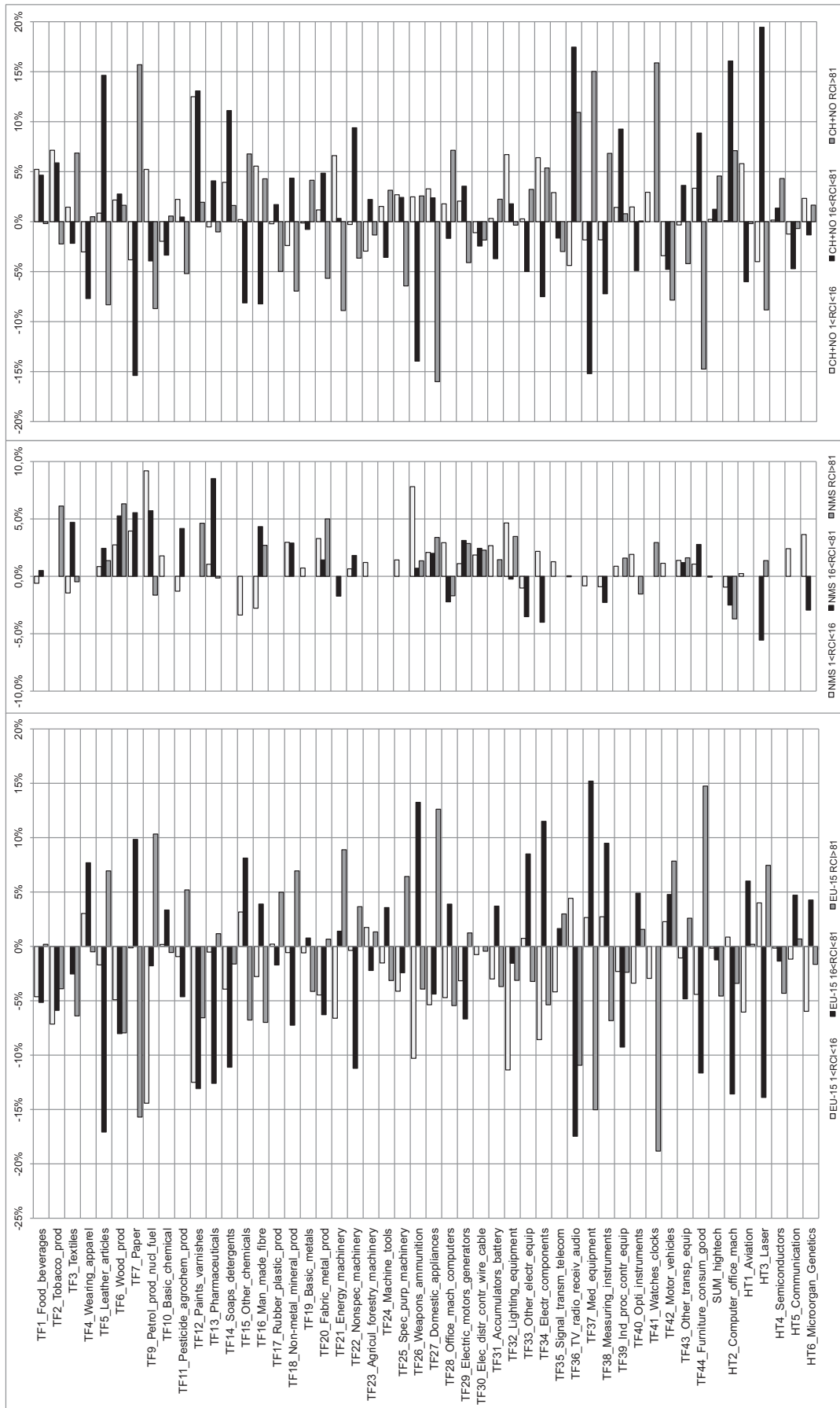


Fig. A.30. Change of research clusters (RCI) in ERA by TF, country group and RCI Class, 2000-2004 vs. 1990-1994
 Source: own calculations and illustration. Notes: change of number of research clusters by technology field, 2000-2004 vs. 1990-1994; calculations based upon OECD RegPAT (2009) database extractions and application of the ISI-SPRU-OST concordance.

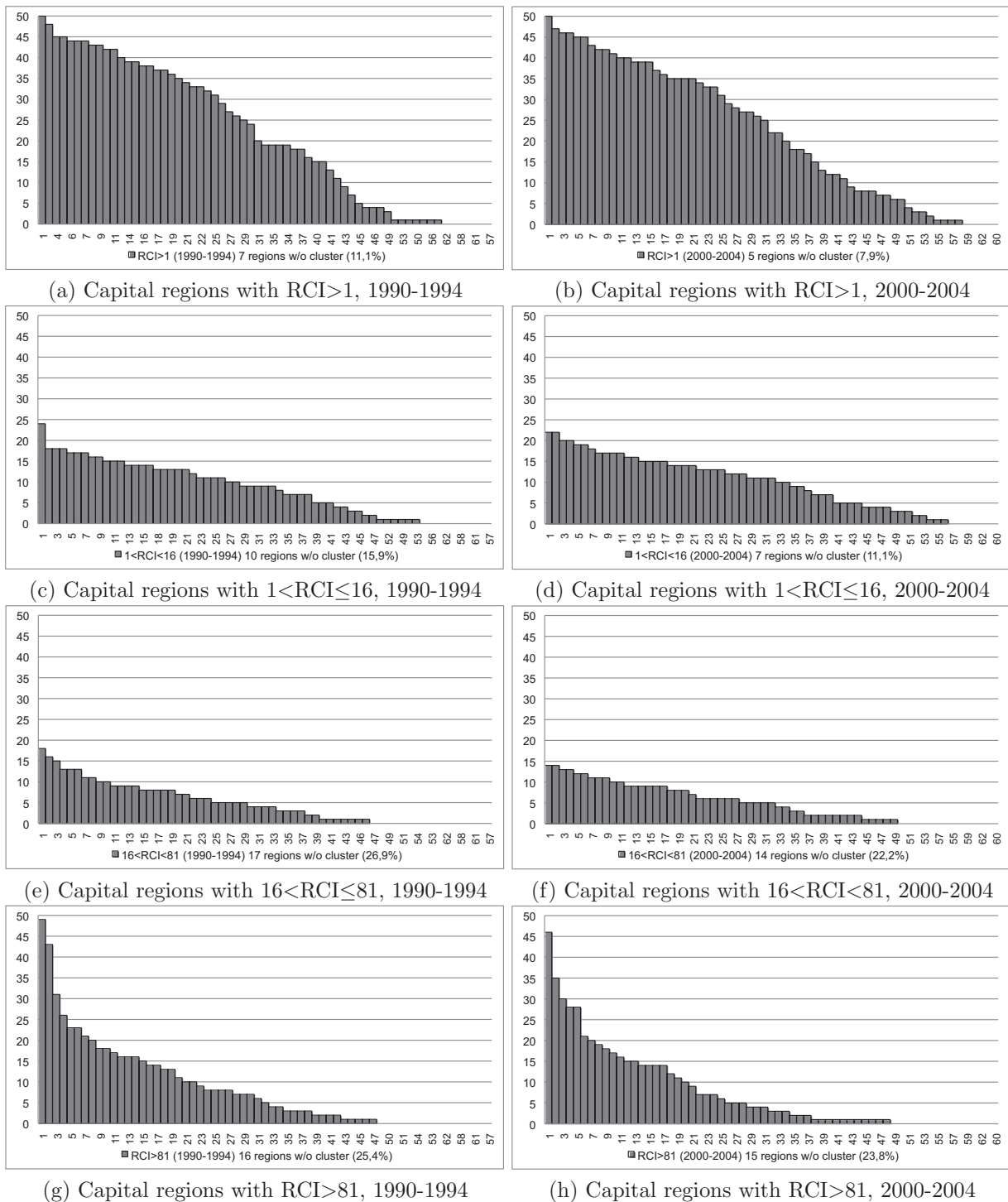


Fig. A.32. Technological diversity, co-agglomeration and clustering in capital regions

Source: own calculations and illustration. *Notes:* Ranking of regions by cumulated number of technology field-specific clusters with $RCI > 1$, $1 < RCI \leq 16$, $16 < RCI \leq 81$ and $RCI > 81$ by region and region type. Each of the 819 European regions can host up to 50 research clusters. Extraction from RegPAT (January 2009); regional typology adapted from OECD (2010) and EUROSTAT (2009).

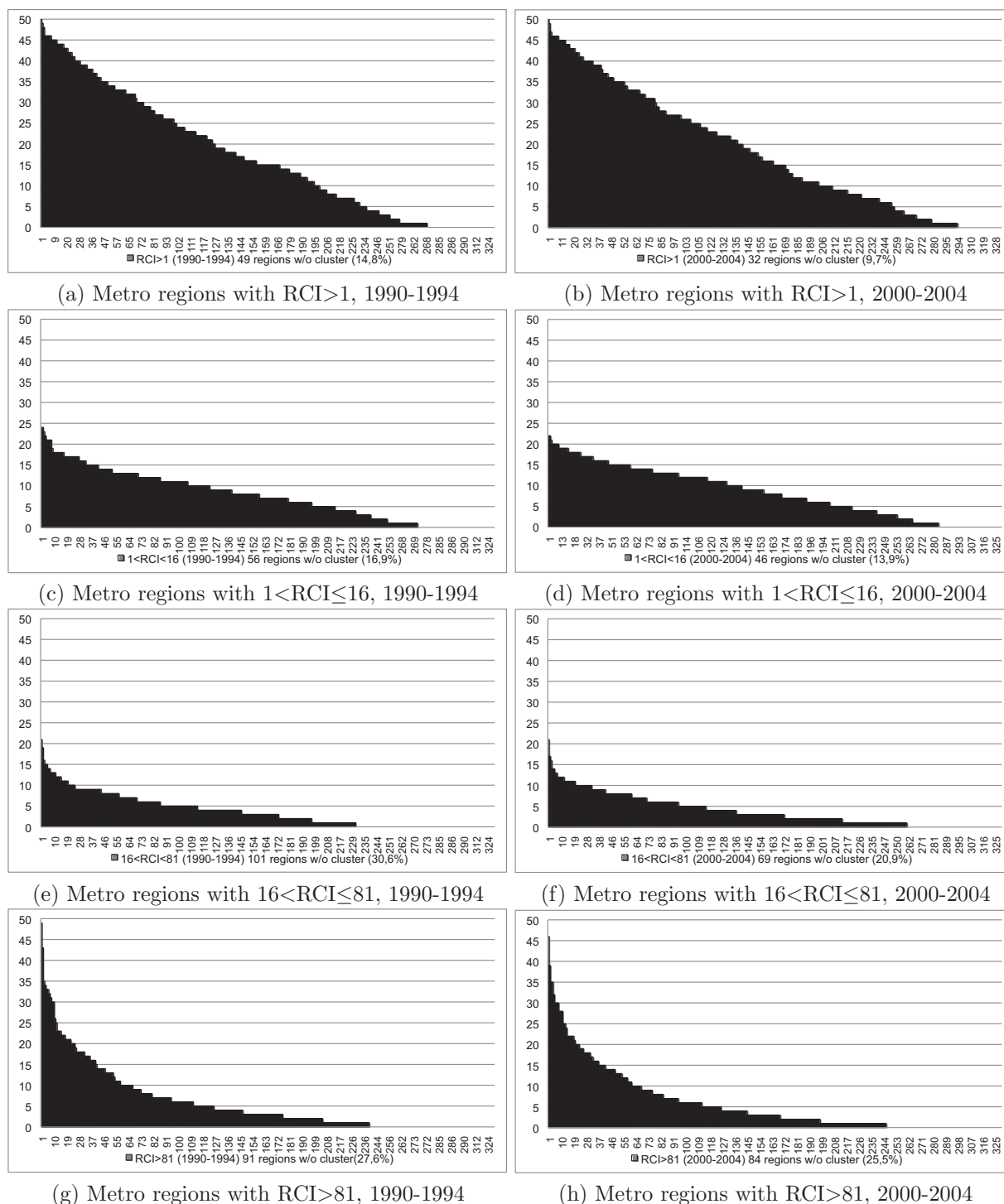


Fig. A.33. Technological diversity, co-agglomeration and clustering in metro regions
Source: own calculations and illustration. *Notes:* Ranking of regions by cumulated number of technology field-specific clusters with $RCI > 1$, $1 < RCI \leq 16$, $16 < RCI \leq 81$ and $RCI > 81$ by region and region type. Each of the 819 European regions can host up to 50 research clusters. Extraction from RegPAT (January 2009); regional typology adapted from OECD (2010) and EUROSTAT (2009).

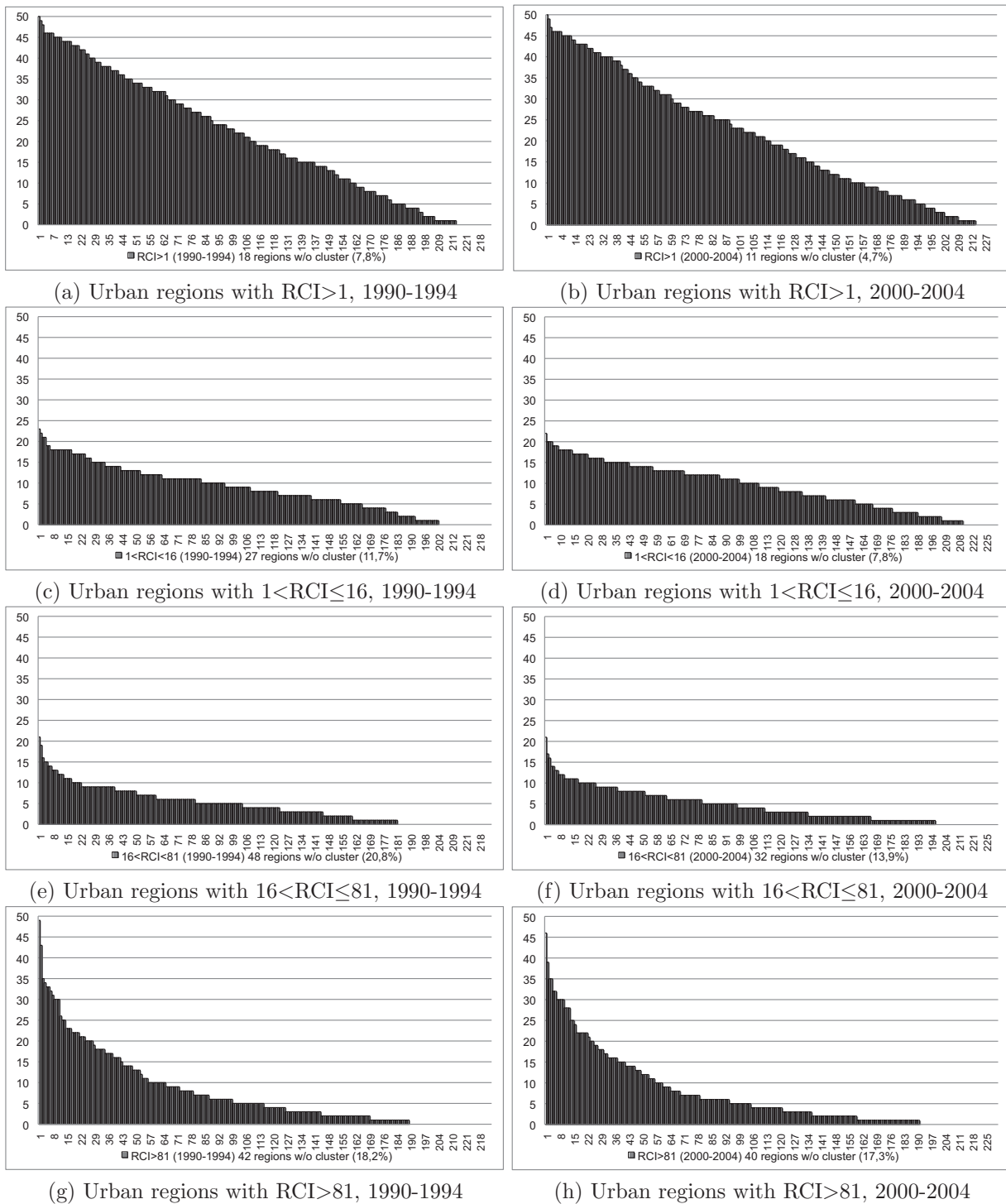
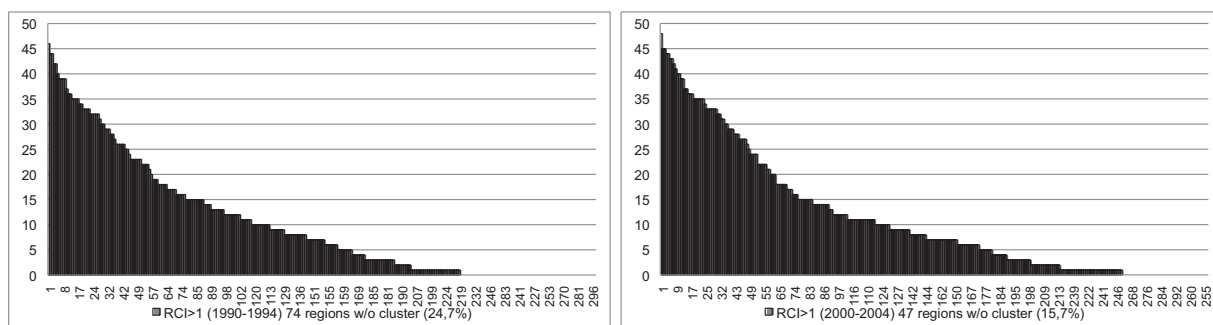


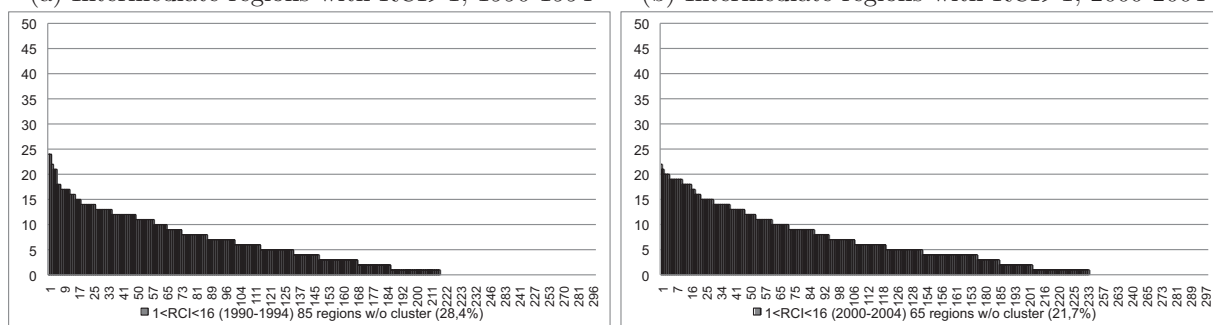
Fig. A.34. Technological diversity, co-agglomeration and clustering in urban regions

Source: own calculations and illustration. *Notes:* Ranking of regions by cumulated number of technology field-specific clusters with $RCI > 1$, $1 < RCI \leq 16$, $16 < RCI \leq 81$ and $RCI > 81$ by region and region type. Each of the 819 European regions can host up to 50 research clusters. Extraction from RegPAT (January 2009); regional typology adapted from OECD (2010) and EUROSTAT (2009).



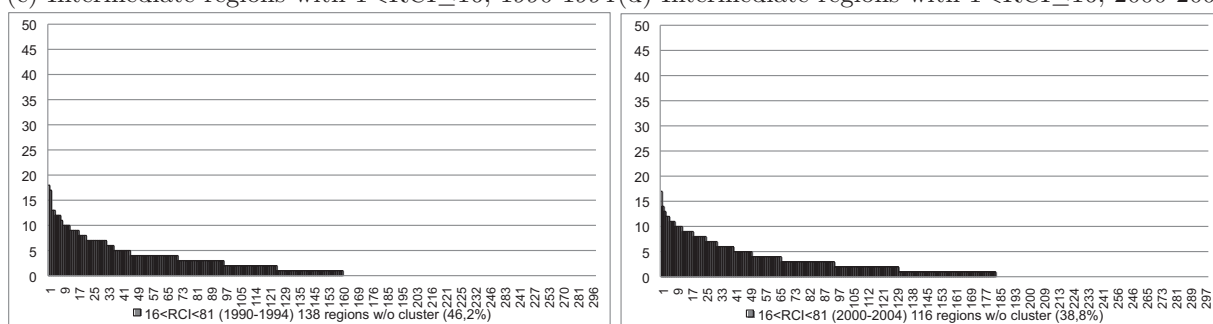
(a) Intermediate regions with $RCI > 1$, 1990-1994

(b) Intermediate regions with $RCI > 1$, 2000-2004



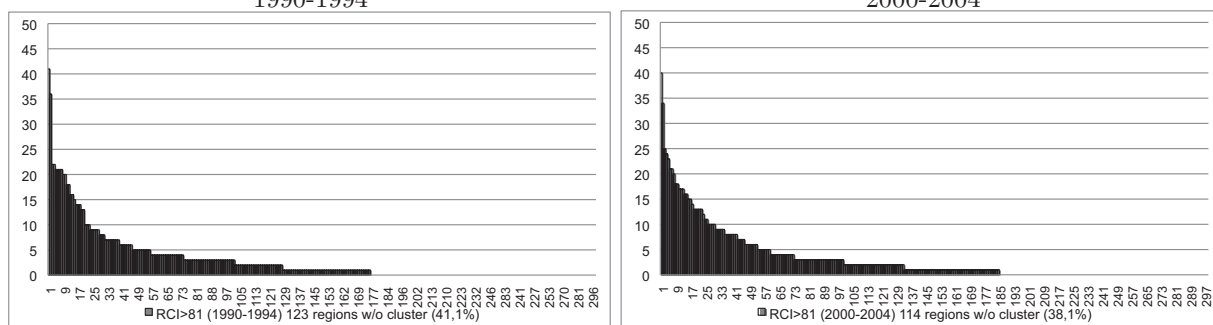
(c) Intermediate regions with $1 < RCI \leq 16$, 1990-1994

(d) Intermediate regions with $1 < RCI \leq 16$, 2000-2004



(e) Intermediate regions with $16 < RCI \leq 81$, 1990-1994

(f) Intermediate regions with $16 < RCI \leq 81$, 2000-2004



(g) Intermediate regions with $RCI > 81$, 1990-1994

(h) Intermediate regions with $RCI > 81$, 2000-2004

Fig. A.35. Technological diversity, co-agglomeration and clustering in intermediate regions
Source: own calculations and illustration. *Notes:* Ranking of regions by cumulated number of technology field-specific clusters with $RCI > 1$, $1 < RCI \leq 16$, $16 < RCI \leq 81$ and $RCI > 81$ by region and region type. Each of the 819 European regions can host up to 50 research clusters. Extraction from RegPAT (January 2009); regional typology adapted from OECD (2010) and EUROSTAT (2009).

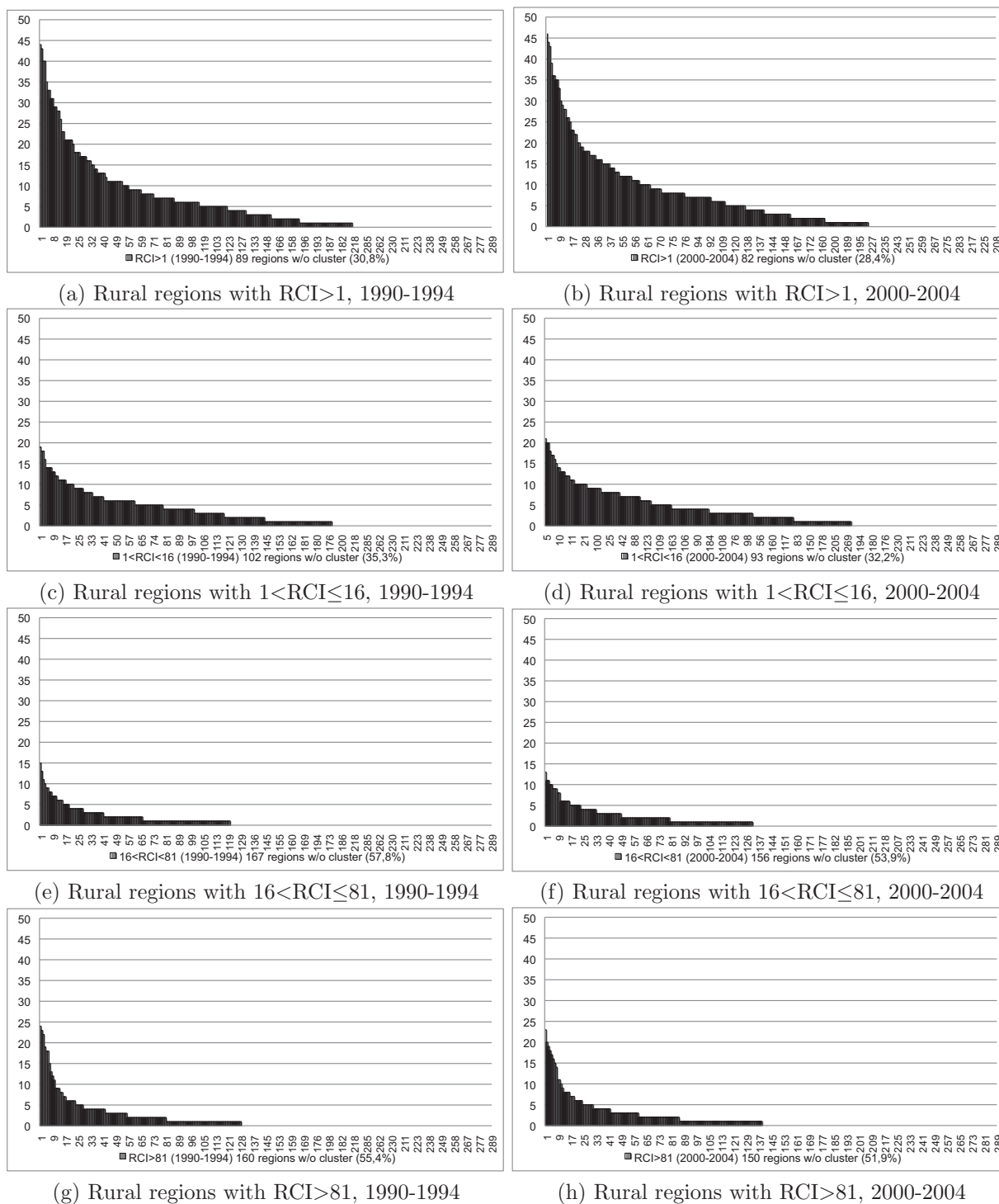


Fig. A.36. Technological diversity, co-agglomeration and clustering in rural regions

Source: own calculations and illustration. *Notes:* Ranking of regions by cumulated number of technology field-specific clusters with $RCI > 1$, $1 < RCI \leq 16$, $16 < RCI \leq 81$ and $RCI > 81$ by region and region type. Each of the 819 European regions can host up to 50 research clusters. Extraction from RegPAT (January 2009); regional typology adapted from OECD (2010) and EUROSTAT (2009).

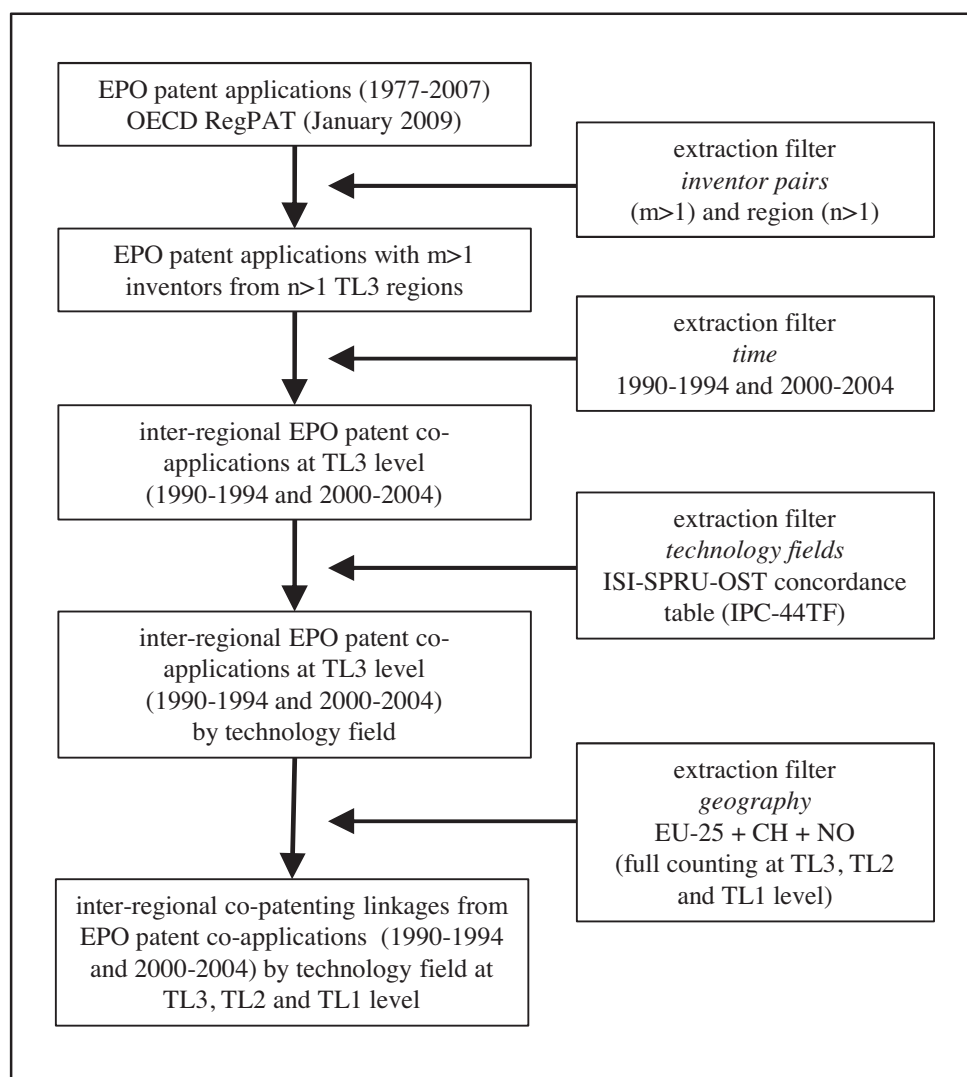


Fig. A.37. Data selection method for inter-regional co-inventorship network analysis
Source: own illustration.

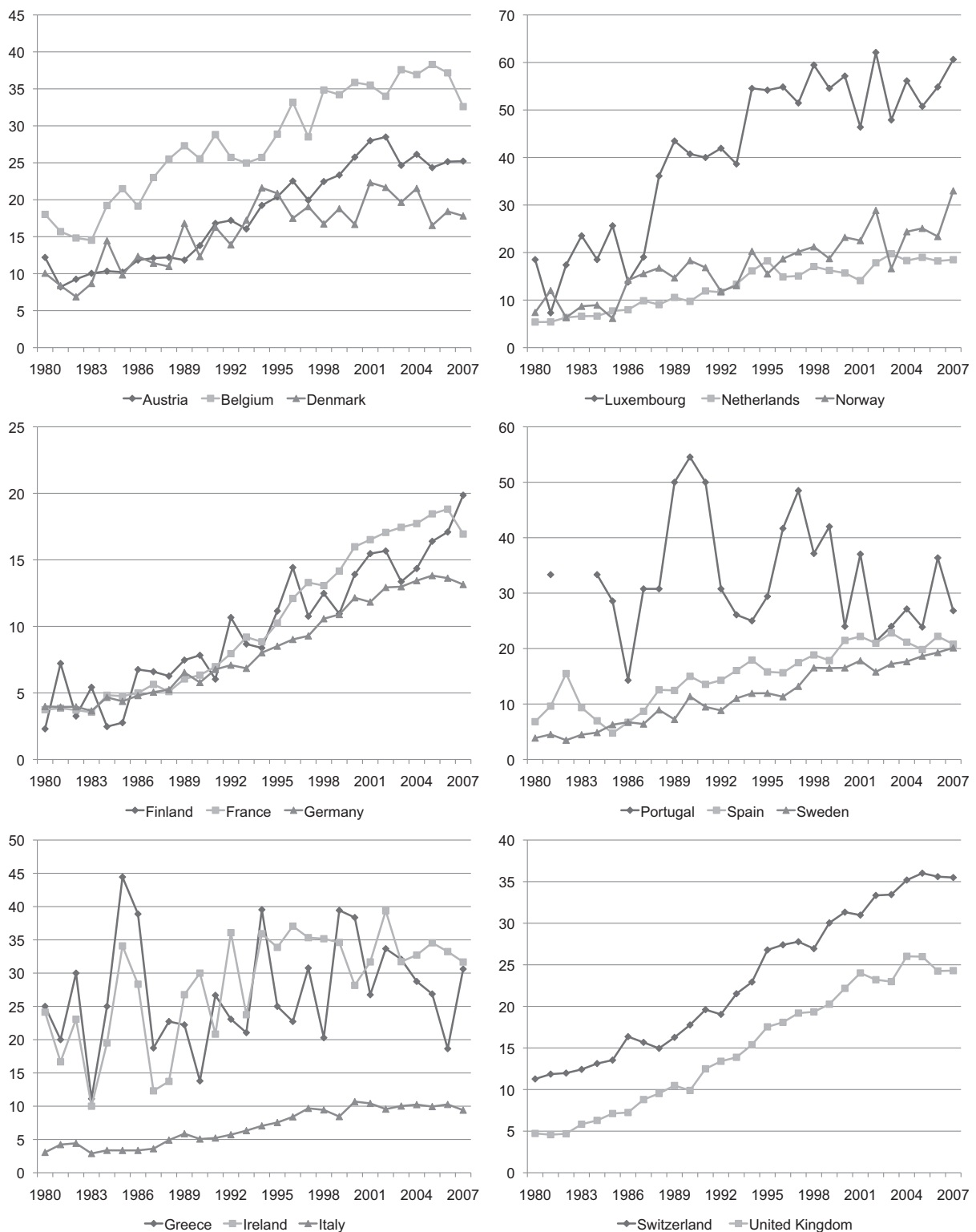


Fig. A.38. Share of EPO patents with foreign co-inventors by country (1)

Source: own calculations and illustration. *Notes:* Share of national EPO patents with foreign co-inventors by country; EU-15 countries, CH and NO, 1980-2007; data extracted from OECD RegPAT (January 2009) and OECD (2009d); fractional counts.

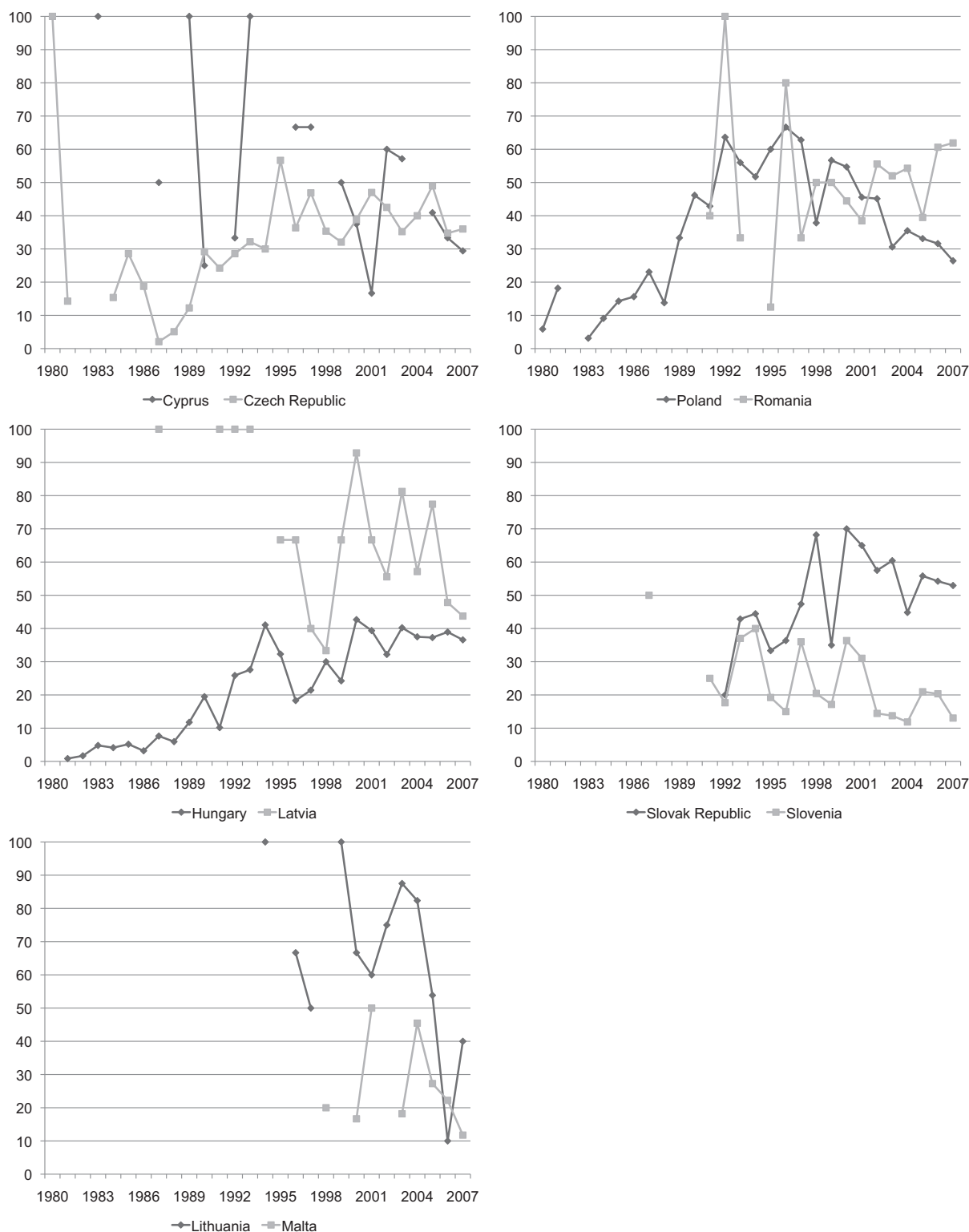


Fig. A.39. Share of EPO patents with foreign co-inventors by country (2)
Source: own calculations and illustration. *Notes:* Share of national EPO patents with foreign co-inventors by country; NMS countries, 1980-2007; data extracted from OECD RegPAT (January 2009) and OECD (2009d); fractional counts.

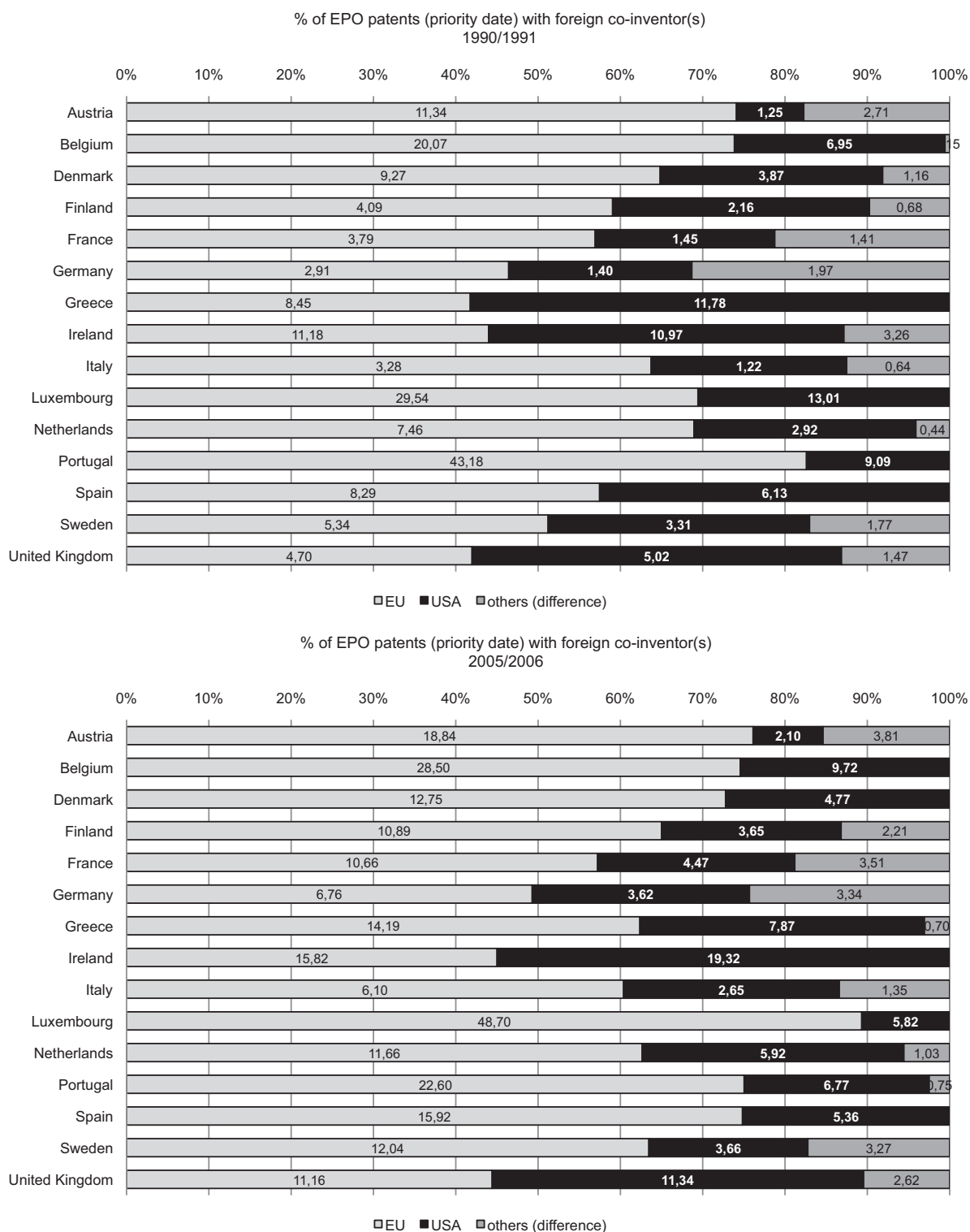


Fig. A.40. Foreign co-inventorship structure by country

Source: own calculations and illustration. *Notes:* Share of EPO patents with foreign co-inventors by country since 1980; co-operations with abroad by aggregate; EU-15, EU-25, NMS and CH and NO; data extracted from OECD RegPAT (January 2009) and OECD (2009d); fractional counts.

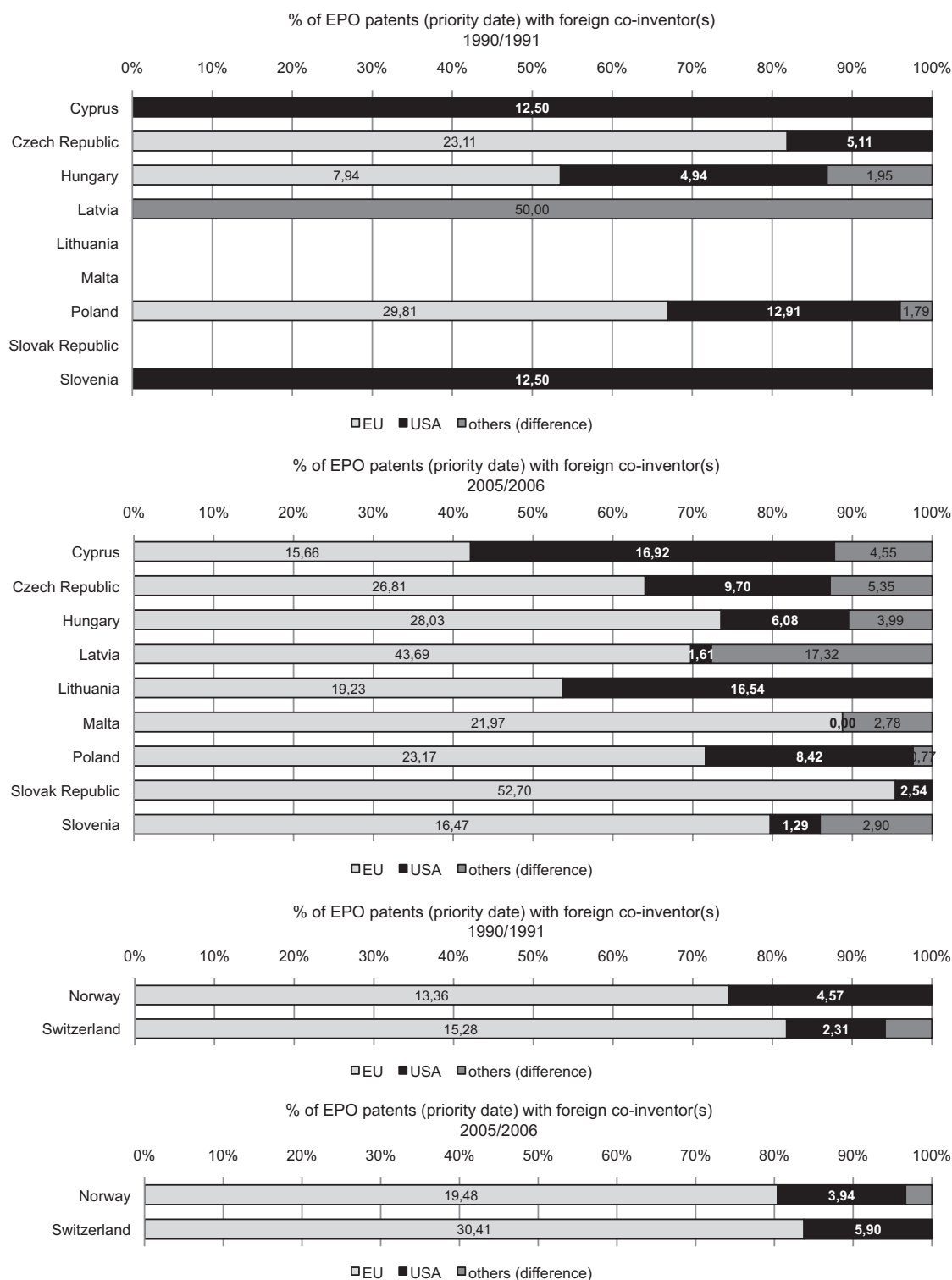


Fig. A.41. Foreign co-inventorship structure by country (cont'd)

Source: own calculations and illustration. *Notes:* Share of EPO patents with foreign co-inventors by country since 1980; co-operations with abroad by aggregate; EU-15, EU-25, NMS and CH and NO; data extracted from OECD RegPAT (January 2009) and OECD (2009d); fractional counts.

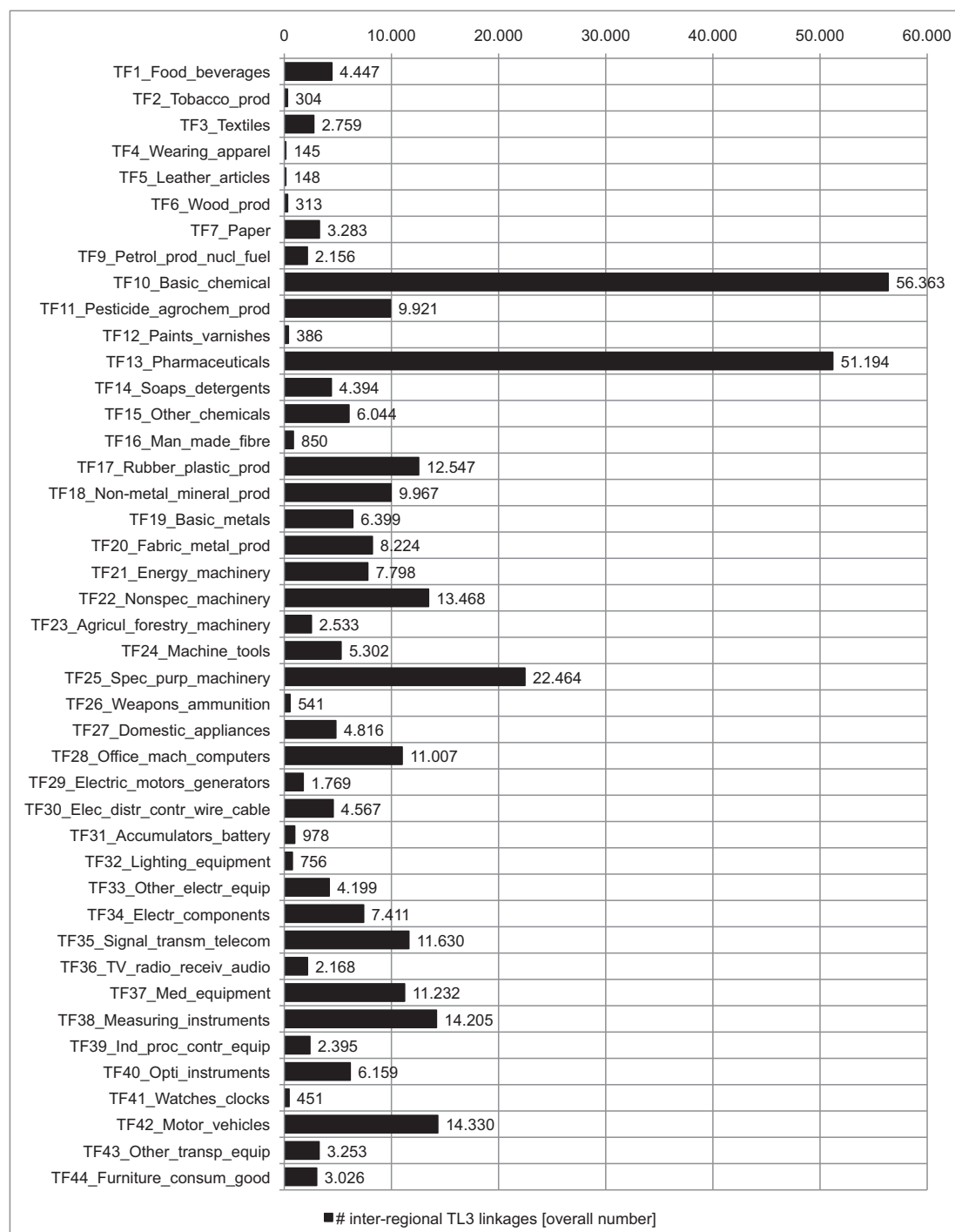


Fig. A.42. Number of European co-patenting network linkages, 1990-1994

Source: own calculations and illustration. *Notes:* Number of linkages by technology-specific co-patenting networks (1990-1994 and 2000-2004).

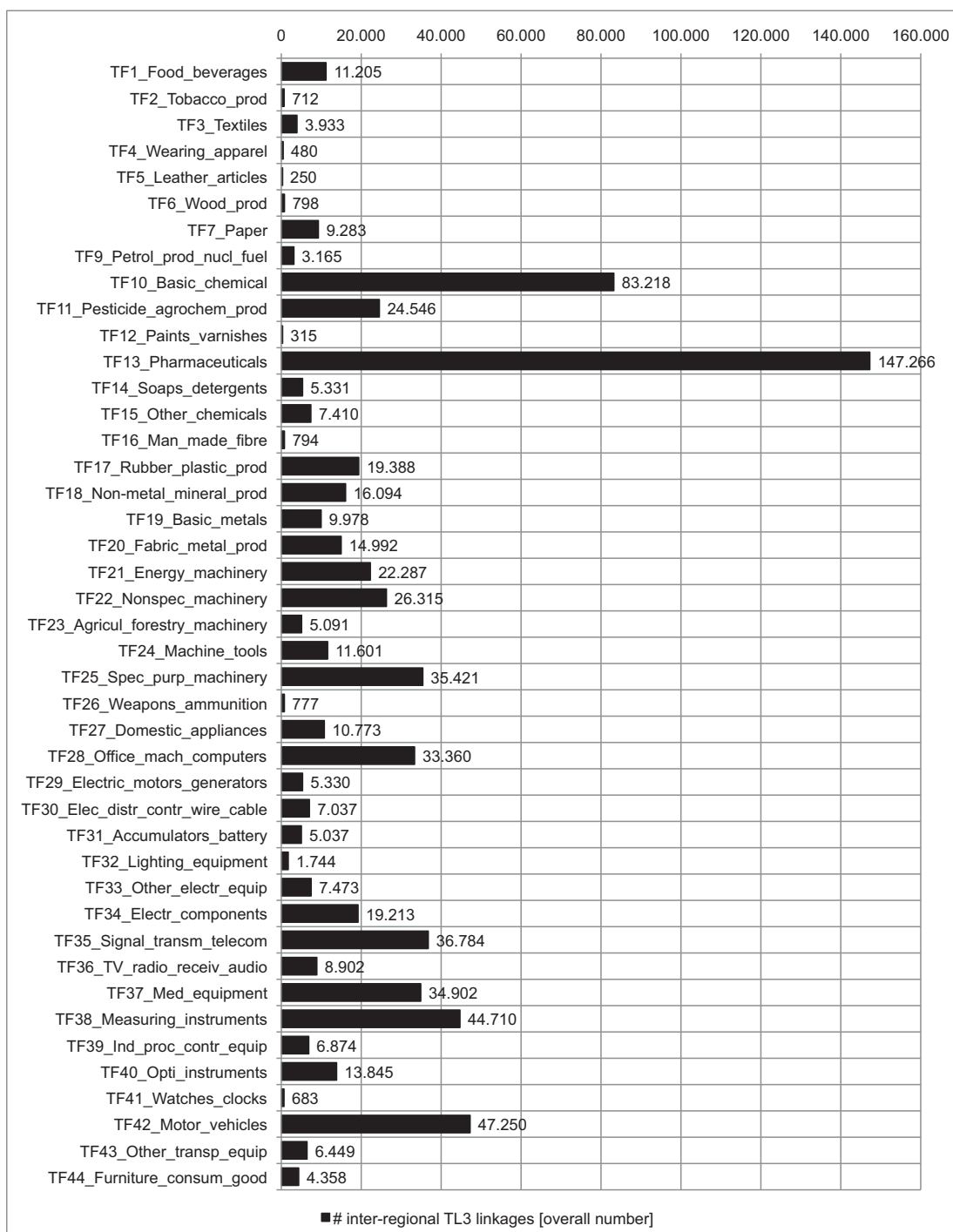


Fig. A.43. Number of European co-patenting network linkages, 2000-2004

Source: own calculations and illustration. Notes: Number of linkages by technology-specific co-patenting networks (1990-1994 and 2000-2004).

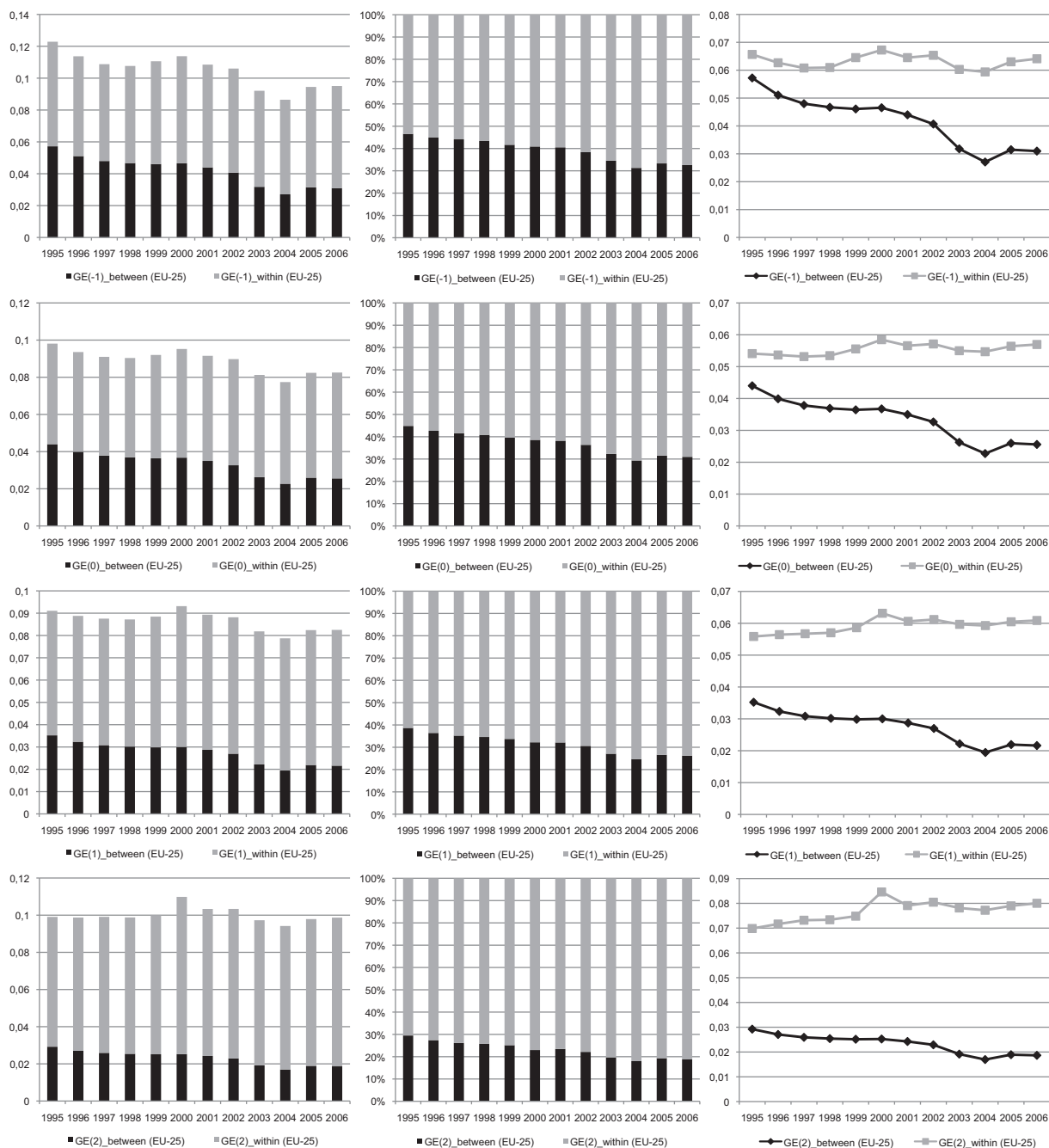
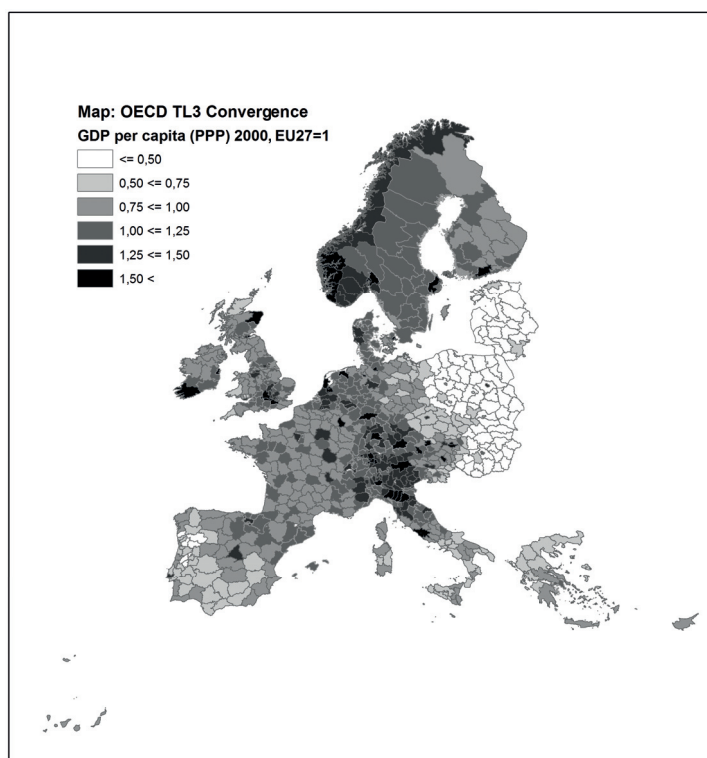
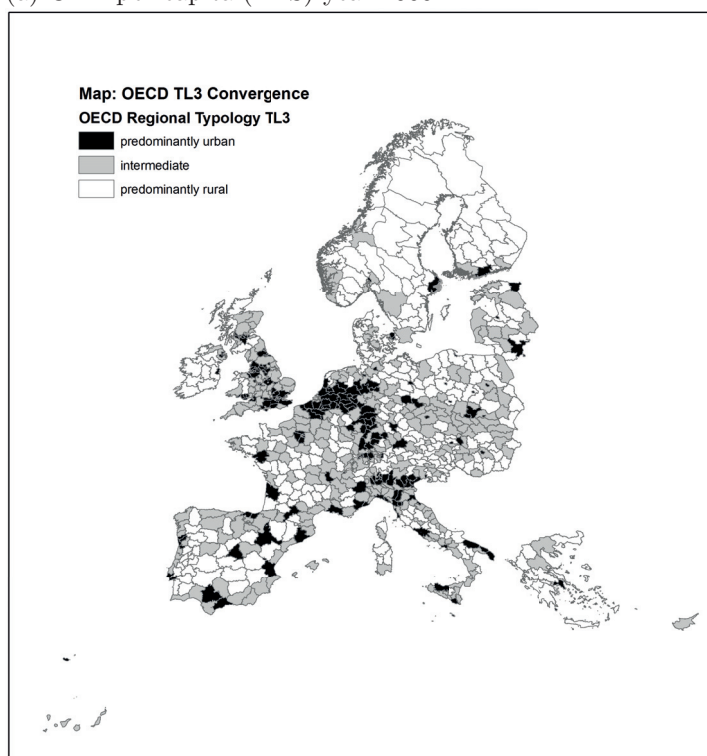


Fig. A.46. Income inequality decomposition: EU-15 vs. NMS

Source: own calculations and illustration. *Notes:* GDP per capita in the EU-15 vs. NMS; Inequality composition is done for GE(-1), GE(0), GE(1), GE(2) and Atkinson indices. Subgroups represented by EU-15 and NMS group IDs.



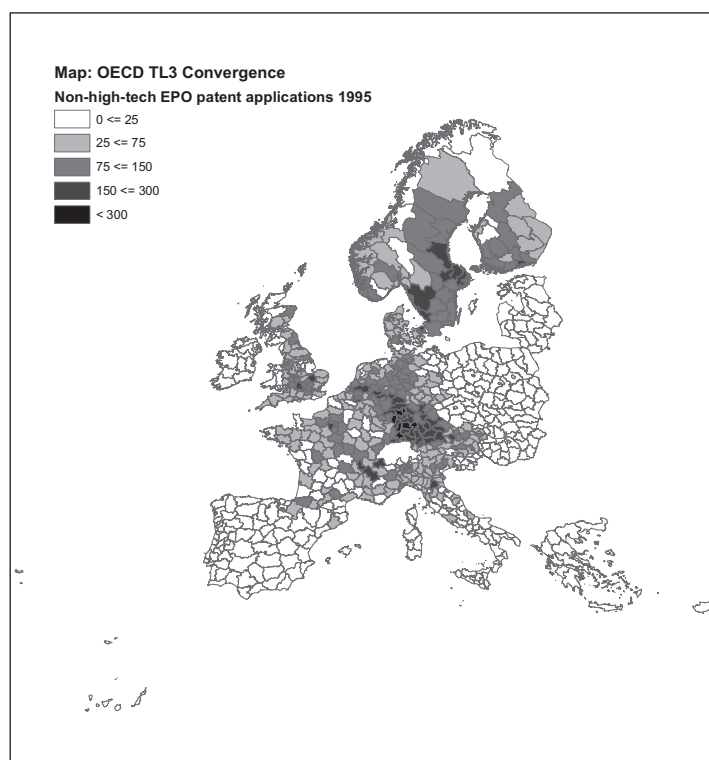
(a) GDP per capita (PPS) year 2000



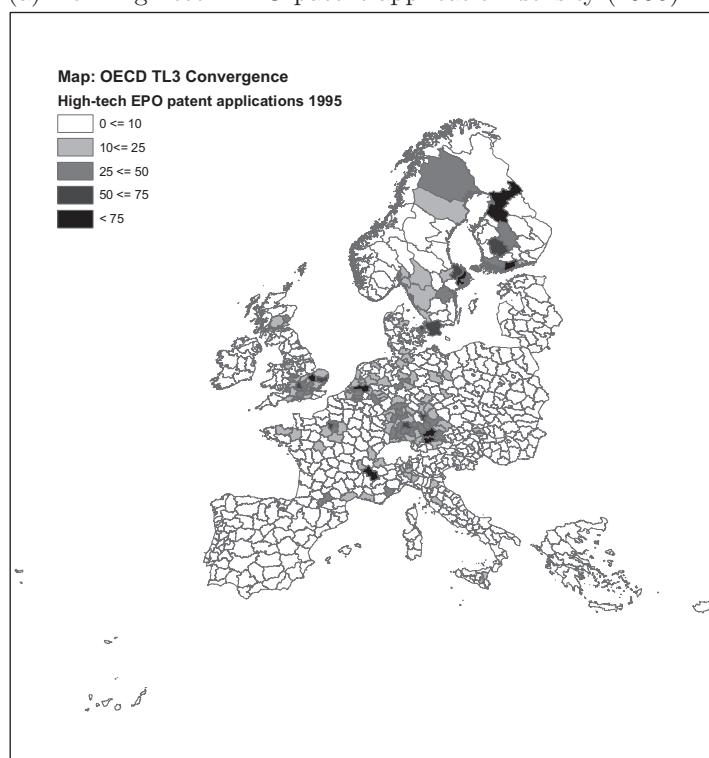
(b) Regional Typology in the year 1995

Fig. A.47. GDP per capita (2000) and Regional Typology

Source: own calculations and illustration. *Notes:* Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.



(a) Non High-tech EPO patent application density (1995)



(b) High-tech EPO patent application density (1995)

Fig. A.48. Patenting Activity in Europe 1995

Source: own calculations and illustration. *Notes:* Shapefile generation and polygon projection with ArcGIS 9.3.1. environment.

B. Appendix: Tables

Table B.1. Overview of studies: patents, innovations, productivity, employment, GDP

Author/Year	Country	MAR	Jacobs	Porter	Spatial Unit	Depend. Var.
Jaffe (1989)†	USA	n.a.	n.a.	n.a.	29 states	innov./patent
Jaffe <i>et al.</i> (1993)‡	USA	n.a.	n.a.	n.a.	states	innov./patent
Acs <i>et al.</i> (1997)†	USA	n.a.	n.a.	n.a.	125 MSA, states	innov. (USSBA)
Audretsch and Feldman (1996)†	USA	(-)	n.a.	n.a.	state	innov. (SBIDB)
Caniëls (1997)	Europe	+	n.a.	n.a.	NUTS1/2	innov./patent
Paci and Usai (1999)	Italy	+	n.a.	+	LMA	innov./patent
Audretsch and Feldman (1999)	USA	-	+	+	MSA/CMSA	innov. (SBIDB)
Combes (2000a)	France	-	+	o	LMA	innov./patent
Bottazzi and Peri (2000)†	Europe	n.a.	n.a.	n.a.	86 NUTS1 regions	innov./patent
Autant-Bernard and Massard (2000)	France	n.a.	n.a.	n.a.	NUTS3	publications
Acs <i>et al.</i> (2002)†	USA	n.a.	n.a.	n.a.	MSA	innov./patent
Massard and Riou (2002)	France	-	n.a.	-	departments	innov./patent
Andersson and Ejermo (2002)†	Sweden	n.a.	n.a.	n.a.	81 regions	innov./patent
Bottazzi and Peri (2003)†	Europe	n.a.	n.a.	n.a.	86 NUTS1 regions	innov./patent
Fischer and Varga (2003)†	Austria	n.a.	n.a.	n.a.	72 political districts	innov./patent
Moreno <i>et al.</i> (2003)†	Europe	+	n.a.	n.a.	138 NUTS1/2	innov./patent
Cabrer-Borras and Serrano-Domingo (2004)	Spain	-	n.a.	o	ZIP code	innov./patent
Acs and Armington (2004)†	USA	n.a.	n.a.	n.a.	MSA/4 US	innov./patent
Moreno <i>et al.</i> (2004)†	Europe	+	n.a.	n.a.	175 NUTS1/2	specialization
Bilbao-Osorio and Rodríguez-Pose (2004)†	Europe	+	n.a.	n.a.	103 NUTS1/2	innov./patent
Greunz (2004)	Europe	+	n.a.	+	153 NUTS2	innov./patent
van der Panne (2004)	Netherlands	+	o	-	98 regions	new products
Greunz (2005)	Europe	+	n.a.	+	NUTS2	innov./patent
Boschma and Weterings (2005)	Netherlands	o	n.a.	-	NUTS3	innov./patent
Andersson and Ejermo (2005)	Sweden	n.a.	+	+	LMA	innov./patent
Fischer <i>et al.</i> (2005)	Europe	n.a.	n.a.	n.a.	188 NUTS1/2	innov./patent
Moreno <i>et al.</i> (2005c)†	Europe	+	n.a.	n.a.	175 NUTS1/2	innov./patent
Fritsch and Slavtchev (2007a)	Germany	+	-	n.a.	327 German Kreise	DPMA patents
OhUallachain and Leslie (2007)	USA	+	(+)	n.a.	50 states	innov./patent
Maggioni <i>et al.</i> (2007)	Europe	-	n.a.	n.a.	109 NUTS 1/2	innov./patent
Crescenzi <i>et al.</i> (2007b)	Europe, USA	(+)	+	n.a.	266 MSA, 96 NUTS	innov./patent
Arancegui <i>et al.</i> (2008)	Spain	-	+	n.a.	20 Basque counties	innov./patent
Usai (2008)†	OECD	n.a.	(+)	n.a.	61-271 regions	innov./patent
Hoekman <i>et al.</i> (2008)	Europe	n.a.	n.a.	n.a.	1319 NUTS3	innov./patent
Hauser <i>et al.</i> (2008)†	Europe	n.a.	n.a.	n.a.	49/51 NUTS1	innov./patent
Andersson and Gräsjö (2009)†	Sweden	n.a.	n.a.	n.a.	municipalities	innov./patent
Glaeser <i>et al.</i> (1992)	USA	-	+	+	SMA, 170 cities	employment
Bradley and Gans (1998)	Australia	n.a.	n.a.	-	cities	employment
Sjöholm (1998)	Indonesia	o	o	+	districts/provinces	productivity
Partridge and Rickman (1999)	USA	+	n.a.	+	states	productivity
Staber (2001)	Germany	+	n.a.	-	10km distance	other
Rosenthal and Strange (2001)	USA	+	n.a.	n.a.	ZIP, county, state	productivity
Dekle (2002)	Japan	-	o	o	prefectures	empl./ prod.
Batisse (2002)	China	-	o	+	provinces	other
Rosenthal and Strange (2003)	USA	+	o	-	ZIP regions	empl./ other
King <i>et al.</i> (2003)	USA	-	+	o	states	employment
Eckey <i>et al.</i> (2004)	Germany	n.a.	n.a.	n.a.	180LLS	output
Viladecans-Marsal (2004)	Spain	+	+	n.a.	cities	empl.
Atzema and van Oort (2004)	Netherlands	+	+	+	municipalities	other
Boix and Trullén (2004)	Spain	+	+	n.a.	cities	empl.
van der Panne (2004)	Netherlands	+	-	o	provinces	productivity
Mukkala (2004)	Finland	+	n.a.	n.a.	NUTS4	productivity
Malpezzi <i>et al.</i> (2004)	USA	n.a.	n.a.	+	SMA	others
Combes <i>et al.</i> (2004)	France	n.a.	o	+	MSA	others
Acs and Armington (2004)	USA	-	o	n.a.	LMA	employment
Autant-Bernard and Massard (2007)a	France	n.a.	n.a.	n.a.	plants	sales
Blien and Suedekum (2005)	Germany	+	n.a.	+	438 NUTS3	employment
Crescenzi and Rodríguez-Pose (2006)a	Europe	n.a.	n.a.	n.a.	NUTS1/2	GDP
Sonobe and Otsuka (2006)	Taiwan	o	n.a.	o	township	employment

Source: own illustration. *Notes:* Table highlights selected studies and is not exhaustive; effects: positive effect (+), negative effect (-), not significant (o); not analyzed (n.a.); †: MAR, Jacobs or Porter not focus of KPF estimation; ‡: patent citation analysis.

Table B.2. SQL database structure

FILE 1: EP_APPLT_REG (EPO applicant)	FILE 2: EP_INVNT_REG (EPO inventorship)
2.126.580 hits	4.897.220 hits
Applt_id (applicant ID)	Invnt_id (inventor ID)
Appln_nr (patent application nr.)	Appln_nr (patent application nr.)
Reg_code (NUTS3 region code)	Reg_code (NUTS3 region code)
Address	Address
Ctry_code (country code)	Ctry_code (country code)
Reg_share (share ≤ 1)	Reg_share (share ≤ 1)
Applt_share (applicant share ≤ 1)	Invnt_share (inventor share ≤ 1)
FILE 3: EP_PRIO_IPC (YEAR, IPC)	FILE 4: RegPAT_REGIONS (Concordance)
9.521.012 hits	Ctry_code (Country)
Appln_nr (patent application nr.)	Up_level_code (NUTS2 level code)
Appn_year (filing year)	Up_level_label (macro level region's name)
Prio_year (priority year of first filing)	Reg_code (NUTS3 level code)
IPC (IPC classes)	Reg_label (micro level region's name)
FILE 5: IPC Concordance	
IPC fields vs. 43 technology fields	
IPC fields vs. 6 high-technology fields	

Source: own illustration based on OECD RegPAT (January 2009). *Notes:* The relational database covers 819 OECD TL3 regions. Inventor counting is based on full counting method. IDs are counted several times if inventor IDs correspond to several technology fields.

Table B.3. RegPAT and the NUTS3/TL3 classification

Ctry.	Label	Micro-Region (NUTS3)	Micro-Region (TL3)	Meso-Region (NUTS2)	Macro-Region (NUTS1)	Inventor address
AT	Austria	35 NUTS3	35 TL3	9 NUTS2	3 NUTS1	43.084
BE	Belgium	43 NUTS3	11 TL3	11 NUTS2	3 NUTS1	48.362
CH	Switzerland	26 NUTS3	26 TL3	7 NUTS2	7 NUTS1	105.939
CY	Cyprus	1 NUTS3	1 TL3	1 NUTS2	1 NUTS1	168
CZ	Czech Republic	14 NUTS3	14 TL3	8 NUTS2	8 NUTS1	2.956
DE	Germany	439 NUTS3	97 TL3	41 NUTS2	16 NUTS1	940.797
DK	Denmark	15 NUTS3	15 TL3	1 NUTS2	1 NUTS1	32.851
EE	Estonia	5 NUTS3	5 TL3	1 NUTS2	1 NUTS1	323
ES	Spain	52 NUTS3	52 TL3	19 NUTS2	7 NUTS1	25.689
FI	Finland	20 NUTS3	20 TL3	5 NUTS2	4 NUTS1	47.212
FR	France	100 NUTS3	100 TL3	26 NUTS2	9 NUTS1	302.475
GR	Greece	51 NUTS3	13 TL3	13 NUTS2	4 NUTS1	2061
HU	Hungary	20 NUTS3	20 TL3	7 NUTS2	3 NUTS1	12.719
IE	Ireland	8 NUTS3	8 TL3	2 NUTS2	2 NUTS1	8.021
IT	Italy	103 NUTS3	103 TL3	21 NUTS2	5 NUTS1	125.173
LT	Lithuania	10 NUTS3	10 TL3	1 NUTS2	10 NUTS1	309
LU	Luxembourg	1 NUTS3	1 TL3	1 NUTS2	1 NUTS1	2.923
LV	Latvia	6 NUTS3	6 TL3	1 NUTS2	6 NUTS1	360
MT	Malta	2 NUTS3	1 TL3	1 NUTS2	2 NUTS1	106
NL	Netherlands	40 NUTS3	12 TL3	12 NUTS2	4 NUTS1	95.286
NO	Norway	19 NUTS3	19 TL3	7 NUTS2	7 NUTS1	15.691
PL	Poland	45 NUTS3	45 TL3	16 NUTS2	6 NUTS1	3.809
PT	Portugal	30 NUTS3	30 TL3	7 NUTS2	3 NUTS1	1.433
SE	Sweden	21 NUTS3	21 TL3	8 NUTS2	8 NUTS1	86.369
SI	Slovenia	12 NUTS3	12 TL3	1 NUTS2	12 NUTS1	1.939
SK	Slovak Republic	8 NUTS3	8 TL3	4 NUTS2	4 NUTS1	731
UK	United Kingdom	133 NUTS3	133 TL3	37 NUTS2	12 NUTS1	237.390
Σ	27 NUTS0	1259 NUTS3	819 TL3	268 NUTS2	149 NUTS1	2.144.176

Source: own illustration based on OECD RegPAT (January 2009). *Notes:* The relational database covers 819 OECD TL3 micro regions. For Belgium, Greece and the Netherlands, the OECD TL3 corresponds to the EUROSTAT NUTS2 level. For Germany, 97 “Raumordnungsregionen” are used (OECD, 2003).

Table B.4. IPC - technology field concordance

No.	Field Name (Technology)	IPC Subclasses
TF1	Food, beverages	A01H, A21D, A23B, A23C, A23D, A23F, A23G, A23J, A23K, A23L, A23P, C12C, C12F, C12G, C12H, C12I, C13F, C13I, C13K
TF2	Tobacco products	A24B, A24D, A24F
TF3	Textiles	D04D, D04G, D04H, D06C, D06I, D06M, D06N, D06F, D06Q
TF4	Wearing apparel	A41B, A41C, A41D, A41F
TF5	Leather articles	A43B, A43C, B68B, B68C
TF6	Wood products	B27D, B27H, B27M, B27N, B04G
TF7	Paper	B41M, B42D, B42F, B44F, D21C, D21H, D21J
TF9	Petroleum products, nuclear fuel	C10G, C10L, G01V
TF10	Basic chemical	B01J, B09B, B09C, B29B, C01B, C01C, C01D, C01F, C01G, C02F, C05B, C08C, C08D, C08F, C08G, C08I, C08K, C08L, C09B, C09C, C09D, C09K, C10B, C10C, C10K, C10L, C10K, C12S, C25B, F17C, F17D, F25J, G21F
TF11	Pesticides & agro-chemical prod.	A01N
TF12	Paints, varnishes	B27K
TF13	Pharmaceuticals	A61K, A61P, C07D, C07H, C07K, C12N, C12P, C12Q
TF14	Soaps & detergents	C09F, C11D, D06L
TF15	Other chemicals	A62D, C06B, C06C, C06D, C08H, C09G, C09H, C09I, C10M, C11C, C14C, C23F, C23G, D01C, F42B, F42D, G03C
TF16	Man-made fibres	D01F
TF17	Rubber and plastics products	A45C, B29C, B29D, B60C, B65D, B67D, E02B, F16L, H02G
TF18	Non-metallic mineral products	B24D, B28B, B28C, B32B, C03C, C04B, E04B, E04C, E04D, E04F, G21B
TF19	Basic metals	B21C, B21G, B22D, C21B, C21C, C21D, C22B, C22C, C22F, C25C, C25F, C30B, D07B, E03F, E04H, F27D, H01B
TF20	Fabricated metal products	A01L, A44B, A47K, B21K, B21L, B22F, B25B, B25C, B25F, B25H, B26B, B27G, B44C, B65F, B82B, C23D, C25D, E01D, E01F, E02C, E03B, E03C, E05B, E05C, E05D, E05F, E05G, E06B, F01K, F15D, F16B, F16F, F16S, F16T, F17B, F22B, F22G, F24I, G21H
TF21	Energy machinery	B23F, F01B, F01C, F03D, F03C, F03D, F04B, F04C, F04D, F15B, F16C, F16D, F16F, F16H, F16K, F16M, F23R
TF22	Non-specific purpose machinery	A62C, B01D, B04C, B05B, B61B, B65G, B66B, B66C, B66D, B66F, C10F, C12L, F16G, F22D, F23B, F23C, F23D, F23G, F23H, F23J, F23K, F23L, F23M, F24F, F24H, F25B, F27B, F28B, F28C, F28D, F28F, F28G, G01G, H05F
TF23	Agricultural & forestry mach.	A01B, A01C, A01D, A01F, A01G, A01J, A01K, A01M, B27L
TF24	Machine-tools	B21D, B21H, B21J, B23B, B23C, B23D, B23G, B23K, B23P, B23Q, B24B, B24C, B24D, B25D, B25I, B26F, B27B, B27C, B27E, B27I, B28D, B30B, E21C
TF25	Special purpose machinery	A21C, A22B, A22C, A23N, A24C, A41H, A42C, A43D, B01F, B02B, B02C, B03B, B03C, B03D, B05C, B05D, B06B, B07B, B07C, B08B, B21B, B22C, B26D, B31D, B31C, B31E, B41B, B41C, B41D, B41F, B41G, B41H, B42B, B42C, B44B, B65B, B65C, B65D, B67C, B68F, C13C, C13D, C13G, C13H, C14B, C23C, D01B, D01D, D01G, D01H, D02G, D02H, D02I, D03C, D03D, D03J, D04B, D04C, D05B, D05C, D06B, D06G, D06H, D21B, D21D, D21F, D21G, E01C, E02D, E02F, E21B, E21D, E21F, F04F, F16N, F26B, H05H
TF26	Weapons and ammunition	B65G, F41A, F41B, F41C, F41F, F41H, F41J, F42C, G21J
TF27	Domestic appliances	A21B, A45D, A47G, A47I, A47L, B01B, D06F, E06C, F23N, F24B, F24C, F24D, F25C, F25D, H05B
TF28	Office machinery and computers	B41J, B41K, B43M, G02F, G03G, G03F, G06C, G06D, G06E, G06F, G06G, G06H, G06K, G06M, G06N, G06T, G07B, G07C, G07D, G07E, G07G, G09D, G09G, G10L, G11B, H03K, H03L
TF29	Electric motors, generators	H02K, H02N, H02P
TF30	Electric distribution, control, wire, cable	H01H, H01R, H02B
TF31	Accumulators, battery	H01M
TF32	Lighting equipment	F21H, F21K, F21L, F21M, F21S, F21V, H01K
TF33	Other electrical equipment	B60M, B61L, F21P, F21Q, G08B, G08G, G10K, G12C, G21D, H01T, H02H, H02M, H05C
TF34	Electronic components	B81B, B81C, G11C, H01C, H01F, H01G, H01J, H01L
TF35	Signal transmission, telecomms	G09B, G09C, H01P, H01Q, H01S, H02J, H03B, H03C, H03D, H03F, H03G, H03H, H04B, H04C, H04E, H04H, H04S
TF36	TV & radio receivers, audiovisual electronics	G03H, H03J, H04H, H04N, H04R, H04S
TF37	Medical equipment	A61B, A61C, A61D, A61F, A61G, A61H, A61J, A61L, A61M, A61N, A62B, B01L, B04B, C12M, G01T, G21G, G21K, H05G
TF38	Measuring instruments	F15C, G01B, G01C, G01D, G01F, G01H, G01I, G01M, G01N, G01R, G01S, G01W, G12B
TF39	Industrial process control equip.	G01K, G01L, G05B, G08C
TF40	Optical instruments	G02B, G02C, G03B, G03D, G03F, G09F
TF41	Watches, clocks	G04B, G04C, G04D, G04F, G04G
TF42	Motor vehicles	B60B, B60D, B60G, B60H, B60I, B60K, B60L, B60N, B60P, B60Q, B60R, B60S, B60T, B62D, E01H, F01L, F01M, F01N, F01P, F02B, F02D, F02F, F02G, F02M, F02N, F02P, F16I, G01P, G05D, G05G
TF43	Other transport equipment	B60F, B60V, B61C, B61D, B61F, B61G, B61H, B61J, B61K, B62C, B62H, B62I, B62K, B62L, B62M, B63B, B63C, B63H, B63J, B64B, B64C, B64D, B64E, B64G, B64H, F02C, F02K, F03H
TF44	Furniture, consumer goods	A41G, A42B, A44C, A45B, A45F, A46B, A46D, A47B, A47C, A47D, A47E, A63B, A63C, A63G, A63H, A63I, A63K, B43L, B44D, B62B, B68G, C06F, F23Q, G10B, G10C, G10D, G10F, G10G, G10H
HT1	Aviation	B64B, B64C, B64D, B64F, B64G
HT2	Computers and automated business equipment	B41J, G06C, G06D, G06E, G06F, G06G, G06I, G06K, G06M, G06N, G06T, G11C
HT3	Lasers	H01S
HT4	Semiconductors	H01L
HT5	Communication technology	H04B, H04H, H04J, H04K, H04L, H04M, H04N, H04Q, H04R, H04S
HT6	Micro-organism and genetic engineering	C12M, C12N, C12P, C12Q

Source: own illustration based on Schmoech *et al.* (2003) and EUROSTAT (2009).

Table B.5. Distance weights and spatial lags

Distance concept	conceptualization	neighboring effects
Polygon contiguity distance	units that share edges and/or corners of polygons	first-, second-, third-, nth-order neighborhood (row-standardization)
Fixed distance bands	specified critical distance in miles, kilometers, travel time (minutes); first-, second-, nth-order distance band	units inside the distance band are recognized (row-standardization); threshold distance guarantees at least one neighbor
k-nearest neighbors	k is a predefined number of neighbors	every unit has k neighboring units with the same (unweighted) influence (row-standardization)
Inverse distance	distance decay effects (miles, kilometers, travel time)	every unit is recognized to effect all other units; influence decreases with distance

Source: illustration based on Anselin and Florax (1995), Anselin (2006), Anselin (2007) and Andersson and Gråsjö (2009). *Notes:* The table summarizes the basic classifications of distance matrices but is not necessarily exhaustive.

Table B.6. Research clusters by TF and country with $RCI > 1$, 1990-1994

Technology Field	AT	BE	CH	CY	CZ	DE	DK	EE	ES	FI	FR	GR	HU	IE	IT	LT	LU	LV	MT	NL	NO	PL	PT	SE	SI	SK	UK	Σ
TF1 Food beverages	3%	3%	8%	0%	0%	22%	5%	0%	0%	2%	18%	0%	1%	0%	7%	0%	0%	0%	0%	5%	1%	0%	0%	1%	0%	0%	22%	100%
TF2 Tobacco prod	3%	2%	11%	0%	0%	25%	1%	0%	4%	0%	9%	0%	0%	1%	8%	0%	0%	0%	0%	3%	0%	0%	0%	2%	0%	0%	31%	100%
TF3 Textiles	4%	4%	8%	0%	0%	29%	4%	0%	1%	2%	11%	0%	0%	0%	10%	0%	1%	0%	0%	1%	0%	1%	0%	1%	0%	0%	24%	100%
TF4 Wearing apparel	5%	2%	9%	0%	0%	21%	5%	0%	1%	1%	15%	0%	0%	1%	11%	0%	0%	0%	0%	4%	1%	0%	0%	7%	0%	0%	17%	100%
TF5 Leather articles	11%	0%	6%	0%	0%	28%	2%	0%	2%	0%	14%	0%	1%	0%	20%	0%	0%	0%	0%	2%	1%	0%	0%	3%	0%	0%	10%	100%
TF6 Wood prod	7%	2%	5%	0%	0%	27%	5%	0%	2%	3%	15%	0%	0%	1%	7%	0%	0%	0%	0%	4%	1%	0%	0%	6%	0%	0%	12%	100%
TF7 Paper	5%	2%	9%	0%	0%	22%	3%	0%	1%	6%	11%	0%	1%	1%	4%	0%	0%	0%	0%	3%	1%	0%	1%	5%	1%	0%	26%	100%
TF9 Petrol prod. nucl. fuel	5%	2%	4%	0%	1%	25%	3%	0%	0%	2%	17%	1%	0%	1%	6%	0%	1%	0%	0%	3%	5%	1%	0%	2%	0%	0%	23%	100%
TF10 Basic chemical	3%	3%	13%	0%	0%	27%	2%	0%	0%	2%	11%	0%	1%	0%	6%	0%	0%	0%	0%	5%	2%	0%	0%	1%	0%	0%	25%	100%
TF11 Pesticide agrochem prod	2%	4%	9%	0%	0%	18%	3%	0%	1%	2%	15%	1%	1%	0%	3%	0%	0%	0%	0%	3%	0%	1%	0%	0%	0%	0%	37%	100%
TF12 Paints, varnishes	3%	1%	3%	0%	1%	36%	6%	0%	1%	7%	11%	0%	0%	0%	5%	0%	0%	0%	0%	5%	0%	0%	0%	9%	0%	0%	11%	100%
TF13 Pharmaceuticals	4%	3%	10%	0%	0%	20%	2%	0%	0%	1%	11%	0%	2%	1%	7%	0%	0%	0%	0%	5%	1%	1%	0%	2%	0%	0%	30%	100%
TF14 Soaps, detergents	2%	8%	6%	0%	0%	21%	5%	0%	1%	0%	11%	0%	0%	0%	8%	0%	1%	0%	0%	3%	0%	0%	0%	1%	0%	0%	33%	100%
TF15 Other chemicals	3%	4%	12%	0%	0%	27%	2%	0%	1%	1%	14%	0%	1%	1%	2%	0%	0%	0%	1%	2%	1%	0%	0%	3%	0%	0%	27%	100%
TF16 Man made fibre	6%	2%	6%	0%	0%	30%	2%	0%	0%	4%	9%	0%	0%	0%	13%	0%	1%	0%	0%	4%	0%	2%	0%	0%	0%	0%	21%	100%
TF17 Rubber, plastic prod	6%	2%	9%	0%	0%	25%	3%	0%	0%	2%	13%	0%	0%	0%	8%	0%	0%	0%	0%	3%	2%	0%	0%	3%	0%	0%	23%	100%
TF18 Non-metal mineral prod	7%	3%	10%	0%	0%	27%	3%	0%	0%	3%	12%	0%	0%	0%	6%	0%	0%	0%	0%	3%	1%	0%	0%	3%	0%	0%	22%	100%
TF19 Basic metals	7%	3%	10%	0%	0%	24%	2%	0%	2%	2%	14%	0%	0%	0%	5%	0%	0%	0%	0%	2%	2%	0%	0%	2%	0%	0%	22%	100%
TF20 Fabric metal prod	7%	1%	9%	0%	0%	26%	3%	0%	0%	2%	14%	0%	0%	0%	10%	0%	0%	0%	0%	2%	0%	0%	0%	6%	0%	0%	19%	100%
TF21 Energy machinery	4%	0%	9%	0%	0%	30%	4%	0%	0%	1%	15%	0%	0%	0%	8%	0%	0%	0%	0%	1%	1%	0%	0%	4%	0%	0%	22%	100%
TF22 Nonspec machinery	6%	2%	9%	0%	0%	28%	3%	0%	0%	3%	12%	0%	0%	0%	8%	0%	0%	0%	0%	3%	1%	0%	0%	5%	0%	0%	19%	100%
TF23 Agricul. forestry machinery	6%	2%	6%	0%	0%	22%	5%	0%	1%	2%	17%	0%	1%	2%	5%	0%	0%	0%	0%	5%	4%	0%	0%	5%	0%	0%	17%	100%
TF24 Machine tools	8%	0%	11%	0%	0%	29%	2%	0%	0%	2%	10%	0%	0%	0%	12%	0%	0%	0%	0%	1%	0%	0%	0%	5%	0%	0%	20%	100%
TF25 Spec. pump machinery	7%	3%	10%	0%	0%	28%	3%	0%	0%	3%	9%	0%	0%	0%	11%	0%	0%	0%	0%	3%	1%	0%	0%	5%	0%	0%	17%	100%
TF26 Weapons, ammunition	5%	1%	8%	0%	0%	22%	1%	0%	1%	2%	20%	0%	0%	1%	5%	0%	0%	0%	0%	2%	5%	0%	0%	6%	0%	0%	22%	100%
TF27 Domestic appliances	6%	1%	10%	0%	0%	26%	3%	0%	2%	1%	15%	0%	0%	0%	13%	0%	0%	0%	0%	3%	0%	0%	0%	3%	0%	0%	17%	100%
TF28 Office mach. computers	2%	2%	12%	0%	0%	25%	1%	0%	0%	2%	10%	0%	0%	1%	5%	0%	0%	0%	0%	3%	1%	0%	0%	2%	2%	0%	32%	100%
TF29 Electric motors, generators	7%	1%	12%	0%	0%	33%	3%	0%	1%	2%	11%	0%	0%	0%	10%	0%	0%	1%	0%	1%	1%	0%	0%	2%	0%	0%	18%	100%
TF30 Elec. distr. contr. wire, cable	3%	2%	13%	0%	0%	33%	1%	0%	0%	1%	18%	0%	0%	1%	6%	0%	0%	0%	1%	1%	0%	0%	0%	3%	2%	0%	15%	100%
TF31 Accumulators battery	5%	2%	10%	0%	0%	28%	4%	0%	0%	1%	12%	1%	1%	0%	9%	0%	1%	0%	0%	2%	2%	0%	0%	3%	0%	0%	20%	100%
TF32 Lighting equipment	5%	3%	7%	0%	1%	28%	2%	0%	1%	1%	16%	0%	1%	0%	10%	0%	0%	0%	0%	2%	2%	0%	0%	3%	0%	0%	18%	100%
TF33 Other electr. equip	6%	1%	9%	0%	0%	27%	1%	0%	0%	1%	16%	0%	0%	0%	6%	0%	0%	0%	0%	2%	0%	0%	0%	5%	1%	0%	23%	100%
TF34 Electr. components	6%	1%	12%	0%	0%	30%	1%	0%	0%	1%	14%	0%	1%	0%	6%	0%	0%	0%	0%	1%	0%	0%	0%	3%	0%	0%	25%	100%
TF35 Signal transm. telecom	3%	3%	13%	0%	0%	26%	2%	0%	0%	3%	10%	0%	0%	1%	3%	0%	0%	0%	0%	3%	0%	0%	0%	3%	1%	0%	28%	100%
TF36 TV radio receiv. audio	4%	3%	12%	0%	0%	25%	3%	0%	0%	3%	12%	0%	0%	0%	6%	0%	0%	0%	0%	2%	1%	0%	0%	1%	0%	0%	29%	100%
TF37 Med. equipment	2%	2%	10%	0%	0%	22%	2%	0%	0%	1%	12%	0%	0%	1%	7%	0%	0%	0%	0%	4%	1%	0%	0%	3%	0%	0%	31%	100%
TF38 Measuring instruments	2%	2%	11%	0%	0%	27%	3%	0%	0%	1%	10%	0%	0%	0%	8%	0%	0%	0%	0%	4%	1%	0%	0%	4%	1%	0%	30%	100%
TF39 Ind. proc. contr. equip	2%	1%	9%	0%	0%	30%	2%	0%	0%	1%	13%	0%	0%	0%	4%	0%	0%	0%	0%	2%	2%	0%	0%	2%	0%	0%	25%	100%
TF40 Opt. instruments	4%	2%	13%	0%	0%	27%	2%	0%	0%	1%	12%	0%	1%	1%	6%	0%	0%	0%	1%	2%	2%	0%	0%	2%	0%	0%	28%	100%
TF41 Watches, clocks	6%	3%	21%	0%	0%	26%	0%	0%	1%	1%	17%	0%	0%	0%	11%	0%	0%	0%	0%	2%	0%	0%	0%	2%	0%	0%	15%	100%
TF42 Motor vehicles	4%	1%	9%	0%	0%	33%	2%	0%	0%	1%	17%	0%	0%	0%	6%	0%	1%	0%	0%	2%	0%	0%	0%	4%	0%	0%	21%	100%
TF43 Other transp. equip	8%	0%	8%	0%	0%	24%	2%	0%	0%	3%	13%	0%	0%	0%	9%	0%	0%	0%	0%	3%	5%	0%	0%	4%	0%	0%	21%	100%
TF44 Furniture consum. good	7%	1%	10%	0%	0%	23%	4%	0%	1%	2%	14%	0%	0%	1%	11%	0%	0%	0%	0%	3%	2%	0%	0%	3%	0%	0%	18%	100%
SUM hightech	3%	3%	11%	0%	0%	26%	2%	0%	0%	2%	9%	0%	0%	1%	5%	0%	0%	0%	0%	4%	1%	0%	0%	2%	1%	0%	31%	100%
HT2 Computer office mach	2%	2%	9%	0%	0%	22%	1%	0%	0%	3%	13%	0%	1%	2%	7%	0%	0%	0%	0%	4%	1%	0%	0%	3%	2%	0%	32%	100%
HT1 Aviation	3%	1%	3%	1%	0%	26%	2%	0%	0%	1%	21%	0%	0%	0%	5%	0%	0%	0%	0%	1%	2%	0%	1%	3%	0%	0%	29%	100%
HT3 Laser	4%	1%	15%	0%	0%	22%	3%	0%	0%	0%	13%	0%	0%	1%	8%	0%	0%	0%	0%	3%	0%	0%	0%	3%	0%	0%	28%	100%
HT4 Semiconductors	4%	1%	13%	0%	0%	33%	1%	0%	0%	1%	10%	0%	0%	0%	9%	0%	0%	0%	0%	1%	1%	0%	0%	1%	0%	0%	22%	100%
HT5 Microcommunication	2%	3%	14%	0%	0%	24%	3%	0%	1%	1%	11%	0%	0%	0%	3%	0%	0%	0%	0%	3%	0%	0%	0%	3%	0%	0%	31%	100%
HT6 Microorgan. Genetics	3%	4%	8%	0%	1%	17%	4%	0%	2%	2%	10%	1%	1%	1%	4%	0%	0%	0%	0%	4%	2%	0%	0%	2%	1%	1%	33%	100%
Σ cluster regions	463	190	915	1	8	2458	242	0	47	175	1247	5	24	40	705	0	15	1	5	267	116	14	3	317	24	3	2188	9463
share cluster regions	5%	2%	10%	0%	0%	26%	3%	0%	2%	2%	13%	0%	0%	0%	7%	0%	0%	0%	0%	3%	1%	0%	0%	3%	0%	0%	23%	100%

Source: own calculations. Notes: Calculations based upon OECD RegPAT (2009) extractions and application of ISI-SPRU-OST concordance.

Table B.7. Research clusters by TF and country with $RCI > 16$, 1990-1994

Technology Field	AT	BE	CH	CY	CZ	DE	DK	EE	ES	FI	FR	GR	HU	IE	IT	LT	LU	LV	MT	NL	NO	PL	PT	SE	SI	SK	UK	Σ
TF1_Food_beverages	3%	3%	14%	0%	0%	15%	10%	0%	0%	1%	15%	0%	1%	0%	5%	0%	0%	0%	0%	8%	2%	0%	0%	1%	0%	0%	23%	105
TF2_Tobacco_prod	3%	3%	12%	0%	0%	22%	1%	0%	4%	0%	3%	1%	0%	1%	8%	0%	0%	0%	0%	2%	0%	0%	0%	2%	0%	0%	33%	100
TF3_Textiles	3%	3%	8%	0%	0%	30%	6%	0%	0%	2%	13%	0%	0%	0%	10%	0%	1%	0%	0%	2%	0%	1%	0%	0%	1%	0%	22%	100
TF4_Wearing_apparel	5%	2%	8%	0%	0%	18%	5%	0%	2%	2%	15%	0%	0%	2%	12%	0%	0%	0%	0%	3%	1%	0%	0%	7%	0%	0%	19%	130
TF5_Leather_articles	16%	0%	10%	0%	0%	20%	2%	0%	1%	0%	16%	0%	0%	0%	21%	0%	0%	0%	0%	4%	2%	0%	0%	1%	0%	0%	12%	100
TF6_Wood_prod	10%	2%	5%	0%	0%	27%	5%	0%	2%	4%	12%	0%	0%	1%	6%	0%	1%	0%	0%	4%	2%	0%	0%	6%	0%	0%	12%	100
TF7_Paper	6%	4%	13%	0%	0%	29%	3%	0%	1%	7%	7%	0%	0%	0%	0%	0%	0%	0%	0%	3%	1%	0%	0%	6%	1%	0%	23%	100
TF9_Petrol_prod_nucl_fuel	5%	1%	5%	0%	0%	23%	3%	0%	0%	1%	14%	0%	0%	1%	6%	0%	0%	0%	0%	3%	9%	1%	0%	1%	0%	0%	28%	100
TF10_Basic_chemical	3%	4%	17%	0%	0%	30%	3%	0%	0%	1%	10%	0%	0%	0%	4%	0%	0%	0%	0%	3%	0%	0%	0%	0%	0%	0%	23%	100
TF11_Pesticide_agrochem_prod	3%	4%	10%	0%	0%	28%	6%	0%	0%	1%	9%	0%	0%	0%	4%	0%	0%	0%	0%	3%	0%	0%	0%	0%	0%	0%	35%	100
TF12_Paints_varnishes	4%	1%	4%	0%	1%	32%	6%	0%	1%	8%	10%	0%	0%	0%	5%	0%	0%	0%	0%	5%	0%	0%	0%	9%	0%	0%	13%	100
TF13_Pharmaceuticals	2%	5%	11%	0%	0%	20%	4%	0%	0%	0%	14%	0%	1%	0%	5%	0%	0%	0%	0%	3%	1%	0%	0%	3%	0%	0%	29%	100
TF14_Soaps_detergents	0%	11%	5%	0%	0%	23%	6%	0%	2%	0%	16%	0%	0%	0%	5%	0%	0%	0%	0%	3%	0%	0%	0%	0%	0%	0%	30%	100
TF15_Other_chemicals	3%	6%	16%	0%	0%	29%	1%	0%	0%	1%	12%	0%	0%	0%	3%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	26%	100
TF16_Man_made_fibre	9%	0%	8%	0%	0%	27%	1%	0%	0%	4%	9%	0%	0%	0%	11%	0%	1%	0%	0%	4%	0%	1%	0%	0%	0%	0%	25%	100
TF17_Rubber_plastic_prod	6%	2%	18%	0%	0%	36%	2%	0%	0%	1%	11%	0%	0%	0%	4%	0%	1%	0%	0%	1%	0%	0%	0%	2%	0%	0%	14%	100
TF18_Non-metal_mineral_prod	10%	2%	17%	0%	0%	35%	3%	0%	0%	2%	13%	0%	0%	0%	3%	0%	1%	0%	0%	1%	0%	0%	0%	2%	0%	0%	13%	100
TF19_Basic_metals	9%	2%	15%	0%	0%	30%	3%	0%	0%	1%	17%	0%	0%	0%	2%	0%	1%	0%	0%	1%	0%	0%	0%	0%	0%	0%	15%	100
TF20_Fabric_metal_prod	8%	0%	18%	0%	0%	40%	3%	0%	0%	1%	11%	0%	0%	0%	5%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	9%	100
TF21_Energy_machinery	2%	0%	13%	0%	0%	40%	2%	0%	0%	1%	16%	0%	1%	0%	7%	0%	0%	0%	0%	1%	0%	0%	0%	0%	0%	0%	16%	100
TF22_Nonspec_machinery	6%	1%	15%	0%	0%	38%	3%	0%	0%	2%	7%	0%	0%	0%	5%	0%	0%	0%	0%	4%	0%	0%	0%	0%	0%	0%	12%	100
TF23_Agricul_forestry_machinery	5%	2%	6%	0%	0%	26%	8%	0%	1%	1%	13%	0%	0%	0%	8%	0%	0%	0%	0%	10%	2%	0%	0%	0%	0%	0%	16%	100
TF24_Machine_tools	7%	0%	18%	0%	0%	36%	0%	0%	0%	1%	7%	0%	0%	0%	10%	0%	0%	0%	0%	1%	0%	0%	0%	6%	0%	0%	13%	100
TF25_Spec_pump_machinery	4%	2%	20%	0%	0%	38%	2%	0%	0%	3%	6%	0%	0%	0%	13%	0%	0%	0%	0%	2%	0%	0%	0%	2%	0%	0%	7%	100
TF26_Weapons_ammunition	7%	1%	9%	0%	0%	21%	0%	0%	1%	1%	20%	0%	0%	0%	1%	0%	0%	0%	0%	2%	0%	2%	0%	0%	0%	0%	24%	100
TF27_Domestic_appliances	5%	0%	19%	0%	0%	35%	3%	0%	0%	0%	12%	0%	0%	0%	11%	0%	0%	0%	0%	3%	0%	0%	0%	2%	0%	0%	11%	100
TF28_Office_mach_computers	2%	1%	16%	0%	0%	27%	0%	0%	0%	0%	10%	0%	0%	0%	3%	0%	0%	0%	0%	2%	1%	0%	0%	1%	2%	0%	35%	100
TF29_Electric_motors_generators	6%	0%	16%	0%	0%	33%	2%	0%	1%	1%	12%	0%	0%	0%	10%	0%	0%	0%	0%	1%	0%	0%	0%	3%	0%	0%	16%	100
TF30_Elec_distr_contr_wire_cable	2%	3%	18%	0%	0%	37%	0%	0%	0%	1%	17%	0%	0%	0%	6%	0%	0%	0%	0%	2%	0%	0%	0%	1%	0%	0%	9%	100
TF31_Accumulators_battery	6%	2%	13%	0%	0%	25%	5%	0%	0%	0%	14%	1%	0%	0%	9%	0%	0%	0%	0%	1%	0%	0%	0%	1%	0%	0%	22%	100
TF32_Lighting_equipment	5%	2%	10%	0%	2%	29%	3%	0%	1%	0%	13%	0%	2%	0%	8%	0%	0%	0%	0%	2%	1%	0%	0%	2%	0%	0%	21%	100
TF33_Other_electr equip	6%	0%	15%	0%	0%	32%	0%	0%	0%	1%	16%	0%	0%	0%	7%	0%	0%	0%	0%	3%	0%	0%	0%	4%	1%	0%	18%	100
TF34_Electr_components	4%	0%	18%	0%	0%	38%	0%	0%	0%	0%	11%	0%	1%	0%	4%	0%	0%	0%	0%	1%	0%	0%	0%	1%	0%	0%	18%	100
TF35_Signal_transm_telecom	1%	3%	13%	0%	0%	30%	1%	0%	0%	5%	15%	0%	0%	0%	3%	0%	0%	0%	0%	3%	0%	0%	0%	1%	0%	0%	25%	100
TF36_TV_radio_receiv_audio	4%	1%	11%	0%	0%	21%	4%	0%	0%	4%	13%	0%	0%	0%	4%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	36%	100
TF37_Med equipmnet	2%	1%	16%	0%	0%	26%	3%	0%	0%	2%	8%	0%	0%	0%	3%	0%	0%	0%	0%	3%	2%	0%	0%	0%	0%	0%	29%	100
TF38_Measuring_instruments	2%	1%	16%	0%	0%	32%	0%	0%	0%	2%	9%	0%	0%	0%	1%	0%	0%	0%	0%	0%	1%	0%	0%	0%	2%	0%	31%	100
TF39_Ind_proc_contr equip	4%	0%	12%	0%	0%	35%	2%	0%	0%	1%	12%	0%	0%	0%	3%	0%	0%	0%	0%	4%	0%	0%	0%	2%	0%	0%	25%	100
TF40_Optr_instruments	3%	2%	22%	0%	0%	24%	4%	0%	0%	0%	11%	0%	0%	0%	4%	0%	0%	0%	1%	2%	0%	0%	0%	1%	0%	0%	28%	100
TF41_Watches_clocks	8%	2%	31%	0%	0%	23%	0%	0%	0%	0%	12%	0%	0%	0%	11%	0%	0%	0%	0%	3%	0%	0%	0%	3%	0%	0%	11%	100
TF42_Motor_vehicles	5%	0%	8%	0%	0%	53%	1%	0%	0%	1%	16%	0%	0%	0%	2%	0%	0%	0%	0%	0%	0%	0%	0%	2%	0%	0%	11%	100
TF43_Other_transp equip	7%	0%	8%	0%	0%	28%	2%	0%	0%	2%	17%	0%	0%	0%	5%	0%	0%	0%	0%	1%	8%	0%	0%	3%	1%	0%	20%	100
TF44_Furniture_consum good	8%	1%	20%	0%	0%	25%	5%	0%	1%	2%	12%	0%	0%	0%	9%	0%	0%	0%	0%	0%	2%	0%	0%	0%	0%	0%	13%	100
SUM_hightech	1%	5%	11%	0%	0%	22%	4%	0%	0%	4%	13%	0%	0%	0%	3%	0%	0%	0%	0%	3%	0%	0%	0%	2%	0%	0%	31%	100
HT2_Computer_office_mach	1%	1%	11%	0%	0%	21%	0%	0%	0%	1%	12%	0%	0%	0%	6%	0%	0%	0%	0%	3%	0%	0%	0%	2%	3%	0%	37%	100
HT3_Laser	3%	0%	4%	0%	0%	23%	2%	0%	0%	0%	23%	0%	0%	0%	5%	0%	0%	0%	0%	0%	2%	0%	0%	3%	0%	0%	34%	100
HT4_Semiconductors	3%	0%	17%	0%	0%	19%	0%	0%	0%	0%	16%	0%	0%	0%	10%	0%	0%	0%	0%	1%	0%	1%	0%	0%	0%	0%	30%	100
HT5_Semiconductors	4%	1%	16%	0%	0%	39%	0%	0%	0%	0%	13%	0%	0%	0%	7%	0%	0%	0%	0%	1%	0%	0%	0%	1%	0%	0%	17%	100
HT5_Communication	1%	3%	12%	0%	0%	24%	1%	0%	0%	5%	14%	0%	0%	0%	1%	0%	0%	0%	0%	4%	0%	0%	0%	1%	0%	0%	33%	100
HT6_Microorgan_Genetics	4%	4%	7%	0%	0%	19%	4%	0%	0%	2%	9%	0%	1%	0%	2%	0%	0%	0%	0%	6%	2%	0%	0%	3%	0%	0%	38%	100
Σ cluster regions	251	92	683	0	3	1497	144	0	16	77	643	2	7	13	310	0	8	0	3	114	44	5	0	138	11	1	1092	5154
share cluster regions	5%	2%	13%	0%	0%	29%	3%	0%	0%	1%	12%	0%	0%	0%	6%	0%	0%	0%	0%	2%	1%	0%	0%	3%	0%	0%	21%	100%

Source: own calculations. Notes: Calculations based upon OECD RegPAT (2009) extractions and application of ISI-SPRU-OST concordance.

Table B.8. Changing number of research clusters by TF and country with $RCI > 1$, 2000-2004 vs. 1990-1994

Technology Field	AT	BE	CH	CY	CZ	DE	DK	EE	ES	FI	FR	GR	HU	IE	IT	LT	LU	LV	MT	NL	NO	PL	PT	SE	SI	SK	UK	Σ	
TF1 Food beverages	-2	3	3	0	0	-10	-1	0	7	1	-9	1	0	0	5	0	0	1	-1	1	5	1	1	1	-1	-1	-16	-11	
TF2 Tobacco prod	-1	-1	-3	0	0	-4	1	0	0	0	-2	-1	2	0	1	0	0	0	0	0	0	1	0	1	0	0	-15	-21	
TF3 Textiles	4	3	9	0	-1	-5	0	0	2	15	0	0	0	1	11	0	0	0	0	2	0	-1	3	3	0	0	-7	42	
TF4 Wearing apparel	2	2	-2	0	16	-2	0	5	2	15	0	0	0	8	0	1	0	0	0	-2	3	0	1	-3	0	0	18	65	
TF5 Leather articles	1	2	1	0	1	-2	1	0	3	0	4	0	-1	1	19	0	0	0	1	0	2	2	0	4	0	0	14	53	
TF6 Wood prod	3	2	6	1	2	6	-3	0	5	0	-14	0	0	1	18	0	-1	0	0	-1	1	3	-5	8	0	0	5	37	
TF7 Paper	2	2	6	0	1	3	-1	0	-2	3	-8	0	-1	5	0	0	0	0	0	0	-1	1	-1	-2	4	0	-9		
TF9 Petrol prod nucl fuel	-1	2	-2	0	0	-7	-1	2	0	2	-11	-1	2	-1	2	0	-1	1	0	2	-1	5	0	0	0	0	8	1	
TF10 Basic chemical	3	3	-1	0	1	2	0	0	0	2	0	0	0	0	4	0	0	1	0	0	0	0	0	2	1	0	-2	16	
TF11 Pesticide agrochem prod	1	-1	1	0	1	14	0	0	2	-1	-3	-1	0	0	8	0	0	0	0	2	0	0	0	1	0	0	-7	17	
TF12 Paints varnishes	6	3	4	0	-1	5	2	0	1	2	-2	1	0	0	0	0	1	0	0	-1	1	0	4	-6	5	0	-10	15	
TF13 Pharmaceuticals	1	2	4	0	1	6	2	0	0	1	4	0	-1	0	0	0	0	0	0	0	-1	0	-1	0	4	1	-5	19	
TF14 Soaps detergents	1	-1	6	0	0	3	-1	0	0	0	0	0	0	0	4	0	-1	0	0	2	0	0	0	-1	0	0	5	16	
TF15 Other chemicals	2	-1	0	0	0	4	1	0	-1	2	2	0	-2	-1	7	0	0	0	-1	2	1	0	1	0	0	0	-14	2	
TF16 Man made fibre	0	6	0	1	0	-5	1	0	4	-3	8	0	0	0	3	0	0	0	0	2	5	2	0	0	0	0	4	28	
TF17 Rubber plastic prod	0	3	-1	0	0	-2	0	0	3	-1	0	0	0	0	10	0	0	0	0	0	-1	-2	0	1	-1	0	0	-3	4
TF18 Non-metal mineral prod	6	1	-3	0	0	4	6	0	2	-1	-2	0	0	0	15	0	0	0	0	0	0	0	0	-1	6	0	-20	13	
TF19 Basic metals	4	2	1	0	0	4	1	1	1	1	-2	0	0	0	2	0	0	0	0	1	2	0	1	0	0	0	-19	0	
TF20 Fabric metal prod	4	3	1	0	0	3	2	0	2	-1	-5	0	0	0	8	0	0	0	0	2	-1	0	0	-3	9	0	-12	12	
TF21 Energy machinery	4	3	2	0	0	10	3	0	1	-2	-12	0	-1	0	6	0	1	0	0	0	0	0	0	-3	0	0	-12	0	
TF22 Non-spec machinery	4	-1	0	0	0	3	3	0	1	1	-10	0	0	0	10	0	0	0	0	1	2	0	0	-6	2	0	-11	-1	
TF23 Agricul forestry machinery	3	4	-4	0	0	-1	1	0	2	2	-13	1	-1	-3	14	0	0	0	0	-1	2	0	0	-4	2	1	12	17	
TF24 Machine tools	-1	0	1	0	0	10	0	0	2	2	0	0	0	0	2	0	0	0	0	2	0	0	0	0	0	0	-20	-5	
TF25 Spec purp machinery	4	1	1	0	0	2	-2	2	0	1	3	-6	0	0	6	0	-1	0	0	1	1	0	0	-1	0	0	-5	7	
TF26 Weapons ammunition	5	3	2	0	4	4	4	0	2	-1	-13	0	0	-1	4	0	0	0	0	-2	-5	1	0	0	1	0	-17	-13	
TF27 Domestic appliances	1	4	-4	0	0	-4	1	0	1	0	-4	0	0	-1	6	0	0	0	1	0	0	0	0	-1	5	0	3	8	
TF28 Office mach computers	2	1	2	0	0	1	3	0	1	1	0	0	1	1	-3	3	0	0	0	-4	0	0	0	2	-3	0	-9	-3	
TF29 Electric motors generators	0	-1	-1	0	1	-4	0	0	-1	0	0	0	0	0	6	0	1	0	-1	0	2	0	0	0	0	3	1	-4	21
TF30 Elec disir conir wire cable	4	-1	-1	0	1	10	3	0	3	4	-2	0	-1	0	-5	0	0	0	0	1	0	0	0	-3	5	0	-8	22	
TF31 Accumulators battery	0	1	4	0	1	17	0	0	3	0	2	-1	-1	0	-5	0	0	0	0	1	0	-1	0	-4	1	0	3	22	
TF32 Lighting equipment	3	0	7	0	0	8	3	0	-1	-3	-9	1	-1	1	5	0	0	0	0	-2	0	1	0	-3	6	0	-3	19	
TF33 Other electr equip	5	1	0	0	0	7	0	0	2	3	-6	0	0	2	7	0	0	0	0	-2	0	-1	0	-3	0	0	-4	14	
TF34 Elect components	2	4	6	0	0	7	1	0	0	1	-5	0	0	2	3	0	0	0	0	0	2	1	0	2	0	0	-1	26	
TF35 Signal transm telecom	3	-1	-3	0	0	-4	2	0	-1	1	-3	0	1	0	-2	0	0	0	0	-2	3	0	0	0	3	0	0	-9	-10
TF36 TV radio receiv audio	-3	0	2	0	0	-4	2	0	0	1	-4	0	1	0	-5	0	0	0	0	1	2	0	0	2	-1	0	-10	-16	
TF37 Med equipment	4	2	1	0	0	5	4	0	0	1	-10	0	0	2	1	0	0	0	0	-2	0	-1	0	-1	0	0	-2	4	
TF38 Measuring instruments	2	4	-1	0	0	7	0	0	0	1	-4	0	0	0	1	0	1	0	0	-3	0	-1	0	-1	-1	0	-7	-2	
TF39 Ind proc contr equip	6	1	4	0	1	1	3	0	-1	2	-10	0	0	1	-2	0	0	0	1	-3	1	0	0	2	0	0	-15	-8	
TF40 Opti instruments	1	4	-1	0	0	5	1	0	0	1	-2	0	0	-1	0	0	0	0	0	0	-1	0	0	0	0	0	-4	6	
TF41 Watches clocks	-4	-1	0	0	0	1	4	0	1	1	0	0	0	0	-6	0	0	0	0	-1	0	0	0	-2	0	0	-3	-9	
TF42 Motor vehicles	3	1	-1	0	0	-1	-2	0	3	1	-3	0	0	0	-2	0	0	0	1	-2	0	0	0	-3	0	0	-18	-33	
TF43 Other transp equip	-1	3	2	0	0	6	0	0	4	-3	3	1	0	0	0	0	0	0	0	-1	0	-1	0	2	4	0	0	20	0
TF44 Furniture consum good	7	3	-1	0	0	-3	0	0	1	-2	-5	0	-1	-1	13	0	0	0	0	3	-2	0	0	4	5	0	17	42	
SUM_hightech	1	1	1	0	0	2	2	0	0	2	0	0	1	0	-5	0	0	0	0	-1	1	0	0	0	0	0	-9	8	
HT2 Computer office mach	2	2	7	0	0	0	4	0	1	0	-6	0	0	-1	-5	0	1	0	0	-4	1	0	0	0	-4	0	-14	-16	
HT1 Aviation	1	5	5	-1	1	12	2	0	5	0	-1	0	1	0	2	0	1	0	0	2	0	0	-1	0	0	0	8	43	
HT3 Laser	2	1	-1	0	0	8	2	0	1	3	-3	0	0	1	4	0	0	0	0	-1	2	0	0	1	-2	0	9	27	
HT4 Semiconductors	5	4	7	0	0	6	2	0	0	0	-1	0	0	0	-1	0	0	0	0	0	1	0	0	0	1	0	5	30	
HT5 Communication	0	0	-4	0	0	4	2	0	-1	1	-1	0	1	-1	-1	0	0	0	0	2	3	0	0	4	1	0	-5	7	
HT6 Microorgan Genetics	-1	0	4	0	0	-1	17	0	1	0	2	-1	0	1	-4	0	0	0	0	-1	0	-1	0	0	0	0	-13	6	

Source: own calculations. Notes: Calculations based upon OECD RegPAT (2009) extractions and application of ISI-SPRU-OST concordance.

Table B.9. Betweenness centrality ranking of TOP10 regions (1-5)

technology field	TOP10 ranking of TL3 regions (betweenness centrality in descending order) positions 1-5				
	1	2	3	4	5
TF1_Food_beverages	NL33 ZUID-HOLLAND	DE93 München	ITC45 Milano	CH011 Vaud	DE51 Rhein-Main
TF2_Tobacco_prod	DE5 Schleswig-Holstein Süd	DE6 Hamburg	UKJ32 Southampton	UKJ33 Hampshire CC	CH021 Bern
TF3_Textiles	DE11 Rhein-Main	DE68 Unterer Neckar	DE42 Dusseldorf	CH056 Graubünden	FR222 Oise
TF4_Wearing_apparel	DE84 Oberfranken-Ost	FR714 Isère	FR711 Ain	FR718 Haute-Savoie	FR101 Paris
TF5_Leather_articles	ITD34 Treviso	DE42 Dusseldorf	DE65 Wiesplatz	DE41 Duisburg/Essen	DE72 Stuttgart
TF6_Wood_prod	DE58 Oberes Elbtal/Osterzgebirge	DE72 Stuttgart	DE96 Oberland	DE41 Duisburg/Essen	CH033 Aargau
TF7_Paper	FI181 Uusimaa	DE52 Starkenburg	DE51 Rhein-Main	DE66 Industrieregion Mittelfranken	FR714 Isère
TF9_Petrol_prod_nucl_fuel	NL32 NOORD-HOLLAND	NL23 FLEVOLAND	ITC45 Milano	UKD22 Cheshire CC	DE42 Dusseldorf
TF10_Basic_chemical	ITC45 Milano	DE42 Dusseldorf	DE42 Dusseldorf	FR716 Rhône	DE66 Rheinplaz
TF11_Pesticide_agrochem_prod	FR716 Rhône	DE44 Köln	DE42 Dusseldorf	DE51 Rhein-Main	CH056 Graubünden
TF12_Paints_varnishes	DE41 Duisburg/Essen	DE40 Ernscher-Lippe	DE66 Rheinplaz	DE68 Unterer Neckar	DE70 Mittlerer Oberrhein
TF13_Pharmaceuticals	ITC45 Milano	DE51 Rhein-Main	FR101 Paris	DE93 München	CH056 Graubünden
TF14_Soaps_detergents	DE42 Dusseldorf	BE24 PROV. VLAAMS-BRABANT	NL33 ZUID-HOLLAND	UKD54 Wirral	ITE43 Roma
TF15_Other_chemicals	DE42 Dusseldorf	ITC45 Milano	FR716 Rhône	FR101 Paris	DE41 Duisburg/Essen
TF16_Man_made_fibre	FR716 Rhône	FR422 Haut-Rhin	DE51 Rhein-Main	FR421 Bas-Rhin	BE10 REGION DE BRUXELLES-
TF17_Rubber_plastic_prod	ITC45 Milano	DE42 Dusseldorf	DE42 Dusseldorf	DE93 München	CH011 Vaud
TF18_Non-metal_mineral_prod	DE51 Rhein-Main	ITC45 Milano	SE044 Skåne län	DE42 Dusseldorf	FR222 Oise
TF19_Basic_metals	DE42 Dusseldorf	ITC45 Milano	FR101 Paris	FR714 Isère	DE86 Industrieregion Mittelfranken
TF20_Fabric_metal_prod	DE93 München	DE42 Dusseldorf	FR103 Yvelines	ITC45 Milano	DE72 Stuttgart
TF21_Energy_machinery	DE72 Stuttgart	DE93 München	ITC11 Torino	DE70 Mittlerer Oberrhein	ITC45 Milano
TF22_Nonspec_machinery	DE72 Stuttgart	DE51 Rhein-Main	DE93 München	SE010 Stockholms län	ITC45 Milano
TF23_Agricul_forestry_machinery	FR101 Paris	FR612 Rhône	FR612 Rhône	SE044 Skåne län	DE51 Rhein-Main
TF24_Machine_tools	DE93 München	DE72 Stuttgart	CH057 Thurgau	CH040 Zürich	ITC45 Milano
TF25_Spec_pump_machinery	DE42 Dusseldorf	ITC45 Milano	DE51 Rhein-Main	DE72 Stuttgart	FI181 Uusimaa
TF26_Weapons_ammunition	DE76 Schwarzwald-Baar-Heuberg	FR715 Loire	FR103 Yvelines	DE88 Augsburg	DE3 Schleswig-Holstein Mitte
TF27_Domestic_appliances	DE93 München	DE51 Rhein-Main	SE010 Stockholms län	ITC45 Milano	DE72 Stuttgart
TF28_Office_mach_computers	DE93 München	ITC45 Milano	FR101 Paris	FR714 Isère	UKH12 Cambridgeshire CC
TF29_Electric_motors_generators	DE72 Stuttgart	ITC45 Milano	DE93 München	SE025 Västmanlands län	DE70 Mittlerer Oberrhein
TF30_Elec_distr_contr_wire_cable	DE51 Rhein-Main	DE36 Bielefeld	DE72 Stuttgart	DE42 Dusseldorf	ITC45 Milano
TF31_Accumulators_battery	DE72 Stuttgart	ITC45 Milano	ITE21 Perugia	DE70 Mittlerer Oberrhein	UKJ33 Hampshire CC
TF32_Lighting_equipment	DE72 Stuttgart	DE93 München	CH031 Basel-Stadt	FR101 Paris	DE52 Starkenburg
TF33_Other_electr equip	DE93 München	DE72 Stuttgart	FR623 Haute-Garonne	ITC45 Milano	FR103 Yvelines
TF34_Electr_components	ITC45 Milano	München	DE72 Stuttgart	DE58 Oberes Elbtal/Osterzgebirge	NL41 NOORD-BRABANT
TF35_Signal_transm_telecom	DE93 München	ITC45 Milano	SE010 Stockholms län	FI181 Uusimaa	DE72 Stuttgart
TF36_TV_radio_recviv_audio	DE93 München	FR101 Paris	FR623 Ille-et-Vilaine	ITC45 Milano	UKH12 Cambridgeshire CC
TF37_Med_equipment	DE51 Rhein-Main	FR101 Paris	ITE43 Roma	DE93 München	Unter Neckar
TF38_Measuring_instruments	FR101 Paris	DE93 München	UKH12 Cambridgeshire CC	ITC45 Milano	SE010 Stockholms län
TF39_Ind_proc_contr equip	DE72 Stuttgart	DE68 Unterer Neckar	DE42 Dusseldorf	DE93 München	ITC45 Milano
TF40_Opt_instruments	DE93 München	ITC45 Milano	SE010 Stockholms län	DE52 Starkenburg	Hampshire CC
TF41_Watches_clocks	DE71 Nordschwarzwald	FR431 Doubs	CH012 Valais	DE72 Stuttgart	Rhein-Main
TF42_Motor_vehicles	DE72 Stuttgart	ITC11 Torino	CH012 Valais	FR103 Yvelines	DE51 Rhein-Main
TF43_Other_transp equip	DE93 München	ITC45 Milano	FR103 Yvelines	FR623 Haute-Garonne	CH057 Thurgau
TF44_Furniture_consum_good	UK111 Inner London - West	ITC45 Milano	CH033 Aargau	DE75 Neckar-Alb	FR101 Paris

Source: own calculations and illustration. Notes: Betweenness centrality ranking of TL3 regions (descending order).

Table B.10. Betweenness centrality ranking of TOP10 regions (6-10)

technology field	TOP10 ranking of TL3 regions (betweenness centrality in descending order) positions 6-10									
	6	7	8	9	10					
TF1_Food_beverages	AT126	Freiburg	DE66	Rheinplatz	FI181	Uusimaa	UKH22	Bedfordshire CC		
TF2_Tobacco_prod	DE84	Oberfranken-Ost	CH022	Freiburg	DE14	Hamburg-Umland-Süd	NI32	NOORD-HOLLAND		
TF3_Textiles	DE72	Stuttgart	ITC45	Köln	UKJ23	Surrey	BE10	RÉGION DE BRUXELLES-		
TF4_Weaving_apparel	FR107	Val-de-Marne	DE51	Rhein-Main	DE75	Neckar-Alb	ES611	Barcelona		
TF5_Leather_articles	DE88	Unterer Neckar	DE86	Industrieregion Mittelfranken	DE43	Bochum/Hagen	ITD35	Venezia		
TF6_Wood_prod	DE22	Braunschweig	CH040	Zürich	DE93	München	DE14	Hamburg-Umland-Süd		
TF7_Paper	FR103	Yvelines	DE93	München	BE24	PROV. VLAAMS-BRABANT	FR716	Rhône		
TF9_Petrol_prod_nucl_fuel	UKJ14	Oxfordshire	UKJ23	Surrey	BE24	PROV. VLAAMS-BRABANT	FR232	Seine-Maritime		
TF10_Basic_chemical	DE68	Unterer Neckar	BE24	Rheinplatz	HU101	Budapest	DE52	Starkenbur		
TF11_Pesticide_agrochem_prod	UKJ11	Berkshire	DE66	Rheinplatz	UKJ23	Outer London - West and North West	FR101	Paris		
TF12_Paints_varnishes	DE46	Bonn	DE66	Rheinplatz	FR23	Haute-Garonne	AT312	Linz-Wels		
TF13_Pharmaceuticals	SE010	Stockholms län	FR105	Hauts-de-Seine	ITE43	Roma	DE68	Unterer Neckar		
TF14_Soaps_detergents	DE51	Rhein-Main	DE66	Rheinplatz	BE10	RÉGION DE BRUXELLES-	FR101	Paris		
TF15_Other_chemicals	DE6	Hamburg	SE044	Skåne län	DE66	Rheinplatz	BE21	PROV. ANTWERPEN		
TF16_Man_made_fibre	BE24	PROV. VLAAMS-BRABANT	BE31	PROV. BRABANT WALLON	DE66	Rheinplatz	DE78	Hochrhein-Bodensee		
TF17_Rubber_plastic_prod	CH021	Bern	FI181	Uusimaa	CH022	Freiburg	FR101	Paris		
TF18_Non-metal_mineral_prod	FR103	Yvelines	DE93	München	CH021	Bern	FR101	Paris		
TF19_Basic_metals	DE41	Duisburg/Essen	CH057	Thurgau	DE52	Starkenbur	FR101	Paris		
TF20_Fabric_metal_prod	UKJ14	Oxfordshire	UKG13	Warwickshire	DE44	Köln	ITC11	Torino		
TF21_Energy_machinery	FR103	Yvelines	DE51	Rhein-Main	AT130	Wien	FR103	Yvelines		
TF22_Nonspc_machinery	DE62	Mittelfhein-Westerrwald	DE42	Düsseldorf	FR301	Nord	FR103	Yvelines		
TF23_Agricul_forestry_machinery	SE02	Västra Götalands län	DE35	Münster	UKH23	Hertfordshire	FR511	Loire-Atlantique		
TF24_Machine_tools	SE02	Västra Götalands län	UKH23	Hertfordshire	ITC11	Torino	FR511	Loire-Atlantique		
TF25_Spec_pulp_machinery	FR103	Yvelines	DE6	Hamburg	DE49	Mittelhessen	SE044	Skåne län		
TF26_Weapons_ammunition	DE48	Nordhessen	CH040	Zürich	FR241	Cher	DE20	Sudheide		
TF27_Domestic_appliances	DE97	Südostoberbayern	DE42	Düsseldorf	FR103	Yvelines	UKH12	Cambridgeshire CC		
TF28_Office_mach_computers	SE010	Stockholms län	FI181	Uusimaa	UKJ33	Hampshire CC	UK111	Inner London - West		
TF29_Electric_motors_generators	CH057	Thurgau	DE81	Würzburg	ITC11	Torino	ES300	Madrid		
TF30_Elec_distr_contr_wire_cable	FR103	Yvelines	UKH33	Essex CC	DE86	Industrieregion Mittelfranken	CH033	Aargau		
TF31_Accumulators_battery	DE93	München	ES300	Madrid	UKJ14	Oxfordshire	DE45	Aachen		
TF32_Lighting_equipment	DE42	Düsseldorf	DE51	Rhein-Main	DE88	Unterer Neckar	UKJ33	Hampshire CC		
TF33_Other_electr equip	FR714	Isère	DE42	Düsseldorf	UKJ33	Hampshire CC	SE025	Västmanlands län		
TF34_Electr_components	DE86	Industrieregion Mittelfranken	UKH12	Cambridgeshire CC	FR1714	Isère	FR101	Paris		
TF35_Signal_transm_telecom	FR105	Hauts-de-Seine	DE30	Berlin	FR101	Paris	UKJ33	Hampshire CC		
TF36_TV_radio_recv_audio	UK23	Outer London - West and North West	FR714	Isère	UK23	Surrey	UKJ23	Surrey		
TF37_Med_equipment	ITC45	Milano	CH040	Zürich	FR716	Rhône	DE67	Saar		
TF38_Measuring_instruments	DE51	Rhein-Main	DE68	Unterer Neckar	FR105	Hauts-de-Seine	FR105	Hauts-de-Seine		
TF39_Ind_proc_contr equip	FR107	Val-de-Marne	DE45	Aachen	DE66	Rheinplatz	FR181	Uusimaa		
TF40_Opt_instruments	NI33	ZUID-HOLLAND	DE73	Ostwürtemberg	UKH12	Cambridgeshire CC	NL41	NOORD-BRABANT		
TF41_Watches_clocks	CH021	Bern	DE93	München	CH040	Zürich	DE79	Bodensee-Oberschwaben		
TF42_Motor_vehicles	SE042	Västra Götalands län	DE70	Mittlerer Oberrhein	ITD35	Bologna	FR105	Hauts-de-Seine		
TF43_Other_transp equip	CH040	Zürich	DE51	Rhein-Main	DE30	Berlin	AT130	Wien		
TF44_Furniture_consum_good	UKJ23	Surrey	AT130	Wien	FR718	Haute-Savoie	DE72	Stuttgart		

Source: own calculations and illustration. Notes: Betweenness centrality ranking of TL3 regions (descending order).

Table B.11. Spatial maximum likelihood regression (ML-SAR) for EU-15

Model	(41)	(42)	(43)	(44)	(45)
	EU-15	EU-15	EU-15	EU-15	EU-15
<i>dependent variable:</i> $1/T\ln(y_{i,2006}/y_{i,1995})$					
CTRYDUMMY	no	no	no	no	no
GDPLEVEL	-0,0062*** (0,0017)	-0,0051*** (0,0015)	-0,0064*** (0,0017)	-0,0053*** (0,0015)	-0,0066*** (0,0017)
NATBORDER	-0,0002 (0,0007)		-9,5096 (0,0007)		0,0000 (0,0007)
EUBORDER	-0,0009 (0,0013)		-0,0008 (0,0013)		-0,0007 (0,0013)
INDUSTRY	-0,0047*** (0,0017)	-0,0060*** (0,0012)	-0,0049*** (0,0018)	-0,0064*** (0,0012)	-0,0045** (0,0018)
SERVICES	0,0018 (0,0029)		0,0018 (0,0029)		0,0027 (0,0030)
CAPITAL	0,0041*** (0,0014)		0,0045*** (0,0014)		0,0045*** (0,0015)
URBAN	0,0008 (0,0009)		0,0005 (0,0010)		0,0001 (0,0010)
INTERMEDIAT	-0,0008 (0,0008)		-0,0009 (0,0008)		-0,0011 (0,0008)
POPDENSITY		0,0004 (0,0003)		0,0004 (0,0003)	
HTEPOPAT	0,0003 (0,0005)	0,0007** (0,0003)	0,0004 (0,0005)	0,0008** (0,0003)	0,0006 (0,0005)
NHTEPOPAT	0,0002 (0,0004)		0,0002 (0,0004)		0,0001 (0,0004)
ρ	0,7765*** (0,0401)	0,7915*** (0,0387)	0,7922*** (0,0419)	0,8064*** (0,0405)	0,8012*** (0,0440)
N	640	640	640	640	640
W-matrix	W250km	W250km	W300km	W300km	W350km
LR-test	221,4160***	244,8882***	201,5465***	224***	111,9282***
AIC	-4304,13	-4302,61	-4284,26	-4282,15	-4194,6400
log likelihood	2164,06	2157,31	2154,13	2147,08	2109,3200
R-squared	0,4586	0,4486	0,4358	0,4244	0,4171

Source: own estimations. *Notes:* Growth regressions for period 1995-2006 w/o CTRYDUMMY and spatial growth spillovers; standard errors in parentheses; SAR-Maximum Likelihood estimation with spatial lagged dependent variable (ρ); standard errors in parentheses; spatial lags are statistically significant due to omitted country dummy variables; constant not reported; significance levels of coefficients: *** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.10 level. Reference category for settlement type effects is RURAL. W-matrix is the geographic distance matrix used for spatial analysis. Further information on regression details are available upon request from the author.

Table B.12. Spatial maximum likelihood regression (ML-SAR) for NMS

Model	(51)	(52)	(53)
	NMS	NMS	NMS
<i>dependent variable:</i> $1/T\ln(y_{i,2006}/y_{i,1995})$			
CTRYDUMMY	no	no	no
GDPLEVEL	-0,0189*** (0,0038)	-0,0180*** (0,0040)	-0,0196*** (0,0042)
NATBORDER	-0,0020 (0,0019)	-0,0017 (0,0020)	-0,0019 (0,0021)
EUBORDER	0,0008 (0,0022)	-0,0008 (0,0023)	-0,0020 (0,0024)
INDUSTRY	0,0111** (0,0046)	0,0106** (0,0047)	0,0119** (0,0049)
SERVICES	0,0099 (0,0064)	0,0080 (0,0066)	0,0076 (0,0069)
CAPITAL	0,0245*** (0,0036)	0,0257*** (0,0037)	0,0262*** (0,0039)
URBAN	0,0142*** (0,0037)	0,0133*** (0,0039)	0,0134*** (0,0041)
INTERMEDIAT	0,0030 (0,0021)	0,0021 (0,0022)	0,0014 (0,0023)
HTEPOPAT	-0,0049 (0,0043)	-0,0066 (0,0044)	-0,0059 (0,0046)
NHTEPOPAT	0,0048*** (0,0018)	0,0051*** (0,0018)	0,0053*** (0,0019)
ρ	0,5683*** (0,0794)	0,6372*** (0,0912)	0,6216*** (0,1095)
W-matrix	W150km	W200km	W250km
LR-test	39,4764***	34,4250***	26,9331***
AIC	-747,2560	-742,2050	-734,7130
log likelihood	385,6280	383,1020	379,3560
N	120	120	120
R-squared	0,6928	0,6748	0,6472

Source: own estimations. *Notes:* Growth regressions for period 1995-2006 w/o CTRYDUMMY and with spatial growth spillovers; standard errors in parentheses; SAR-Maximum Likelihood estimation with spatial lagged dependent variable (ρ); standard errors in parentheses; spatial lags are statistically significant due to omitted country dummy variables; constant not reported; significance levels of coefficients: *** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.10 level. Reference category for settlement type effects is RURAL. W-matrix is the geographic distance matrix used for spatial analysis. Further information on regression details are available upon request from the author.

Bibliography

- ABRAMOVITZ, M. (1986). Catching up, forging ahead, and falling behind. *Journal of Economic History*, **46**, 385–406.
- ABREU, M., DE GROOT, H. L. F. and FLORAX, R. J. G. M. (2004). *Space and growth*. Tinbergen Institute Discussion Papers 04-129/3, Tinbergen Institute.
- , — and — (2005). A meta-analysis of beta-convergence: The legendary 2%. *Journal of Economic Surveys*, **19** (3), 389–420.
- ABRHAM, J. and VOSTA, M. (2006). *New member states of the EU: Current trends in regional disparities*. ERSA conference papers ersa06p148, European Regional Science Association.
- ACS, Z. J. (2002). *Innovation and the Growth of Cities*. Cheltenham: Edward Elgar.
- , ANSELIN, L. and VARGA, A. (1997). Local geographic spillovers between university research and high technology innovations. *Journal of Urban Economics*, **42** (3), 422–448.
- , — and — (2002). Patents and innovation counts as measures of regional production of new knowledge. *Research Policy*, **31** (7), 1069–1085.
- and ARMINGTON, C. (2004). Employment growth and entrepreneurial activity in cities. *Regional Studies*, **38** (8), 911–927.
- AGHION, P. and HOWITT, P. (1992). A model of growth through creative destruction. *Econometrica*, **60** (2), 323–351.
- AGRAWAL, A., COCKBURN, I. and MCHALE, J. (2003). *Gone but not forgotten: Labor flows, knowledge spillovers, and enduring social capital*. NBER Working Papers 9950, National Bureau of Economic Research, Inc.
- , — and — (2006). Gone but not forgotten: Knowledge flows, labor mobility, and enduring social relationships. *Journal of Economic Geography*, **6**, 571–591.
- AIGINGER, K. and PFAFFERMAYR, M. (2004). The single market and geographic concentration in europe. *Review of International Economics*, **12** (1), 1–11.
- ALCACER, J. and GITTELMAN, M. (2004). *How do I know what you know? Patent examiners and the generation of patent citations*. SSRN Working Paper, Harvard University, <http://ssrn.com/abstract=548003>.
- ALMEIDA, P. (1996). Knowledge sourcing by foreign multinationals: Patent citation analysis in the U.S. semiconductor industry. *Strategic Management Journal*, **17**, 155–165.

- and KOGUT, B. (1999). Localization of knowledge and the mobility of engineers in regional networks. *Management Science*, **45**, 905–917.
- ALONSO, W. (1964). *Location and Land Use. Towards a General Theory of Land Rent*. Cambridge: Harvard University Press.
- AMIN, A. and THRIFT, N. (1992). Neo-Marshallian nodes in global networks. *International Journal of Urban and Regional Research*, **16**, 571–587.
- AMITI, M. (1997). *Specialisation patterns in Europe*. CEP Discussion Papers dp0363, Centre for Economic Performance, LSE.
- (1998). New trade theories and industrial location in the EU: A survey of evidence. *Oxford Review of Economic Policy*, **14** (2), 45–53.
- (1999). Specialization patterns in Europe. *Review of World Economics (Weltwirtschaftliches Archiv)*, **135** (4), 573–593.
- ANDERSSON, M. and EJERMO, O. (2002). *Knowledge production in Swedish functional regions 1993-1999*. CESPRI Working Papers 139, CESPRI, Centre for Research on Innovation and Internationalisation, Universita' Bocconi, Milano, Italy.
- and — (2005). How does accessibility to knowledge sources affect the innovativeness of corporations? Evidence from Sweden. *The Annals of Regional Science*, **39** (4), 741–765.
- and GRÅSJÖ, U. (2009). Spatial dependence and the representation of space in empirical models. *The Annals of Regional Science*, **43** (1), 159–180.
- ANDERSSON, R., QUIGLEY, J. M. and WILHELMSSON, M. (2005). *Agglomeration and the spatial distribution of creativity*. Working Paper Series in Economics and Institutions of Innovation 42, Royal Institute of Technology, CESIS - Centre of Excellence for Science and Innovation Studies.
- ANSELIN, L. (1988a). *Spatial Econometrics: Methods and Models*. Kluwer: Dordrecht.
- (1988b). A test for spatial autocorrelation in seemingly unrelated regressions. *Economics Letters*, **28** (4), 335–341.
- (1992). Space and applied econometrics: Introduction. *Regional Science and Urban Economics*, **22** (3), 307–316.
- (1995). Local indicators of spatial association – LISA. *Geographical Analysis*, **27**, 93–115.
- (1999). *Spatial econometrics*. Working paper, Bruton Center School of Social Sciences University of Texas at Dallas Richardson, TX.
- (2000). Geographical spillovers and university research: A spatial econometric perspective. *Growth and Change*, **31** (4), 501–515.

- (2002). *Spatial externalities, spatial multipliers and spatial econometrics*. Tech. rep., Regional Economics Applications Laboratory (REAL) and Department of Agricultural and Consumer Economics University of Illinois, Urbana-Champaign.
- (2006). *Spatial regression*. Tech. rep., Spatial Analysis Laboratory, Department of Geography and National Center for Supercomputing Applications, University of Illinois, Urbana-Champaign.
- (2007). Spatial econometrics in rsue: Retrospect and prospect. *Regional Science and Urban Economics*, **37** (4), 450–456.
- and BERA, A. K. (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. In D. Giles and A. Ullah (eds.), *Handbook of Applied Economic Statistics*, London: Taylor and Francis CRC Press, pp. 237–289.
- , —, FLORAX, R. J. and YOON, M. J. (1996). Simple diagnostic tests for spatial dependence. *Regional Science and Urban Economics*, **26** (1), 77–104.
- and FLORAX, R. J. (1995). New directions in spatial econometrics: Introduction. In L. Anselin and J. G. M. Florax (eds.), *New Directions in Spatial Econometrics*, Heidelberg: Springer, pp. 21–74.
- and GETIS, A. (1992). Spatial statistical analysis and geographic information systems. *The Annals of Regional Science*, **26** (1), 19–33.
- and REY, S. (1991). Properties of tests for spatial dependence in linear regression models. *Geographical Analysis*, **23**, 112–131.
- ARANCEGUI, M., MARTINS, J. and LA PORTA, M. (2008). *Knowledge spillovers at the subregional level. The countries of the Basque country*. Discussion paper, Draft for 11th EUNIP Conference.
- ARBIA, G. (1989). *Spatial Data Configuration in Statistical Analysis of Regional Economics and Related Problems*. Kluwer: Dordrecht.
- (2001). The role of spatial effects in empirical analysis of regional concentration. *Journal of Geographical Systems*, **3** (3), 271–281.
- , DE DOMINICIS, L. and PIRAS, G. (2005). *The relationship between regional growth and regional inequality in EU and transition countries - a spatial econometric approach*. ERSa conference papers ersa05p168, European Regional Science Association.
- , LE GALLO, J. and PIRAS, G. (2008). Does evidence on regional economic convergence depend on the estimation strategy? Outcomes from analysis of a set of NUTS2 EU regions. *Spatial Economic Analysis*, **3** (2), 209–224.
- and PETRARCA, F. (2010). *Effects of MAUP on spatial econometric models*. Tech. rep.
- ARCHIBUGI, D. and PIANTA, M. (1992). Specialization and size of technological activities in industrial countries: The analysis of patent data. *Research Policy*, **21** (1), 79–93.

- ARROW, K. (1962a). The economic implications of learning by doing. *The Review of Economic Studies*, **29** (3), 155–173.
- (1962b). Economic welfare and the allocation of resources for invention. In R. R. Nelson (ed.), *The Rate and Direction of Inventive Activity*, Princeton, NJ.: Princeton University Press.
- ASHEIM, B. (2000). Industrial districts: The contribution of Marshall and beyond. In G. L. Clark, M. S. Gertler and M. P. Feldman (eds.), *The Oxford Handbook of Economic Geography*, Oxford: Oxford University Press, pp. 413–431.
- and GERTLER, M. (2005). The geography of innovation. In J. Fagerberg, D. Mowery and R. Nelson (eds.), *The Oxford Handbook of Innovation*, Oxford: Oxford University Press, pp. 291–317.
- and ISAKSEN, A. (2002). Regional innovation systems: The integration of local 'sticky' and global 'ubiquitous' knowledge. *The Journal of Technology Transfer*, **27** (1), 77–86.
- ATHREYE, S. and WERKER, C. (2004). Marshall's disciples: Knowledge and innovation driving regional economic development and growth. *Journal of Evolutionary Economics*, **14** (5), 505–523.
- ATZEMA, O. A. L. C. and VAN OORT, F. (2004). On the conceptualization of agglomeration economies: The case of new firm formation in the dutch ict sector. *The Annals of Regional Science*, **38** (2), 263–290.
- AUDRETSCH, D. B. (1998). Agglomeration and the location of innovative activity. *Oxford Review of Economic Policy*, **14** (2), 18–29.
- , FALCK, O., FELDMAN, M. P. and HEBLICH, S. (2008). *The lifecycle of regions*. Tech. rep., CEPR Discussion Paper 6757.
- and FELDMAN, M. P. (1995). *Innovative clusters and the industry life cycle*. CEPR Discussion Papers 1161, C.E.P.R. Discussion Papers.
- and — (1996). R&D spillovers and the geography of innovation and production. *American Economic Review*, **86** (3), 630–640.
- and — (1999). Innovation in cities: Science-based diversity, specialization and localized competition. *European Economic Review*, **43** (2), 409–429.
- and — (2004). Knowledge spillovers and the geography of innovation. In J. V. Henderson and J. F. Thisse (eds.), *Handbook of Regional and Urban Economics*, vol. 4, **61**, Amsterdam: Elsevier, pp. 2713–2742.
- and FRITSCH, M. (2002). Growth regimes over time and space. *Regional Studies*, **36** (2), 113–124.
- and KEILBACH, M. (2004). Entrepreneurship capital and economic performance. *Regional Studies*, **38** (8), 949–959.

- and — (2008). Resolving the knowledge paradox: Knowledge-spillover entrepreneurship and economic growth. *Research Policy*, **37** (10), 1697–1705.
- , LEHMANN, E. E. and WARNING, S. (2005). University spillovers and new firm location. *Research Policy*, **34** (7), 1113–1122.
- and THURIK, R. (2001). *Linking entrepreneurship to growth*. OECD Science, Technology and Industry Working Papers 2001/2, OECD Publishing.
- AUTANT-BERNARD, C., MAIRESSE, J. and MASSARD, N. (2007). Spatial knowledge diffusion through collaborative networks. *Papers in Regional Science*, **86** (3), 341–350.
- and MASSARD, N. (2000). *Scientific interactions, geographic spillovers and innovation: An empirical study on the French case*. ERSA conference papers ersa00p131, European Regional Science Association.
- and — (2007). Pecuniary and knowledge externalities as agglomeration forces: Empirical evidence from individual french data. In J. Surinach, R. Moreno and E. Vaya (eds.), *Knowledge Externalities, Innovation Clusters and Regional Development*, Cheltenham: Edward Elgar, pp. 111–135.
- AYDALOT, P. (1986). *Milieux Innovateurs en Europe*. GREMI, Paris.
- BAHLMANN, M., HUYSMAN, M. and ELFRING, T. (2009). *Global pipelines or global buzz?: A micro-level approach towards the knowledge-based view of clusters*. Serie Research Memoranda 0002, VU University Amsterdam, Faculty of Economics, Business Administration and Econometrics.
- BALCONI, M., BRESCHI, S. and LISSONI, F. (2004). Networks of inventors and the role of academia: An exploration of Italian patent data. *Research Policy*, **33** (1), 127–145.
- BALDWIN, R. E. and FORSLID, R. (1999). Incremental trade policy and endogenous growth: A q-theory approach. *Journal of Economic Dynamics and Control*, **23** (5-6), 797–822.
- and — (2000a). The core-periphery model and endogenous growth: Stabilizing and destabilizing integration. *Economica*, **67** (267), 307–24.
- and — (2000b). Trade liberalisation and endogenous growth: A q-theory approach. *Journal of International Economics*, **50** (2), 497–517.
- , —, MARTIN, P., OTTAVIANO, G. and ROBERT-NICOUD, F. (2001a). *Agglomeration and growth with and without capital mobility*. Discussion Paper Series 26403, Hamburg Institute of International Economics, <http://ideas.repec.org/p/ags/hiiidp/26403.html>.
- and KRUGMAN, P. (2001). *Agglomeration, integration and tax harmonization*. HEI Working Papers HEIWP01-2001, Economics Section, The Graduate Institute of International Studies.
- and — (2004). Agglomeration, integration and tax harmonisation. *European Economic Review*, **48** (1), 1–23.

- and MARTIN, P. (2003). *Agglomeration and regional growth*. CEPR Discussion Papers 3960, C.E.P.R. Discussion Papers.
- and — (2004). Agglomeration and regional growth. In J. V. Henderson and J. F. Thisse (eds.), *Handbook of Regional and Urban Economics*, vol. 4, 60, Amsterdam: Elsevier, pp. 2671–2713.
- , — and OTTAVIANO, G. I. P. (2001b). Global income divergence, trade, and industrialization: The geography of growth take-offs. *Journal of Economic Growth*, **6** (1), 5–37.
- BARRO, R. J. (1991). *Economic growth in a cross section of countries*. NBER Working Papers 3120, National Bureau of Economic Research, Inc.
- and SALA-I-MARTIN, X. (1991). Convergence across states and regions. *Brookings Papers on Economic Activity*, **22** (1991-1), 107–182.
- and SALA-I-MARTIN, X. (1992). Convergence. *Journal of Political Economy*, **100** (2), 223–251.
- and SALA-I-MARTIN, X. (2003). *Economic Growth, 2nd Edition, MIT Press Books*, vol. 1. Cambridge, MA: The MIT Press.
- BATHELT, H. and GLÜCKLER, J. (2003). Toward a relational economic geography. *Journal of Economic Geography*, **3** (2), 117–144.
- , MALMBERG, A. and MASKELL, P. (2004). Clusters and knowledge: Local buzz, global pipelines and the process of knowledge creation. *Progress in Human Geography*, **28**, 31–56.
- BATISSE, C. (2002). Dynamic externalities and local growth: A panel data analysis applied to chinese provinces. *China Economic Review*, **13** (2-3), 231–251.
- BATTISTI, M. and VAIO, G. D. (2008). A spatially filtered mixture of beta-convergence regressions for EU regions, 1980-2002. *Empirical Economics*, **34** (1), 105–121.
- BAUMOL, W. J. (1986). Productivity growth, convergence, and welfare: What the long-run data show. *American Economic Review*, **76** (5), 1072–85.
- (2008). Indivisibilities. In S. N. Durlauf and L. E. Blume (eds.), *The New Palgrave Dictionary of Economics*, Basingstoke: Basingstoke: Palgrave Macmillan.
- BAUMONT, C., ERTUR, C. and LE GALLO, J. (2000). *Geographic spillover and growth: A spatial econometric analysis for European regions*. LATEC - Document de travail - Economie (1991-2003) 2000-07, LATEC, Laboratoire d'Analyse et des Techniques Economiques, CNRS UMR 5118, Université de Bourgogne.
- , — and — (2002). *The European regional convergence process, 1980-1995: Do spatial regimes and spatial dependence matter?* Econometrics 0207002, EconWPA.
- , — and — (2003). Spatial convergence clubs and the European regional growth process. In B. Fingleton (ed.), *European Regional Growth*, Heidelberg: Springer, pp. 131–158.

- BBR (2011). BBR Raumordnungsregionen in Deutschland: homepage http://www.bbr.bund.de/nn_103086/BBSR/DE/Raubeobachtung/Werkzeuge/Raumabgrenzungen/Raumordnungsregionen/raumordnungsregionen.html, accessed: 02.01.2011.
- BEAUDRY, C. and SCHIFFAUEROVA, A. (2009). Who's right, Marshall or Jacobs? The localization versus urbanization debate. *Research Policy*, **38** (2), 318–337.
- BECATTINI, G. (2002). Industrial sectors and industrial districts: Tools for industrial analysis. *European Planning Studies*, **10**, 483–493.
- BEHRENS, K. and ROBERT-NICOUD, F. (2008). *Survival of the fittest in cities: Agglomeration, selection, and polarisation*. CEP Discussion Papers dp0894, Centre for Economic Performance, LSE.
- and THISSE, J.-F. (2006). Agglomeration versus product variety: Implications for regional inequalities. *Journal of Regional Science*, **46** (5), 867–880.
- and — (2007). Regional economics: A new economic geography perspective. *Regional Science and Urban Economics*, **37** (4), 457–465.
- BELITZ, H., EDLER, J. and GRENZMANN, C. (2006). Internationalisation of industrial R&D. In U. Schmoch, C. Rammer and H. Legler (eds.), *National Systems of Innovation in Comparison*, Heidelberg: Springer, pp. 47–66.
- BERGMAN, E. (2009). Embedding network analysis in spatial studies of innovation. *The Annals of Regional Science*, **43** (3), 559–565.
- and MAIER, G. (2009). Network central: Regional positioning for innovative advantage. *The Annals of Regional Science*, **43** (3), 615–644.
- and USAI, S. (2009). *Knowledge diffusion in European regions*. Tech. rep., IAREG.
- BESSEN, J. and HUNT, R. M. (2007). An empirical look at software patents. *Journal of Economics & Management Strategy*, **16** (1), 157–189.
- BILBAO-OSORIO, B. and RODRÍGUEZ-POSE, A. (2004). From R&D to innovation and economic growth in the EU. *Growth and Change*, **35** (4), 434–455.
- BLACK, D. and HENDERSON, V. (1999a). Spatial evolution of population and industry in the United States. *American Economic Review*, **89** (2), 321–327.
- and — (1999b). A theory of urban growth. *Journal of Political Economy*, **107** (2), 252–284.
- BLIEN, U. and SUEDEKUM, J. (2005). *Local economic structure and industry development in Germany, 1993-2001*. IAB Discussion Paper 200501, Institut für Arbeitsmarkt und Berufsforschung (IAB), Nürnberg Institute for Employment Research, Germany.
- BLIND, K., EDLER, J., FRIETSCH, R. and SCHMOCH, U. (2006). Motives to patent: Empirical evidence from Germany. *Research Policy*, **35** (5), 655–672.

- BLUM, U. (2008). Institutions and clusters. In C. Karlsson (ed.), *Handbook of Research on Innovation and Clusters: Cases and Policies*, Cheltenham: Edward Elgar, pp. 361–373.
- BOIX, R. and TRULLÉN, J. (2004). *Knowledge, networks of cities and growth in regional urban systems: theory, measurement and policy implications*. ERSA conference papers ersa04p85, European Regional Science Association.
- BOSCHMA, R. A. and FRENKEN, K. (2006). Why is economic geography not an evolutionary science? Towards an evolutionary economic geography. *Journal of Economic Geography*, **6** (3), 273–302.
- and — (2009a). *Applications of evolutionary economic geography*. DRUID Working Papers 06-26, DRUID, Copenhagen Business School, <http://ideas.repec.org/p/aal/abbswp/06-26.html>.
- and — (2009b). Technological relatedness and regional branching. In H. Bathelt, M. Feldman and D. Kogler (eds.), *Dynamic Geographies of Knowledge Creation and Innovation*, London: Routledge.
- and — (2010). *The emerging empirics of evolutionary economic geography*. Eindhoven Center for Innovation Studies (ECIS) working paper series 10-10, Eindhoven Center for Innovation Studies (ECIS).
- and IAMMARINO, S. (2007). *Related variety and regional growth in Italy*. SPRU Electronic Working Paper Series 162, University of Sussex, SPRU - Science and Technology Policy Research.
- and — (2009). Related variety, trade linkages and regional growth in Italy. *Economic Geography*, **85** (3), 289–311.
- and LAMBOOY, J. G. (2002). Knowledge, market structure, and economic coordination: Dynamics of industrial districts. *Growth and Change*, **33** (3), 291–311.
- and WETERINGS, A. B. (2005). *The effect of regional differences on the performance of software firms in the Netherlands*. Papers in Evolutionary Economic Geography (PEEG) 0506, Utrecht University, Section of Economic Geography.
- BOTTAZZI, L. and PERI, G. (2000). *Innovation and spillovers: Evidence from European regions*. CESifo Working Paper Series CESifo Working Paper No., CESifo GmbH.
- and — (2003). Innovation and spillovers in regions: Evidence from European patent data. *European Economic Review*, **47** (4), 687–710.
- BRADLEY, R. and GANS, J. S. (1998). Growth in Australian cities. *The Economic Record*, **74** (226), 266–278.
- BRAKMAN, S. and GARRETSEN, H. (2009). *Trade and geography: Paul Krugman and the 2008 Nobel Prize in Economics*. CESifo Working Paper Series CESifo Working Paper No., CESifo GmbH.

- , —, GORTER, J., VAN DER HORST, A. and SCHRAMM, M. (2005). *New economic geography, empirics, and regional policy*. CPB Special Publications 56, CPB Netherlands Bureau for Economic Policy Analysis.
- , — and VAN MARREWIJK, C. (2009). Economic geography within and between European nations: The role of market potential and density across space and time. *Journal of Regional Science*, **49** (4), 777–800.
- and VAN MARREWIJK, C. (2008). It's a big world after all: On the economic impact of location and distance. *Cambridge Journal of Regions, Economy and Society*, **1** (3), 411–437.
- BRESCHI, S. (2000). The geography of innovation: A cross-sector analysis. *Regional Studies*, **34** (3), 213–229.
- (2008). Innovation-specific agglomeration economies and the spatial clustering of innovative firms. In C. Karlsson (ed.), *Handbook of Research on Innovation and Clusters: Cases and Policies*, Cheltenham: Edward Elgar, pp. 167–207.
- and LISSONI, F. (2001a). Knowledge spillovers and local innovation systems: A critical survey. *Industrial and Corporate Change*, **10** (4), 975–1005.
- and — (2001b). Localised knowledge spillovers vs. innovative milieux: Knowledge "tacitness" reconsidered. *Papers in Regional Science*, **80** (3), 255–273.
- and — (2003). *Mobility and social networks: Localised knowledge spillovers revisited*. CESPRI Working Papers 142, CESPRI, Centre for Research on Innovation and Internationalisation, Università' Bocconi, Milano, Italy.
- and — (2004). *Knowledge networks from patent data: Methodological issues and research targets*. CESPRI Working Papers 150, CESPRI, Centre for Research on Innovation and Internationalisation, Università' Bocconi, Milano, Italy.
- and — (2006). *Mobility of inventors and the geography of knowledge spillovers. New evidence on US data*. CESPRI Working Papers 184, CESPRI, Centre for Research on Innovation and Internationalisation, Università' Bocconi, Milano, Italy.
- and — (2009). Mobility of skilled workers and co-invention networks: An anatomy of localized knowledge flows. *Journal of Economic Geography*, **9** (4), 439–468.
- , — and MONTOBIO, F. (2005). The geography of knowledge spillovers: Conceptual issues and measurement problems. In S. Breschi and F. Lissoni (eds.), *Clusters, Networks and Innovation*, 13, Oxford: Oxford University Press, pp. 343–371.
- and MALERBA, F. (2001). The geography of innovation and economic clustering: Some introductory notes. *Industrial and Corporate Change*, **10** (4), 817–833.
- BRESNAHAN, T. F., GAMBARDILLA, A. and SAXENIAN, A. (2001). 'Old economy' inputs for 'new economy' outcomes: Cluster formation in the new Silicon Valleys. *Industrial and Corporate Change*, **10** (4), 835–860.

- BRÜLHART, M. and TRAEGER, R. (2005). An account of geographic concentration patterns in Europe. *Regional Science and Urban Economics*, **35** (6), 597–624.
- BRÜLHART, M. (2001). Evolving geographical concentration of European manufacturing industries. *Review of World Economics (Weltwirtschaftliches Archiv)*, **137** (2), 215–243.
- BRÄUNINGER, M. and NIEBUHR, A. (2005). *Convergence, spatial interaction and agglomeration effects in the EU*. ERSA conference papers ersa05p528, European Regional Science Association.
- and — (2008). Agglomeration, spatial interaction and convergence in the EU. *Schmollers Jahrbuch : Journal of Applied Social Science Studies / Zeitschrift für Wirtschafts- und Sozialwissenschaften*, **128** (3), 329–349.
- BRUNSDON, C., FOTHERINGHAM, A. S. and CHARLTON, M. (1998). Spatial nonstationarity and autoregressive models. *Environment and Planning A*, **30** (6), 957–973.
- BRUSCO, S. (1982). The Emilian model: Productive decentralisation and social integration. *Cambridge Journal of Economics*, **6**, 167–184.
- BRUSONI, S., CRESPI, G., FRANCOZ, D., GAMBARDELLA, A., GARCIA-FONTES, W., GEUNA, A., GIURI, P., GONZALES, R., HARHOFF, D., HOISL, K. and LEBAS, C. (2006). *Everything you always wanted to know about inventors (but never asked): Evidence from the PatVal-EU survey*. CEPR Discussion Papers 5752, C.E.P.R. Discussion Papers.
- BURGER, M., OORT, F. v. and KNAAP, G. v. D. (2008). *A treatise on the geographical scale of agglomeration externalities and the modifiable areal unit problem*. Research Paper ERS-2008-076-ORG, Erasmus Research Institute of Management (ERIM), ERIM is the joint research institute of the Rotterdam School of Management, Erasmus University and the Erasmus School of Economics (ESE) at Erasmus Uni.
- BURGER, M. J., OORT, F. V., FRENKEN, K. and KNAAP, B. V. D. (2009). Networks and economic agglomerations: Introduction to the special issue. *Tijdschrift voor Economische en Sociale Geografie*, **100** (2), 139–144.
- CABRER-BORRAS, B. and SERRANO-DOMINGO, G. (2004). The effect of knowledge spillovers on productivity growth inequalities in Spanish regions. *Environment and Planning A*, **36** (4), 731–753.
- CAIRNCROSS, F. (2001). *The Death of Distance 2.0. How the Communications Revolution will Change our Lives*. Cambridge: Harvard Business School Press.
- CAMAGNI, R. (1991a). Introduction: From the local milieu to innovation through cooperation networks. In R. Camagni (ed.), *Innovation Networks: Spatial Perspectives*, London: Belhaven Press, pp. 1–9.
- (1991b). Local milieu, uncertainty and innovation networks: Towards a new dynamic theory of economic space. In R. Camagni (ed.), *Innovation Networks: Spatial Perspectives*, London: Belhaven Press.

- (1995). The concept of innovative milieu and its relevance for public policies in European lagging regions. *Papers in Regional Science*, **4**, 317–340.
- CANIËLS, M. C. J. (1996). *Regional Differences in Technology: Theory and Empirics*. Tech. rep., MERIT.
- CANIËLS, M. C. J. (1997). *The geographic distribution of patents and value added across European regions*. Merit discussion paper, MERIT, Maastricht Economic Research Institute on Innovation and Technology, University of Maastricht.
- CANIËLS, M. C. J. (2000). *Knowledge Spillovers and Economic Growth*. Cheltenham: Edward Elgar.
- CANIËLS, M. C. J. and VERSPAGEN, B. (2001). Barriers to knowledge spillovers and regional convergence in an evolutionary model. *Journal of Evolutionary Economics*, **11** (3), 307–329.
- CAPELLO, R. (2007). *Regional Economics*. London: Routledge.
- (2009). Indivisibilities, synergy and proximity: The need for an integrated approach to agglomeration economies. *Tijdschrift voor economische en sociale geografie*, **100** (2), 145–159.
- and FAGGIAN, A. (2005). Collective learning and relational capital in local innovation processes. *Regional Studies*, **39** (1), 75–87.
- CAPPELLIN, R. (2001). *The governance of regional networks in the process of European integration*. ERSA conference papers ersa01p247, European Regional Science Association.
- CARLINO, G. A. (2001). Knowledge spillovers: Cities' role in the new economy. *Business Review*, (Q4), 17–26.
- , CARR, J., HUNT, R. M. and SMITH, T. E. (2010). *The agglomeration of R&D labs*. Working Papers 10-33, Federal Reserve Bank of Philadelphia.
- , CHATTERJEE, S. and HUNT, R. (2001). *Knowledge spillovers and the new economy of cities*. Tech. rep., Federal Reserve Bank of Philadelphia, 01-14.
- CASTELLACCI, F. (2007). Evolutionary and new growth theories. Are they converging? *Journal of Economic Surveys*, **21** (3), 585–627.
- (2008). Innovation and the competitiveness of industries: Comparing the mainstream and the evolutionary approaches. *Technological Forecasting & Social Change*, **75**, 984–1006.
- and ARCHIBUGI, D. (2008). The technology clubs: The distribution of knowledge across nations. *Research Policy*, **37** (10), 1659–1673.
- CASTELLS, M. (1996). *The Rise of the Network Society (The Information Age: Economy, Society and Culture*, vol. 1. Malden, MA: Blackwell Publishers.

- CERINA, F. and MUREDDU, F. (2009). *Is agglomeration really good for growth? Global efficiency and interregional equity*. Working Paper CRENoS 200913, Centre for North South Economic Research, University of Cagliari and Sassari, Sardinia.
- and PIGLIARU, F. (2005). *Agglomeration and growth in the NEG: A critical assessment*. Working Paper CRENoS 200510, Centre for North South Economic Research, University of Cagliari and Sassari, Sardinia, <http://ideas.repec.org/p/cns/cnsewp/200510.html>.
- CHANDRA, R. and SANDILANDS, R. J. (2005). Does modern endogenous growth theory adequately represent Allyn Young? *Cambridge Journal of Economics*, **29** (3), 463–473.
- CHESBROUGH, H. (2003). *Open Innovation: The new imperative for creating and profiting from technology*. Cambridge: Harvard Business School Press.
- CHRIST, J. P. (2007). *Varieties of systems of innovation: A survey of their evolution in growth theory and economic geography*. Violette Reihe Arbeitspapiere 25, Promotions-schwerpunkt Globalisierung und Beschaeftigung.
- (2009). *The geography and co-location of European technology-specific co-inventorship networks*. Violette Reihe Arbeitspapiere 31, Promotions-schwerpunkt Globalisierung und Beschaeftigung.
- CHRISTALLER, W. (1933). *Central Places in Southern Germany*. Englewood Cliffs, N.J.: Prentice Hall.
- CHRISTOPOULOS, D. K. and TSIONAS, E. G. (2004). Convergence and regional productivity differences: Evidence from Greek prefectures. *The Annals of Regional Science*, **38** (3), 387–396.
- CICCONE, A. (2002). Agglomeration effects in Europe. *European Economic Review*, **46** (2), 213–227.
- (2008). Urban production externalities. In S. N. Durlauf and L. E. Blume (eds.), *The New Palgrave Dictionary of Economics*, Basingstoke: Basingstoke: Palgrave Macmillan.
- and HALL, R. E. (1996). Productivity and the density of economic activity. *American Economic Review*, **86** (1), 54–70.
- CLARK, G. L., FELDMAN, M. P. and GERTLER, M. S. (2000). *The Oxford Handbook of Economic Geography*. Oxford: Oxford University Press.
- CLIFF, A. and ORD, J. (1973). *Spatial Autocorrelation*. London: Pion Limited.
- CLUSTER EXCELLENCE (2011). Cluster Excellence: homepage <http://www.cluster-excellence.eu/>, accessed: 19.07.2010 and 04.03.2011.
- COE, D. T. and HELPMAN, E. (1995). International R&D spillovers. *European Economic Review*, **39** (5), 859–887.
- , — and HOFFMAISTER, A. W. (1997). North-south r&d spillovers. *Economic Journal*, **107** (440), 134–149.

- COHEN, W. M. and LEVINTHAL, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly*, **35** (1), 128–152.
- COMBES, P.-P. (2000a). Economic structure and local growth: France, 1984-1993. *Journal of Urban Economics*, **47** (3), 329–355.
- (2000b). *Marshall-Arrow-Romer externalities and city growth*. Tech. rep., CERAS working paper no 99-06.
- and DURANTON, G. (2006). Labour pooling, labour poaching, and spatial clustering. *Regional Science and Urban Economics*, **36** (1), 1–28.
- , — and OVERMAN, H. G. (2005). Agglomeration and the adjustment of the spatial economy. *Papers in Regional Science*, **84** (3), 311–349.
- , MAGNAC, T. and ROBIN, J.-M. (2004). The dynamics of local employment in France. *Journal of Urban Economics*, **56** (2), 217–243.
- , MAYER, T. and THISSE, J.-F. (2008). *Economic Geography: The Integration of Regions and Nations*. Princeton, NJ: Princeton University Press.
- and OVERMAN, H. G. (2004). The spatial distribution of economic activities in the European Union. In J. V. Henderson and J. F. Thisse (eds.), *Handbook of Regional and Urban Economics*, vol. 4, 64, Amsterdam: Elsevier, pp. 2845–2909.
- COOKE, P. (2001). Regional innovation systems, clusters, and the knowledge economy. *Industrial and Corporate Change*, **10** (4), 945–974.
- (2007). Theorizing regional knowledge capabilities: Economic geography under ‘open innovation’. In J. Surinach, R. Moreno and E. Vaya (eds.), *Knowledge Externalities, Innovation Clusters and Regional Development*, Cheltenham: Edward Elgar, pp. 19–41.
- (2008). Regional innovation systems: Origin of the species. *International Journal of Technological Learning, Innovation and Development*, **1** (3), 393–409.
- , GOMEZ URANGA, M. and ETXEBARRIA, G. (1997). Regional innovation systems: Institutional and organisational dimensions. *Research Policy*, **26** (4-5), 475–491.
- COOMBS, R. and GEORGHIOU, L. (2002). A new “industrial ecology”. *Science*, **296** (5567), 471.
- COPUS, A. K. (1999). *Accessibility and Peripherality Indicators*. Tech. rep., Rural Policy Group, Scottish Agricultural College, Aberdeen.
- COWAN, R., DAVID, P. A. and FORAY, D. (2000). The explicit economics of knowledge codification and tacitness. *Industrial and Corporate Change*, **9** (2), 211–253.
- COWELL, F. (1995). *Measuring Inequality*. Hemel Hempstead: Harvester Wheatsheaf.
- CRAFTS, N. and VENABLES, A. (2003). Globalization in history. A geographical perspective. In *Globalization in Historical Perspective*, NBER Chapters, Cambridge, MA: National Bureau of Economic Research, Inc, pp. 323–370.

- CRESCENZI, R. and RODRÍGUEZ-POSE, A. (2006). *R&D, spillovers, innovation systems and the genesis of regional growth in Europe*. ERSA conference papers ersa06p371, European Regional Science Association.
- and RODRÍGUEZ-POSE, A. (2008). *Mountains in a flat world: Why proximity still matters for the location of economic activity*. Working Papers 2008-09, Instituto Madrileño de Estudios Avanzados (IMDEA) Ciencias Sociales.
- , RODRÍGUEZ-POSE, A. and STORPER, M. (2007a). *The geographical processes behind innovation: A Europe-United States comparative analysis*. Departmental Working Papers of Economics - University 'Roma Tre' 0081, Department of Economics - University Roma Tre.
- , — and STORPER, M. (2007b). The territorial dynamics of innovation: A Europe-United States comparative analysis. *Journal of Economic Geography*, **7**, 673–709.
- CRESPO CUARESMA, J., DOPPELHOFER, G. and FELDKIRCHER, M. (2009a). *The determinants of economic growth in European regions*. CESifo Working Paper Series 2519, CESifo Group Munich.
- , — and — (2009b). Economic growth determinants for European regions: Is Central and Eastern Europe different? *Focus on European Economic Integration*, (3), 22–37.
- , FELDKIRCHER, M. and MAYERHOFER, P. (2010). Regional convergence in Europe and the role of urban agglomerations. *Focus on European Economic Integration*, (3), 64–78.
- CRISCUOLO, P. and VERSPAGEN, B. (2008). Does it matter where patent citations come from? Inventor vs. examiner citations in european patents. *Research Policy*, **37** (10), 1892–1908.
- CRUZ, S. C. S. and TEIXEIRA, A. A. (2007). *A new look into the evolution of clusters literature. A bibliometric exercise*. FEP Working Papers 257, Universidade do Porto, Faculdade de Economia do Porto.
- D'AGOSTINO, L. M., LAURSEN, K. and SANTANGELO, G. (2010). *The impact of R&D offshoring on the home knowledge production of OECD investing regions*. Tech. rep., KITes Bocconi Milano.
- DALL'ERBA, S. (2005). Distribution of regional income and regional funds in Europe 1989–1999: An exploratory spatial data analysis. *Annals in Regional Science*, **39** (1), 121–148.
- DAUTH, W. (2010). *Agglomeration and regional employment growth*. IAB Discussion Paper 201007, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg [Institute for Employment Research, Nuremberg, Germany].
- DE DOMINICIS, L., ARBIA, G. and DE GROOT, H. L. F. (2007). *The spatial distribution of economic activities in Italy*. Tinbergen Institute Discussion Papers 07-094/3, Tinbergen Institute.

- , FLORAX, R. J. G. M. and DE GROOT, H. L. F. (2008). A meta-analysis on the relationship between income inequality and economic growth. *Scottish Journal of Political Economy*, **55** (5), 654–682.
- DE GROOT, H. L. F., POOT, J. and SMIT, M. J. (2009). Agglomeration externalities, innovation and agglomeration externalities, innovation and regional growth. Theoretical perspectives and meta-analysis. In R. Capello and P. Nijkamp (eds.), *Handbook of Regional Growth and Development Theories*, Cheltenham: Edward Elgar.
- DE SMITH, M., GOODCHILD, M. and LONGLEY, P. (2007). *Geospatial Analysis - A comprehensive guide to Principles, Techniques and Software Tools*. Leicester: Matador.
- DEBARSY, N. and ERTUR, C. (2006). *The European enlargement process and regional convergence revisited: Spatial effects still matter*. ERSA conference papers ersa06p198, European Regional Science Association.
- DEGNER, H. and STREB, J. (2010). *Foreign patenting in Germany: 1877 - 1932*. FZID Discussion Papers 21-2010, University of Hohenheim, Center for Research on Innovation and Services (FZID).
- DEKLE, R. (2002). Industrial concentration and regional growth: Evidence from the prefectures. *The Review of Economics and Statistics*, **84** (2), 310–315.
- DELGADO, M., PORTER, M. E. and STERN, S. (2010). Clusters and entrepreneurship. *Journal of Economic Geography*, **10** (4), 495–518.
- DESMET, K. and ROSSI-HANSBERG, E. (2010). *Urban Accounting and Welfare*. Tech. rep., CEPR Discussion Paper 8168.
- DEWHURST, J. and MCCANN, P. (2007). Specialization and regional size. In B. Fingleton (ed.), *New Directions in Economic Geography*, Cheltenham: Edward Elgar, pp. 204–229.
- DICKEN, P. (2000). Places and flows: Situating international investments. In G. L. Clark, M. S. Gertler and M. P. Feldman (eds.), *The Oxford Handbook of Economic Geography*, Oxford: Oxford University Press, pp. 275–291.
- DIXIT, A. K. and STIGLITZ, J. E. (1977). Monopolistic competition and optimum product diversity. *American Economic Review*, **67** (3), 297–308.
- DOBLER, C. (2009). *The impact of institutions, culture, and religion on per capita income*. Violette Reihe Arbeitspapiere 28, Promotionsschwerpunkt Globalisierung und Beschäftigung.
- DOLOREUX, D. and PARTO, S. (2005). Regional innovation systems: Current discourse and unresolved issues. *Technology in Society*, **27**, 133–153.
- DÖRING, T. (2004). Räumliche Wissensspillovers und regionales Wirtschaftswachstum Stand der Forschung und wirtschaftspolitische Implikationen. *Schmollers Jahrbuch : Journal of Applied Social Science Studies / Zeitschrift für Wirtschafts- und Sozialwissenschaften*, **124** (1), 95–137.

- DÖRING, T., BLUME, L. and TÜRCK, M. (2008). *Ursachen der unterschiedlichen Wirtschaftskraft der deutschen Wirtschaft*. Baden-Baden: Nomos.
- and SCHNELLENBACH, J. (2006). What do we know about geographical knowledge spillovers and regional growth? a survey of the literature. *Regional Studies*, **40** (3), 375–395.
- DPMA (2011). *Patents - An information brochure on patents*. Tech. rep., DPMA German Patent and Trade Mark Office.
- DUMAIS, G., ELLISON, G. and GLAESER, E. L. (2002). Geographic concentration as a dynamic process. *The Review of Economics and Statistics*, **84** (2), 193–204.
- DURANTON, G. (2008a). *California dreamin': The feeble case for cluster policies*. Tech. rep.
- (2008b). Spatial economics. In S. N. Durlauf and L. E. Blume (eds.), *The New Palgrave Dictionary of Economics*, Basingstoke: Basingstoke: Palgrave Macmillan.
- and JAYET, H. (2005). *Is the division of labour limited by the extent of the market? Evidence from French cities*. CEPR Discussion Papers 5087, C.E.P.R. Discussion Papers.
- and PUGA, D. (1999). *Diversity and specialization in cities: Why, where and when does it matter?* CEPR Discussion Papers 2256, C.E.P.R. Discussion Papers.
- and — (2001). Nursery cities: Urban diversity, process innovation, and the life cycle of products. *American Economic Review*, **91** (5), 1454–1477.
- and — (2004). Micro-foundations of urban agglomeration economies. In J. V. Henderson and J. F. Thisse (eds.), *Handbook of Regional and Urban Economics*, vol. 4, 48, 1st edn., Amsterdam: Elsevier, pp. 2063–2117.
- and RODRÍGUEZ-POSE, A. (2005). When economists and geographers collide, or the tale of the lions and the butterflies. *Environment and Planning A*, **37** (10), 1695–1705.
- DURLAUF, S. N. and QUAH, D. T. (1999). The new empirics of economic growth. In J. B. Taylor and M. Woodford (eds.), *Handbook of Macroeconomics*, vol. 1, 4, Amsterdam: Elsevier, pp. 235–308.
- DURO, J. A. (2004). *Regional income inequalities in Europe: An updated measurement and some decomposition results*. Working Papers wpdea0411, Department of Applied Economics at Universitat Autònoma de Barcelona.
- EATON, J. and KORTUM, S. (2002). Technology, geography, and trade. *Econometrica*, **70** (5), 1741–1779.
- ECKEY, H.-F. (2008). *Regionalökonomie*. Wiesbaden: Gabler Edition Wissenschaft.
- , KOSFELD, R. and TÜRCK, M. (2003). *Intra- und internationale Spillover-Effekte zwischen den EU-Regionen*. Discussion Papers in Economics 50/03, University of Kassel, Institute of Economics, <http://ideas.repec.org/p/kas/wpaper/2003-50.html>.

- , — and TÜRCK, M. (2004). *Regionale Produktionsfunktionen mit Spillover-Effekten für Deutschland*. Discussion Papers in Economics 64/04, University of Kassel, Institute of Economics.
- , — and TÜRCK, M. (2007). Regional convergence in Germany: A geographically weighted regression approach. *Spatial Economic Analysis*, **2** (1), 45–64.
- EDQUIST, C. (2005). Systems of innovation. perspectives and challenges. In J. Fagerberg, D. C. Mowery and R. R. Nelson (eds.), *The Oxford Handbook of Innovation*, Oxford: Oxford University Press, pp. 181–208.
- EDWARDS, B. K. and STARR, R. M. (1987). A note on indivisibilities, specialization, and economies of scale. *The American Economic Review*, **77** (1), 192–194.
- EJERMO, O. and KARLSSON, C. (2004). *Spatial inventor networks as studied by patent coinventorship*. Working Paper Series in Economics and Institutions of Innovation 17, Royal Institute of Technology, CESIS - Centre of Excellence for Science and Innovation Studies.
- and — (2006). Interregional inventor networks as studied by patent coinventorships. *Research Policy*, **35**, 412–430.
- ELLISON, G. and GLAESER, E. L. (1997). Geographic concentration in U.S. manufacturing industries: A dartboard approach. *Journal of Political Economy*, **105** (5), 889–927.
- and — (1999). The geographic concentration of industry: Does natural advantage explain agglomeration? *American Economic Review*, **89** (2), 311–316.
- ERNST, D. (2002). Global production networks and the changing geography of innovation systems. Implications for developing countries. *Economics of Innovation and New Technology*, **11** (6), 497–523.
- and KIM, L. (2002). Global production networks, knowledge diffusion, and local capability formation. *Research Policy*, **31** (8-9), 1417–1429.
- ERTUR, C. and KOCH, W. (2006). Regional disparities in the European Union and the enlargement process: An exploratory spatial data analysis, 1995-2000. *The Annals of Regional Science*, **40** (4), 723–765.
- ESRI (2010). ESRI ArcGIS 9.3.1: homepage <http://webhelp.esri.com/arcgisdesktop/9.3/index.cfm?TopicName=welcome>, accessed: 20.12.2010.
- EUROPE INNOVA (2011). The European Cluster Observatory (ECO): homepage <http://www.clusterobservatory.eu/index.html>, accessed: 19.03.2010, 12.12.2010 and 05.03.2011.
- EUROPEAN COMMISSION (2000). *Towards a European Research Area*. Tech. rep., Commission of the European Communities.
- EUROPEAN COMMISSION (2007a). *The European Research Area: A new Perspective*. Tech. rep., Commission of the European Communities.

- EUROPEAN COMMISSION (2007b). *The European Research Area: Green Paper Consultation. Preliminary results*. Tech. rep., Commission of the European Communities.
- EUROPEAN COMMISSION (2007c). *Regions in the European Union: Nomenclature of Territorial Units for Statistics. NUTS 2006 /EU-27*. Tech. rep., Commission of the European Communities.
- EUROPEAN COMMISSION (2011a). Europe 2020 program: homepage <http://ec.europa.eu/europe2020/index.htm>, accessed: 25.02.2011.
- EUROPEAN COMMISSION (2011b). *The European Research Area*. Tech. rep., Commission of the European Communities, http://ec.europa.eu/research/era/index_en.htm.
- EUROPEAN COMMISSION (2011c). Jobs and growth: homepage http://europa.eu/legislation_summaries/employment_and_social_policy/growth_and_jobs/index_en.htm, accessed: 03.04.2011.
- EUROPEAN COMMISSION (2011d). Regional policy, cooperation: homepage http://ec.europa.eu/regional_policy/cooperation/index_en.htm, accessed: 07.03.2011.
- EUROPEAN COMMISSION (2011e). Regional policy, enlargement: homepage http://ec.europa.eu/enlargement/index_en.htm, accessed: 25.02.2011.
- EUROPEAN COMMISSION (2011f). Regional policy, funds: homepage http://ec.europa.eu/regional_policy/funds/cf/index_en.htm, accessed: 03.02.2011.
- EUROPEAN COMMISSION (2011g). Regional policy: homepage http://ec.europa.eu/regional_policy/atlas2007/index_en.htm, accessed: 29.12.2010 and 03.04.2011.
- EUROPEAN COMMISSION (2011h). Regional policy, objectives: homepage http://ec.europa.eu/regional_policy/policy/object/index_en.htm, accessed: 13.06.2010 and 03.04.2011.
- EUROPEAN COMMISSION (2011i). Research area: homepage http://ec.europa.eu/research/innovation-union/index_en.cfm?pg=home, accessed: 19.12.2010 and 25.02.2011.
- EUROPEAN COMMISSION (2011j). The ERA: homepage http://ec.europa.eu/research/era/index_en.htm, accessed: 26.01.2011.
- EUROPEAN COMMISSION (2011k). The NUTS classification: homepage http://epp.eurostat.ec.europa.eu/portal/page/portal/nuts_nomenclature/introduction.htm, accessed: 01.01.2010, 26.01.2011 and 25.02.2011.
- EUROPEAN COUNCIL (2010). *Resolution on the Developments in the Governance of the European Research Area, 3016th Competitiveness Council meeting*. Tech. rep., Council of the European Union.
- EUROPEAN PATENT OFFICE (2011a). EPC, member states: homepage <http://www.epo.org/about-us/organisation/member-states/date.html>, accessed: 27.04.2011.

- EUROPEAN PATENT OFFICE (2011b). European Patent Office: homepage <http://www.epo.org/>, accessed: 27.02.2011.
- EUROPEAN PATENT OFFICE (2011c). European Patent Office, news: homepage <http://www.epo.org/news-issues/news/2011/20110126.html>, accessed: 25.02.2011.
- EUROPEAN PATENT OFFICE (2011d). The EPC 1973: homepage http://www.epo.org/law-practice/legal-texts/html/epc/1973/e/acii_i.html, accessed: 02.01.2011.
- EUROPEAN PATENT OFFICE (2011e). The EPC 2010: homepage <http://www.epo.org/law-practice/legal-texts/html/epc/2010/e/ma5b.html>, accessed: 02.01.2011.
- EUROPEAN UNION (2009). *Metropolitan regions in the EU*. Tech. rep., European Union Regional Policy.
- EUROSTAT (2009). *Patent classifications and technology areas, June 2009*. Tech. rep., EUROSTAT.
- EZCURRA, R., PASCUAL, P. and RAPÚN, M. (2007). Spatial disparities in the European Union: An analysis of regional polarization. *The Annals of Regional Science*, **41** (2), 401–429.
- FALK, M. and SINABELL, F. (2008). *The effectiveness of objective 1 structural funds in the EU 15: New empirical evidence from NUTS 3 regions*. WIFO Working Papers 310, WIFO.
- FARHAUER, O. and KRÖLL, A. (2009). *Verfahren zur Messung räumlicher Konzentration und regionaler Spezialisierung in der Regionalökonomik*. Volkswirtschaftliche Reihe ISSN 1435-3520 Nr. V-58-09, Universität Passau.
- FEENSTRA, R. C. (2009). Paul R. Krugman, recipient of the 2008 Nobel Prize in Economics: An appreciation. *Challenge*, **52** (1), 97–107.
- FELDKIRCHER, M. (2006). Regional convergence within the EU-25: A spatial econometric analysis. In O. Nationalbank (ed.), *New Regional Economics in Central European Economies: The Future of CENTROPE, Proceedings of OeNB Workshops No. 9*, Wien: Oesterreichische Nationalbank, pp. 101–119.
- FELDMAN, M. P. (1994a). *The Geography of Innovation*. Heidelberg: Springer.
- (1994b). Knowledge complementarity and innovation. *Small Business Economics*, **6** (5), 363–72.
- (1999). The new economics of innovation, spillovers and agglomeration: A review of empirical studies. *The Economics of Innovation and New Technology*, **8**, 5–25.
- (2000). Location and innovation: The new economic geography of innovation, spillovers and agglomeration. In G. Clark, M. P. Feldman and M. Gertler (eds.), *Oxford Handbook of Economic Geography*, Oxford: Oxford University Press, pp. 373–394.

- and KOGLER, D. F. (2010). Stylized facts in the geography of innovation. In B. Hall and N. Rosenberg (eds.), *Handbook of the Economics of Innovation*, Handbooks in Economics, Amsterdam: Elsevier, pp. 381–410.
- FINGLETON, B. (2000). Spatial econometrics, economic geography, dynamics and equilibrium: a third way? *Environment and Planning A*, **32** (8), 1481–1498.
- (2003). Models and simulations of GDP per inhabitant across Europe's regions: A preliminary view. In B. Fingleton (ed.), *European regional growth*, Heidelberg: Springer, pp. 11–53.
- (2007). *New Directions in Economic Geography*. Cheltenham: Edward Elgar.
- , IGLIORI, D., MORRE, B. and ODEDRA, R. (2007). Employment growth and clusters dynamics of creative industries in Great Britain. In K. Polenske (ed.), *The Economic Geography of Innovation*, Cambridge: Cambridge University Press, pp. 60–87.
- and LÓPEZ-BAZO, E. (2006). Empirical growth models with spatial effects. *Papers in Regional Science*, **85** (2), 177–198.
- FISCHER, M. M. (2001). Innovation, knowledge creation and systems of innovation. *The Annals of Regional Science*, **35** (2), 199–216.
- , SCHERNGELL, T. and JANSENBERGER, E. (2005). *The geography of knowledge spillovers between high-technology firms in Europe - evidence from a spatial interaction modelling perspective*. ERSA conference papers ersa05p5, European Regional Science Association.
- , — and — (2009). Patents, patent citations and the geography of knowledge spillovers in Europe. In C. Karlsson, A. E. Andersson, P. C. Cheshire and R. R. Stough (eds.), *New Directions in Regional Economic Development*, Advances in Spatial Science, Heidelberg: Springer, pp. 331–345.
- and STIRBÖCK, C. (2006). Pan-European regional income growth and club-convergence. *The Annals of Regional Science*, **40** (4), 693–721.
- and VARGA, A. (2003). Spatial knowledge spillovers and university research: Evidence from Austria. *The Annals of Regional Science*, **37** (2), 303–322.
- FLORIDA, R. (1995). Toward the learning region. *Futures*, **25**, 527–536.
- (2002a). The economic geography of talent. *Annals of the Association of American Geographers*, **92**, 743–755.
- (2002b). Foreword: Innovation and the growth of cities. In Z. Acs (ed.), *Innovation and the Growth of Cities*, Cheltenham: Edward Elgar, pp. ix–xi.
- (2002c). *The Rise of the Creative Class*. New York: Basic Books.
- (2005). The world is spiky: Globalization has changed the economic playing field, but hasn't leveled it. *The Atlantic Monthly*, **October**, 48–51.

- , GULDEN, T. and MELLANDER, C. (2008). *The rise of the mega-region*. Working Paper Series in Economics and Institutions of Innovation 129, Royal Institute of Technology, CESIS - Centre of Excellence for Science and Innovation Studies.
- and TINAGLI, I. (2004). *Europe in the Creative Age*. Software Industry Center Carnegie Mellon and Demos.
- FORAY, D. (2004). The patent system and the dynamics of innovation in Europe. *Science Public Policy SPP*, **31** (6), 449–456.
- and LISSONI, F. (2010). University research and public-private interaction. In B. Hall and N. Rosenberg (eds.), *Handbook of the Economics of Innovation*, Handbooks in Economics, Amsterdam: Elsevier.
- and STEINMUELLER, E. (2003). On the economics of R&D and technological collaborations: Insights and results from the project colline. *Economics of Innovation and New Technology*, **12** (1), 77–91.
- FORNAHL, D. and BRENNER, T. (2009). Geographic concentration of innovative activities in Germany. *Structural Change and Economic Dynamics*, **20** (3), 163–182.
- FOTHERINGHAM, A., BRUNSDON, C. and CHARLTON, M. (2002). *Geographically Weighted Regression: The Analysis of Spatially Varying Relationships*. Hoboken, NJ: John Wiley & Sons.
- FRANZ, P. (2010). *Knowledge spillovers as a central element in theories about knowledge-based regional development: Advancement in theory and obstacles for empirical research*. IWH Discussion Papers 5-10, Halle Institute for Economic Research.
- FRAUNHOFER (2009). *The impact of collaboration on Europe's scientific and technological performance*. Tech. rep., Fraunhofer Gesellschaft ISI, IdeaConsult and SPRU Sussex.
- FRENKEN, K. and HOEKMAN, J. (2006). Convergence in an enlarged Europe: The role of network cities. *Tijdschrift voor Economische en Sociale Geografie*, **97** (3), 321–326.
- , VAN OORT, F. and VERBURG, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies*, **41** (5), 685–697.
- FREUND, M. C. (2008). *Die räumliche Differenzierung betrieblicher Innovationsaktivität: Ein Produktionsfunktionsansatz auf der regionalen und betrieblichen Ebene*. Wiesbaden: Gabler Edition Wissenschaft.
- FRIEDMAN, T. (2005). *The World Is Flat: A Brief History of the Twenty-first Century*. New York: Farrar, Straus, and Giroux.
- FRIETSCH, R. and JUNG, T. (2009). *Transnational patents - structures, trends and recent developments*. Tech. rep., Fraunhofer Gesellschaft ISI.
- and SCHMOCH, U. (2006). Technological structures and performance as reflected by patent statistics. In U. Schmoch, C. Rammer and H. Legler (eds.), *National Systems of Innovation in Comparison*, Heidelberg: Springer, pp. 89–105.

- FRITSCH, M. and SLAVTCHEV, V. (2007a). *Industry Specialization, Diversity and the Efficiency of Regional Innovation Systems*. Jena Economic Research Papers in Economics 2007-018, Friedrich-Schiller-University Jena, Max-Planck-Institute of Economics.
- and — (2007b). Universities and innovation in space. *Industry & Innovation*, **14** (2), 201–218.
- FUJITA, M. (2010). The evolution of spatial economics: From Thünen to the new economic geography. *The Japanese Economic Review*, **61** (1), 1–32.
- and ISHII, R. (1999). Global location behavior and organizational dynamics of Japanese electronics firms and their impact on regional economies. *The Dynamic Firm*, **1**, 343–384.
- and KRUGMAN, P. (2003). The new economic geography: Past, present and the future. *Papers in Regional Science*, **83** (1), 139–164.
- , — and VENABLES, A. (2001). *The Spatial Economy: Cities, Regions, and International Trade*, MIT Press Books, vol. 1. Cambridge, MA: The MIT Press.
- and MORI, T. (2005). Frontiers of the new economic geography. *Papers in Regional Science*, **84** (3), 377–405.
- and THISSE, J.-F. (1996). Economics of agglomeration. *Journal of the Japanese and International Economies*, **10** (4), 339–378.
- and — (1997). Economie géographique: Problèmes anciens et nouvelles perspectives. *Annales d’Economie et de Statistique*, (45), 03.
- and — (2003). Does geographical agglomeration foster economic growth? And who gains and loses from it? *The Japanese Economic Review*, **54** (2), 121–145.
- and — (2009). New economic geography: An appraisal on the occasion of Paul Krugman’s 2008 Nobel Prize in Economic Sciences. *Regional Science and Urban Economics*, **39** (2), 109–119.
- FUNKE, M. and NIEBUHR, A. (2000a). *Regional Geographic R&D Spillovers and Economic Growth*. Quantitative Macroeconomics Working Papers 20007, Hamburg University, Department of Economics.
- and — (2000b). *Spatial R&D spillovers and economic growth - evidence from West Germany*. Discussion Paper Series 26396, Hamburg Institute of International Economics, <http://ideas.repec.org/p/ags/hiiedp/26396.html>.
- GALLAGHER, R. (2008). *The Economics of Industrial Location: Agglomeration, Co-Agglomeration, and Inventory Management*. Saarbrücken: VDM Verlag Dr. Müller.
- GARRETSEN, H. and MARTIN, R. (2011). The journal of economic geography a decade on: Where do we go from here? *Journal of Economic Geography*.

- GEPPERT, K., GORNIG, M. and WERWATZ, A. (2006). *Economic growth of agglomerations and geographic concentration of industries-evidence for Germany*. SFB 649 Discussion Papers SFB649DP2006-008, Sonderforschungsbereich 649, Humboldt University, Berlin, Germany.
- , HAPPICH, M. and STEPHAN, A. (2005). *Regional disparities in the European Union: Convergence and agglomeration*. Tech. rep., DIW Berlin German Institute for Economic Research.
- and STEPHAN, A. (2008). Regional disparities in the European Union: Convergence and agglomeration. *Papers in Regional Science*, **87** (2), 193–217.
- GERTLER, M. S. (2003). Local knowledge: Tacit knowledge and the economic geography of context, or the undefinable tacitness of being (there). *Journal of Economic Geography*, **3**, 75–99.
- GETIS, A. and ORD, J. (1992). The analysis of spatial association by use of distance statistics. *Geographical Analysis*, **24** (2), 189–206.
- GIDDENS, A. (2000). *Runaway World: How Globalization Is Reshaping Our Lives*. London: Routledge.
- GINI, C. (1921). Measurement of inequality of incomes. *The Economic Journal*, **31**, 124–126.
- GLAESER, E. L. (1996). *Economic growth and urban density: A review essay*. Tech. rep., New Global Economy Conference Proceedings, Vol. 1, Melbourne: Government Printing Office, pp. 227–46.
- (2000). The new economics of urban and regional growth. In G. L. Clark, M. S. Gertler and M. P. Feldman (eds.), *The Oxford Handbook of Economic Geography*, Oxford: Oxford University Press, pp. 83–98.
- (2005a). Edward L. Glaeser, Review of Richard Florida's *The Rise of the Creative Class*. *Regional Science and Urban Economics*, **35** (5), 593–596.
- (2005b). Reinventing Boston: 1630–2003. *Journal of Economic Geography*, **5** (2), 119–153.
- (2008). *The economic approach to cities*. Working Paper Series rwp08-003, Harvard University, John F. Kennedy School of Government.
- , KALLAL, H. D., SCHEINKMAN, J. A. and SHLEIFER, A. (1992). Growth in cities. *Journal of Political Economy*, **100** (6), 1126–1152.
- and RESSEGER, M. G. (2009). *The complementarity between cities and skills*. NBER Working Papers 15103, National Bureau of Economic Research, Inc.
- GLÜCKLER, J. (2007). Economic geography and the evolution of networks. *Journal of Economic Geography*, **7** (5), 619–634.

- GLÄNZEL, W., MEYER, M., SCHLEMMER, B., DU PLESSIS, M., THIJS, B., MAGERMAN, T., DEBACKERE, K. and VEUGELERS, R. (2003). *Biotechnology - an analysis based on publications and patents*. Tech. rep.
- GORDON, I. R. and MCCANN, P. (2000). Industrial clusters: Complexes, agglomeration and/or social networks? *Urban Studies*, **37**, 513–532.
- GOSENS, T. and DE VAAL, A. (2010). *Social ties, knowledge spillovers and regional convergence*. Tech. rep., Nijmegen Center for Economics (NiCE) Working Paper 10-112.
- GRANOVETTER, M. S. (1973). The strength of weak ties. *The American Journal of Sociology*, **78**, 1360–1380.
- GREIF, S. (2001). Patentgeographie: Die raumliche Struktur der Erfindungstätigkeit in Deutschland. *Raumforschung und Raumordnung*, **2-3**, 142–153.
- and SCHMIEDL, D. (2006). *Patentatlas Deutschland : Die Räumliche Struktur der Erfindungstätigkeit*. München: Dt. Patentamt, Referat Statistik.
- GREUNZ, L. (2003a). Geographically and technologically mediated knowledge spillovers between European regions. *The Annals of Regional Science*, **37** (4), 657–680.
- (2003b). The impact of industrial specialisation and diversity on innovation. *Brussels Economic Review/Cahiers Economiques de Bruxelles*, **46** (3), 11–36.
- (2004). Industrial structure and innovation - evidence from European regions. *Journal of Evolutionary Economics*, **14** (5), 563–592.
- (2005). Intra- and inter-regional knowledge spillovers: Evidence from European regions. *European Planning Studies*, **13** (3), 449–473.
- GRILICHES, Z. (1979). Issues in assessing the contribution of research and development to productivity growth. *Bell Journal of Economics*, **10** (1), 92–116.
- (1981). Market value, R&D and patents. *Economic Letters*, **7**, 183–187.
- (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature*, **28** (4), 1661–1707.
- (1992a). Productivity, R&D, and the data constraint. *American Economic Review*, **84**, 1–23.
- (1992b). The search for R&D spillovers. *Scandinavian Journal of Economics*, **94**, 29–47.
- (1992c). *The search for R&D spillovers*. NBER Working Papers 3768, National Bureau of Economic Research, Inc.
- , HALL, B. H. and HAUSMAN, J. (1984). Econometric models for count data with an application to the patents-R&D relationship. *Econometrica*, **52** (4), 909–38.
- and PAKES, A. (1980a). *Patents and R and D at the firm level: A first look*. NBER Working Papers 0561, National Bureau of Economic Research, Inc.

- and — (1980b). Patents and R&D at the firm level: A first report. *Economics Letters*, **5** (4), 377–381.
- GROSSMAN, G. M. and HELPMAN, E. (1991a). Endogenous product cycles. *Economic Journal*, **101** (408), 1214–29.
- and — (1991b). Trade, knowledge spillovers, and growth. *European Economic Review*, **35** (2-3), 517–526.
- and — (1993). *Innovation and Growth in the Global Economy*, MIT Press Books, vol. 1. Cambridge, MA: The MIT Press.
- and — (1994). Endogenous innovation in the theory of growth. *Journal of Economic Perspectives*, **8** (1), 23–44.
- GRUPP, H. (1998). *Foundations of the economics of innovation: Theory, measurement, and practice*. Cheltenham: Edward Elgar.
- GUELLEC, D. and VAN POTTELSBERGHE DE LA POTTERIE, B. (2000). Applications, grants and the value of patent. *Economics Letters*, **69** (1), 109–114.
- and — (2001). The internationalisation of technology analysed with patent data. *Research Policy*, **30** (8), 1253–1266.
- GUILLAIN, R. and LE GALLO, J. (2010). Agglomeration and dispersion of economic activities in and around Paris: An exploratory spatial data analysis. *Environment and Planning B: Planning and Design*, **37** (6), 961–981.
- HAGEDOORN, J. (2003). Sharing intellectual property rights—an exploratory study of joint patenting amongst companies. *Industrial and Corporate Change*, **12** (5), 1035–1050.
- HAGEMANN, H. (2004). The macroeconomics of accession: Growth, convergence, and structural adjustment. *Structural Change and Economic Dynamics*, **15**, 1–12.
- (2006). Wachstums- und Entwicklungstheorien: Vom Beginn der 1960er Jahre bis Ende der 1980er Jahre. In K. Acham, K. W. Nörr and B. Schefold (eds.), *Der Gestaltungsanspruch der Wissenschaft*, Stuttgart: Franz Steiner Verlag, pp. 187–221.
- and GEIGER, N. (2009). Produktivitätsentwicklung in Europa und den USA. New Economy und die Lissabon-Agenda. In B. Knoll and H. Pitlik (eds.), *Entwicklung und Perspektiven der Europäischen Union. Festschrift for Rolf Caesar*, Baden-Baden: Nomos, pp. 81–96.
- and RUKWID, R. (2007). *Perspectives of workers with low qualifications in Germany under the pressures of globalization and technical progress*. Diskussionspapiere aus dem Institut für Volkswirtschaftslehre der Universität Hohenheim 291/2007, Department of Economics, University of Hohenheim, Germany.
- HALL, B. H. (2005). Exploring the patent explosion. *The Journal of Technology Transfer*, **30** (2), 35–48.

- , GRILICHES, Z. and HAUSMAN, J. A. (1986). *Patents and R&D: Is There A Lag?* NBER Working Papers 1454, National Bureau of Economic Research, Inc.
- and ZIEDONIS, R. H. (2001). The patent paradox revisited: An empirical study of patenting in the U.S. semiconductor industry, 1979-1995. *RAND Journal of Economics*, **32** (1), 101–128.
- HANSEN, D., SHNEIDERMAN, B. and SMITH, M. (2009). *Analyzing Social Media Networks: Learning by Doing with NodeXL*. Node XL Tutorial 1.0.1.88, NodeXL.
- HARHOFF, D. (1995). *Firm formation and regional spillovers: Evidence from Germany*. ZEW Discussion Papers 95-11, ZEW - Zentrum für Europäische Wirtschaftsforschung / Center for European Economic Research.
- , SCHERER, F. M. and VOPEL, K. (2003). Citations, family size, opposition and the value of patent rights. *Research Policy*, **32** (8), 1343–1363.
- HARRIS, C. (1954). The market as a factor in the localization of industry in the United States. *Annals of the Association of American Geographers*, **64**, 315–348.
- HARRIS, R. (2008). *Models of regional growth: Past, present and future*. SERC Discussion Papers 0002, Spatial Economics Research Centre, LSE.
- HAUGHTON, J. H. and KHANDKER, S. R. (2009). *Handbook on Poverty and Inequality*. Washington, DC: World Bank Publications.
- HAUSER, C., TAPPEINER, G. and WALDE, J. (2008). Regional knowledge spillovers: Fact or artifact? *Research Policy*, **37** (5), 861–874.
- HEAD, K. and MAYER, T. (2004). The empirics of agglomeration and trade. In J. V. Henderson and J. F. Thisse (eds.), *Handbook of Regional and Urban Economics, Handbook of Regional and Urban Economics*, vol. 4, 59, Elsevier, pp. 2609–2669.
- , RIES, J. and SWENSON, D. (1995). Agglomeration benefits and location choice: Evidence from Japanese manufacturing investments in the United States. *Journal of International Economics*, **38** (3-4), 223–247.
- HEIDENREICH, M. (1998). The changing system of european cities and regions. *European Planning Studies*, **6** (3), 315–332.
- HENDERSON, J. V. (1974). The sizes and types of cities. *American Economic Review*, **64**, 640–656.
- (1999). *Marshall's economies*. NBER Working Papers 7358, National Bureau of Economic Research, Inc.
- (2003a). Marshall's scale economies. *Journal of Urban Economics*, **53** (1), 1–28.
- (2003b). *Urbanization, economic geography, and growth*. Tech. rep., Brown University, draft chapter prepared for Handbook of Economic Growth, Volume 1.
- (2010). Cities and development. *Journal of Regional Science*, **50** (1), 515–540.

- , KUNCORO, A. and TURNER, M. (1995). Industrial development in cities. *Journal of Political Economy*, **103** (5), 1067–1090.
- and THISSE, J. (2004). *Handbook of Regional and Urban Economics, Cities and Geography*, vol. 4. <http://econpapers.repec.org/RePEc:eee:reghes:4>. Amsterdam: Elsevier.
- HENDERSON, R., JAFFE, A. and TRAJTENBERG, M. (2005). Patent citations and the geography of knowledge spillovers: A reassessment: Comment. *American Economic Review*, **95** (1), 461–464.
- HIGGS, R. (1971). American inventiveness, 1870-1920. *Journal of Political Economy*, **79**, 661–667.
- HINLOOPEN, J. and VAN MARREWIJK, C. (2004). *Locating economic concentration*. Tinbergen Institute Discussion Papers 04-066/2, Tinbergen Institute.
- and — (2006). *Comparative advantage, the rank-size rule, and Zipf's law*. Tinbergen Institute Discussion Papers 06-100/1, Tinbergen Institute.
- HIRSCHMAN, A. O. (1958). *The Strategy of Economic Development*. New Haven: Yale University Press.
- HOEKMAN, J., FRENKEN, K. and TIJSSEN, R. J. (2010). Research collaboration at a distance: Changing spatial patterns of scientific collaboration within Europe. *Research Policy*, **39** (5), 662–673.
- , — and VAN OORT, F. (2008). *Collaboration networks as carriers of knowledge spillovers: Evidence from EU27 regions*. CESPRI Working Papers 222, CESPRI, Centre for Research on Innovation and Internationalisation, Università' Bocconi, Milano, Italy.
- , — and — (2009). The geography of collaborative knowledge production in Europe. *The Annals of Regional Science*, **43** (3), 721–738.
- HOFMANN, P. (2009). *Die neue Neue Außenhandelstheorie: Das Melitz-Modell*. Violette Reihe Arbeitspapiere 30/2009, Promotionsschwerpunkt "Globalisierung und Beschaeftigung".
- HOLMES, T. J. (1999). Localization of industry and vertical disintegration. *The Review of Economics and Statistics*, **81** (2), 314–325.
- and STEVENS, J. J. (2004). Spatial distribution of economic activities in north america. In J. V. Henderson and J. F. Thisse (eds.), *Handbook of Regional and Urban Economics*, vol. 4, 63, Amsterdam: Elsevier, pp. 2797–2843.
- HOOVER, E. M. (1936). The measurement of industrial localization. *The Review of Economics and Statistics*, **18** (4), 162–171.
- and GIARRATANI, F. (1984). *An Introduction to Regional Economics (third edition)*. The Web Book of Regional Science, <http://www.rrl.wvu.edu/WebBook/Giarratani/main.htm>.

- HOTZ-HART, B. (2000). Innovation networks, regions, and globalization. In G. L. Clark, M. S. Gertler and M. P. Feldman (eds.), *The Oxford Handbook of Economic Geography*, Oxford: Oxford University Press, pp. 432–450.
- IAMMARINO, S. and MCCANN, P. (2006). The structure and evolution of industrial clusters: Transactions, technology and knowledge spillovers. *Research Policy*, **35** (7), 1018–1036.
- ISARD, W. (1956). *Location and Space-economy. A General Theory Relating to Industrial Location, Market, Areas, Land Use, Trade, and Urban Structure*. Cambridge, MA: The MIT Press.
- JACOBS, J. (1969). *The Economy of Cities*. London: Jonathan Cape.
- JAFFE, A. B. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *American Economic Review*, **76** (5), 984–1001.
- (1989). Real effects of academic research. *American Economic Review*, **79** (5), 957–970.
- and TRAJTENBERG, M. (2002). *Patents, Citations and Innovations: A Window on the Knowledge Economy*. Cambridge, MA: The MIT Press.
- , — and HENDERSON, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics*, **108** (3), 577–598.
- JENKINS, S. P. and KERM, P. V. (2009). The measurement of economic inequality. In T. M. S. Wiemar Salverda, Brian Nolan (ed.), *The Oxford Handbook of Economic Inequality*, 1st edn., Oxford: Oxford University Press.
- JENSEN, M. B., JOHNSON, B., LORENZ, E. and LUNDVALL, B. A. (2007). Forms of knowledge and modes of innovation. *Research Policy*, **36** (5), 680–693.
- JOHANSSON, B. (2005). Parsing the menagerie of agglomeration and network externalities. In C. Karlsson, B. Johansson and R. R. Stough (eds.), *Industrial Clusters and Inter-Firm Networks*, Cheltenham: Edward Elgar, pp. 107–147.
- and QUIGLEY, J. (2003). Agglomeration and networks in spatial economies. *Papers in Regional Science*, **83** (1), 165–176.
- JOHNSON, D. K. N., SIRIPONG, A. and BROWN, A. S. (2006). The demise of distance? The declining role of physical proximity for knowledge transmission. *Growth and Change*, **37** (1), 19–33.
- JONAS, M. (2005). Brücken zur regionalen Clusterforschung: Soziologische Annäherung an ein ökonomisches Erklärungskonzept. *Zeitschrift für Soziologie*, **34**, 270–287.
- JONES, C. I. (1998). *Growth: With or without scale effects?* Working Papers 99001, Stanford University, Department of Economics.
- (1999). Growth: With or without scale effects? *American Economic Review*, **89** (2), 139–144.

- (2004). *Growth and ideas*. NBER Working Papers 10767, National Bureau of Economic Research, Inc.
- KALDOR, N. (1966). Causes of the slow rate of economic growth of the United Kingdom: An inaugural lecture. In N. Kaldor (ed.), *Further Essays on Economic Theory (1968)*, London: Duckworth.
- (1972). The irrelevance of equilibrium economics. *Economic Journal*, **82** (328), 1237–1255.
- KEEBLE, D., OWENS, P. and THOMPSON, C. (1982). Regional accessibility and economic potential in the European community. *Regional Studies*, **16** (6), 419–432.
- KEILBACH, M. (2000). *Spatial Knowledge Spillovers and the Dynamics of Agglomeration and Regional Growth*. Contributions to Economics, Heidelberg: Physica-Verlag, A Springer-Verlag Company.
- KELLER, D., NIEBUHR, A. and STILLER, S. (2004). Die deutsche Forschungslandschaft - starke regionale Disparitäten. *Wirtschaftsdienst*, **84**, 121–125.
- KELLY, M. and HAGEMAN, A. (1999). Marshallian externalities in innovation. *Journal of Economic Growth*, **4** (1), 39–54.
- KENNEY, M. and VON BURG, U. (1999). Technology, entrepreneurship and path dependence: Industrial clustering in Silicon Valley and Route 128. *Industrial and Corporate Change*, **8** (1), 67–103.
- KILKENNY, M. (2010). Urban/regional economics and rural development. *Journal of Regional Science*, **50** (1), 449–470.
- KIM, S. (1995). Expansion of markets and the geographic distribution of economic activities: The trends in U.S. regional manufacturing structure, 1860-1987. *The Quarterly Journal of Economics*, **110** (4), 881–908.
- (2006). *Division of labor and the rise of cities: Evidence from U.S. industrialization, 1850-1880*. NBER Working Papers 12246, National Bureau of Economic Research, Inc.
- KING, C., SILK, A. J. and KETELHÖHN, N. (2003). Knowledge spillovers and growth in the disagglomeration of the U.S. advertising-agency industry. *Journal of Economics & Management Strategy*, **12** (3), 327–362.
- KLEIN, A. and CRAFTS, N. (2010). *Making sense of the manufacturing belt: Determinants of U.S. industrial location, 1880-1920*. CAGE Online Working Paper Series 04, Competitive Advantage in the Global Economy (CAGE).
- KORTUM, S. and LERNER, J. (1997). *Stronger protection or technological revolution: What is behind the recent surge in patenting?* NBER Working Papers 6204, National Bureau of Economic Research, Inc.
- KROLL, H. (2009). *Spillovers and proximity in perspective: A network approach to improving the operationalisation of proximity*. Working Papers Firms and Region Nr. R4/2009, Fraunhofer ISI, Karlsruhe.

- and MALLIG, N. (2009). *Regional patterns of co-patenting by technological fields: A Europe - US comparison*. Tech. rep., Science and Innovation Policy, 2009 Atlanta Conference Proceedings.
- KRUGMAN, P. (1991). Increasing returns and economic geography. *Journal of Political Economy*, **99** (3), 483–499.
- (1992). *Geography and Trade*, MIT Press Books, vol. 1. Cambridge, MA: The MIT Press.
- (1995). *Development, Geography and Economic Theory*, *The Ohlin Lectures*, vol. 6. Cambridge, MA: The MIT Press.
- (2000). Where in the world is the new economic geography. In G. Clark, M. P. Feldman and M. Gertler (eds.), *Oxford Handbook of Economic Geography*, Oxford: Oxford University Press, pp. 49–60.
- (2009). The increasing returns revolution in trade and geography. *American Economic Review*, **99** (3), 561–571.
- (2011). The new economic geography, now middle-aged. *Regional Studies*, **45** (1), 1–7.
- and VENABLES, A. (1995a). Globalization and the inequality of nations. *The Quarterly Journal of Economics*, **110** (4), 857–880.
- and — (1995b). *The seamless world: A spatial model of international specialization*. NBER Working Papers 5220, National Bureau of Economic Research, Inc.
- and — (1996). Integration, specialization, and adjustment. *European Economic Review*, **40** (3-5), 959–967.
- KUZNETS, S. (1955). Economic growth and income inequality. *The American Economic Review*, **45**, 1–28.
- LAGENDIJK, A. (2001). *Scaling knowledge production: How significant is the region?* Tech. rep., University of Nijmegen.
- LAM, A. (2007). Multinationals and transnational social space for learning: Knowledge creation and transfer through global R&D networks. In K. Polenske (ed.), *The Economic Geography of Innovation*, Cambridge: Cambridge University Press, pp. 157–190.
- LAUNHARDT, W. (1882). Die Bestimmung des zweckmässigsten Standortes einer gewerblichen Anlage. *Zeitschrift des Vereines Deutscher Ingenieure*.
- LAURSEN, K. (1998). *Revealed comparative advantage and the alternatives as measures of international specialisation*. DRUID Working Papers 98-30, DRUID, Copenhagen Business School, Department of Industrial Economics and Strategy/Aalborg University, Department of Business Studies.
- LE GALLO, J. and DALL'ERBA, S. (2003). *Spatial econometric analysis of the evolution of the European regional convergence process, 1980-1999*. Urban/Regional 0311001, Econ-WPA Working Paper.

- LEGLER, H. and KRAWCZYK, O. (2006). The global distribution of R&D activities. In U. Schmoch, C. Rammer and H. Legler (eds.), *National Systems of Innovation in Comparison*, Heidelberg: Springer, pp. 31–46.
- , RAMMER, C. and GRENZMANN, C. (2006). R&D activities in the German business sector. In U. Schmoch, C. Rammer and H. Legler (eds.), *National Systems of Innovation in Comparison*, Heidelberg: Springer, pp. 17–30.
- LESAGE, J. P., FISCHER, M. M. and SCHERNGELL, T. (2007). Knowledge spillovers across Europe: Evidence from a Poisson spatial interaction model with spatial effects. *Papers in Regional Science*, **86** (3), 393–421.
- LIM, U. (2004). Knowledge spillovers, agglomeration economies, and the geography of innovative activity: A spatial econometric analysis. *The Review of Regional Studies*, **34** (1), 11–36.
- LISSONI, F. (2001). Knowledge codification and the geography of innovation: The case of Brescia mechanical cluster. *Research Policy*, **30** (9), 1479–1500.
- LITZENBERGER, T. (2007). *Cluster und die New Economic Geography - Theoretische Konzepte, empirische Tests und Konsequenzen für Regionalpolitik in Deutschland*. Frankfurt a. M.: Peter Lang.
- and STERNBERG, R. (2005). Regional clusters and entrepreneurial activities: Empirical evidence from German regions. In C. Karlsson, B. Johansson and R. Stough (eds.), *Industrial Clusters and Inter-Firm Networks*, Cheltenham: Edward Elgar, pp. 260–302.
- and — (2006). Der Clusterindex - eine Methodik zur Identifizierung regionaler Cluster am Beispiel deutscher Industriebranchen. *Geografische Zeitschrift*, **4** (4), 209–224.
- LOBO, J. and STRUMSKY, D. (2008). Metropolitan patenting, inventor agglomeration and social networks: A tale of two effects. *Journal of Urban Economics*, **63** (3), 871–884.
- LÖSCH, A. (1954). *The Economics of Location*. Jena: Fischer.
- LUCAS, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, **22** (1), 3–42.
- (1993). Making a miracle. *Econometrica*, **61** (2), 251–272.
- and ROSSI-HANSBERG, E. (2002). On the internal structure of cities. *Econometrica*, **70**, 1445–1476.
- LUNDVALL, B.-A. (2007). National innovation systems - analytical concept and development tool. *Industry & Innovation*, **14** (1), 95–119.
- MAGGIONI, M. A. (2002). *Clustering Dynamics and the Location of High-Tech-Firms*. Contributions to Economics, Heidelberg: Physica-Verlag, A Springer-Verlag Company.
- , NOSVELLI, M. and UBERTI, T. E. (2007). Space versus networks in the geography of innovation: A European analysis. *Papers in Regional Science*, **86** (3), 471–493.

- and UBERTI, T. (2009). Knowledge networks across Europe: Which distance matters? *The Annals of Regional Science*, **43** (3), 691–720.
- MAGRINI, S. (2004). Regional (di)convergence. In J. V. Henderson and J. F. Thisse (eds.), *Handbook of Regional and Urban Economics, Handbook of Regional and Urban Economics*, vol. 4, 62, Amsterdam: Elsevier, pp. 2741–2796.
- MALECKI, E. J. (2010). Everywhere? The geography of knowledge. *Journal of Regional Science*, **50** (1), 493–513.
- MALERBA, F., MANCUSI, M. L. and MONTOBIO, F. (2003). *Innovation and knowledge spillovers: Evidence from European data*. Economics and Quantitative Methods qf0319, Department of Economics, University of Insubria.
- MALPEZZI, S., SEAH, K.-Y. and SHILLING, J. D. (2004). Is it what we do or how we do it? New evidence on agglomeration economies and metropolitan growth. *Real Estate Economics*, **32** (2), 265–295.
- MANKIW, N. G., ROMER, D. and WEIL, D. N. (1992). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics*, **107**, 407–437.
- MANSFIELD, E. (1968). *The Economics of Technical Change*. New York: W.W.Norton.
- (1986). Patents and innovation: An empirical study. *Management Science*, **32** (2), 173–181.
- MARAUT, S., DERNIS, H., WEBB, C., SPIEZIA, V. and GUELLEC, D. (2008). *The OECD REGPAT database: A presentation*. OECD Science, Technology and Industry Working Papers 2008/2, OECD, Directorate for Science, Technology and Industry.
- MARQUES, H. (2001). *The "new" economic theories*. FEP Working Papers 104, Universidade do Porto, Faculdade de Economia do Porto.
- MARSHALL, A. (1920a). *Industry and Trade: A Study of industrial technique and business organization; and of their influences on the condition of various classes and nations (3th edition)*. London: Macmillan.
- (1920b). *Principles of Economics (8th edition)*. London: Macmillan.
- MARTIN, P. (1998a). Can regional policies affect growth and geography in Europe? *The World Economy*, **21** (6), 757–774.
- (1998b). *Public policies, regional inequalities and growth*. CEPR Discussion Papers 1841, C.E.P.R. Discussion Papers.
- , MAYER, T. and MAYNERIS, F. (2008). *Spatial concentration and firm-level productivity in France*. Tech. rep., CEPR DP 6858.
- and OTTAVIANO, G. I. (1999). Growing locations: Industry location in a model of endogenous growth. *European Economic Review*, **43** (2), 281–302.

- and — (2001). Growth and agglomeration. *International Economic Review*, **42** (4), 947–68.
- MARTIN, R. (1999). The new 'geographical turn' in economics: Some critical reflections. *Cambridge Journal of Economics*, **23** (1), 65–91.
- (2001). EMU versus the regions? regional convergence and divergence in Euroland. *Journal of Economic Geography*, **1** (1), 51–80.
- and SUNLEY, P. (2003). Deconstructing clusters: chaotic concept or policy panacea? *Journal of Economic Geography*, **3** (1), 5–35.
- and — (2005). Deconstructing clusters: Chaotic concept or policy panacea. In S. Breschi and F. Lissoni (eds.), *Clusters, Networks and Innovation*, 16, Oxford: Oxford University Press, pp. 433–469.
- MASKELL, P., BATHELT, H. and MALMBERG, A. (2005). *Building global knowledge pipelines: The role of temporary clusters*. DRUID Working Papers 05-20, DRUID, Copenhagen Business School, Department of Industrial Economics and Strategy/Aalborg University, Department of Business Studies.
- MASSARD, N. and RIOU, S. (2002). L'impact des structures locales sur l'innovation en France: Spécialisation ou diversité? *Région et Développement*, **16**, 111–136.
- MATTSSON, P., LAGET, P., NILSSON, A. and SUNDBERG, C.-J. (2008). Intra-EU vs. extra-EU scientific co-publication patterns in EU. *Scientometrics*, **75**, 555–574.
- MAUREL, F. and SÉDILLOT, B. (1999). A measure of the geographic concentration in French manufacturing industries. *Regional Science and Urban Economics*, **29**, 575–604.
- MAURSETH, P. B. and VERSPAGEN, B. (1999). *Europe: One or several systems of innovation? An analysis based on patent citations*. Open Access publications from Maastricht University urn:nbn:nl:ui:27-18078, Maastricht University.
- and — (2002). Knowledge spillovers in Europe: A patent citations analysis. *Scandinavian Journal of Economics*, **104** (4), 531–45.
- MCCANN, P., ARITA, T. and GORDON, I. R. (2002). Industrial clusters, transactions costs and the institutional determinants of MNE location behaviour. *International Business Review*, **11**, 647–663.
- MELCHIOR, A. (2008). *Regional inequality and convergence in Europe, 1995-2005*. CASE Network Studies and Analyses 0374, CASE-Center for Social and Economic Research.
- MELLINGER, A. D., SACHS, J. D. and GALLIP, J. L. (2000). Climate, coastal proximity, and development. In G. L. Clark, M. Feldman and M. S. Gertler (eds.), *The Oxford Handbook of Economic Geography*, 9, Oxford: Oxford University Press, pp. 169–194.
- MIDELFART-KNARVIK, K. H., OVERMAN, H., REDDING, S. and VENABLES, A. (2004). The location of European industry. In A. Dierx, F. Ilzkovitz and K. Sekkat (eds.), *European Integration and the Functioning of Product Markets*, Cheltenham: Edward Elgar.

- , — and VENABLES, A. (2000). *Comparative advantage and economic geography: Estimating the location of production in the EU*. Papers 18/00, Norwegian School of Economics and Business Administration.
- , OVERMAN, H. G., REDDING, S. and VENABLES, A. (2002). Integration and industrial specialisation in the European Union. *Revue économique*, **53** (3), 469–481.
- , — and VENABLES, A. (2003). *Monetary Union and the economic geography of Europe*. Open Access publications from London School of Economics and Political Science <http://eprints.lse.ac.uk/>, London School of Economics and Political Science.
- and STEEN, F. (1999). Self-reinforcing agglomerations? An empirical industry study. *Scandinavian Journal of Economics*, **101** (4), 515–32.
- MIGUELEZ, E. and MORENO, R. (2010). *Research networks and inventors mobility as drivers of innovation: Evidence from Europe*. IREA Working Papers 201001, University of Barcelona, Research Institute of Applied Economics.
- , — and SURINACH, J. (2009). *Scientists on the move: Tracing scientists mobility and its spatial distribution*. IREA Working Papers 200916, University of Barcelona, Research Institute of Applied Economics.
- MONFORT, P. (2008). *Convergence of EU regions: Measures and Evolution*. Tech. rep., EUROSTAT.
- MORAN, P. (1950). Notes on continuous stochastic phenomena. *Biometrika*, **37**, 17–23.
- MORENO, R., PACI, R. and USAI, S. (2003). *Spatial distribution of innovation activity. The case of European regions*. Working Paper CRENoS 200310, Centre for North South Economic Research, University of Cagliari and Sassari, Sardinia, <http://ideas.repec.org/p/cns/cnscwp/200310.html>.
- , — and — (2004). *Innovation and production clusters in Europe*. ERSA conference papers ersa04p587, European Regional Science Association.
- , — and — (2005a). Geographical and sectoral clusters of innovation in Europe. *The Annals of Regional Science*, **39** (4), 715–739.
- , — and — (2005b). *Innovation clusters in the European regions*. Working Paper CRENoS 200512, Centre for North South Economic Research, University of Cagliari and Sassari, Sardinia, <http://ideas.repec.org/p/cns/cnscwp/200512.html>.
- , — and — (2005c). Spatial spillovers and innovation activity in European regions. *Environment and Planning A*, **37** (10), 1793–1812.
- MUKKALA, K. (2004). Agglomeration economies in the Finnish manufacturing sector. *Applied Economics*, **36** (21), 2419–2427.
- MYRDAL, G. (1957). *Economic Theory and Underdeveloped Regions*. London: Gerald Duckworth and Co. LTD.

- NEARY, J. P. (2001). Of hype and hyperbolas: Introducing the new economic geography. *Journal of Economic Literature*, **39** (2), 536–561.
- (2009). Putting the ‘new’ into new trade theory: Paul Krugman’s Nobel Memorial Prize in Economics. *Scandinavian Journal of Economics*, **111** (2), 217–250.
- NEFFKE, F., HENNING, M. and BOSCHMA, M. R. (2009). *How do regions diversify over time? Industry relatedness and the development of new growth paths in regions*. Papers in Evolutionary Economic Geography (PEEG) 0916, Utrecht University, Section of Economic Geography.
- , —, BOSCHMA, R., LUNDQUIST, K.-J. and OLANDER, L.-O. (2011). The dynamics of agglomeration externalities along the life cycle of industries. *Regional Studies*, **45** (1), 49–65.
- NIEBUHR, A. (2000). *Raumliche Wachstumszusammenhänge - Empirische Befunde für Deutschland*. Discussion Paper Series 26191, Hamburg Institute of International Economics, <http://ideas.repec.org/p/ags/hiiedp/26191.html>.
- (2001). *Convergence and the effects of spatial interaction*. Discussion Paper Series 26351, Hamburg Institute of International Economics, <http://ideas.repec.org/p/ags/hiiedp/26351.html>.
- and SCHLITTE, F. (2004). Convergence, trade and factor mobility in the European Union? Implications for enlargement and regional policy. *Intereconomics: Review of European Economic Policy*, **39** (3), 167–176.
- NOBEL PRIZE COMMITTEE (2008a). *Paul Krugman: International Trade and Economic Geography*. Nobel Prize in Economics documents 2008-1, Nobel Prize Committee.
- NOBEL PRIZE COMMITTEE (2008b). *Paul Krugman: Trade and Geography - Economies of Scale, Differentiated Products and Transport Costs*. Nobel Prize in Economics documents 2008-2, Nobel Prize Committee.
- NONAKA, I. and TAKEUCHI, H. (1995). *The Knowledge-Creating Company: How Japanese Companies Create the Dynamics of Innovation*. Oxford: Oxford University Press.
- NOVOTNÝ, J. (2007). On the measurement of regional inequality: Does spatial dimension of income inequality matter? *The Annals of Regional Science*, **41** (3), 563–580.
- OECD (1999). *Boosting Innovation: The Cluster Approach*. Paris: Organisation for Economic Co-operation and Development (OECD).
- (2000). *Knowledge Management in the Learning Society*. Paris: Organisation for Economic Co-operation and Development (OECD).
- (2003). *Territorial grids of OECD member countries (TL3/NUTS 2003)*. Tech. rep., Organisation for Economic Co-operation and Development (OECD), Paris.
- (2006). *Territorial grids of OECD member countries (TL3/NUTS 2006)*. Tech. rep., Organisation for Economic Co-operation and Development (OECD), Paris.

- (2007a). *Competitive Regional Clusters: National Policy Approaches*. Paris: Organisation for Economic Co-operation and Development (OECD).
- (2007b). *Glossary of statistical terms*. Tech. rep., Organisation for Economic Co-operation and Development (OECD), Paris.
- (2007c). *Science, Technology and Innovation Indicators in a Changing World: Responding to Policy Needs*. Paris: Organisation for Economic Co-operation and Development (OECD).
- (2008). *Compendium of Patent Statistics*. Paris: Organisation for Economic Co-operation and Development (OECD).
- (2009a). *How Regions Grow: Trends and Analysis*. Paris: Organisation for Economic Co-operation and Development (OECD).
- (2009b). *Investing for growth: Building innovative regions (background report)*. Tech. rep., Organisation for Economic Co-operation and Development (OECD), Paris.
- (2009c). *OECD Patent Statistics Manual*. Paris: Organisation for Economic Co-operation and Development (OECD).
- (2009d). OECD Regional Database, Regional Accounts: homepage <http://stats.oecd.org/Index.aspx>, accessed: 01.03.2010, 08.07.2010, 21.12.2010 and 11.12.2010.
- (2009e). OECD RegPAT January 2009: homepage http://www.oecd.org/document/10/0,3746,en_2649_34451_1901066_1_1_1_1,00.html, accessed: 21.03.2011.
- (2009f). *Regions Matter: Economic Recovery, Innovation and Sustainable Growth*. Paris: Organisation for Economic Co-operation and Development (OECD).
- (2010). *OECD Regional typology*. Tech. rep., Organisation for Economic Co-operation and Development (OECD), Paris.
- OERLEMANS, L. A., MEEUS, M. T. and BOEKEMA, F. W. (2001). Firm clustering and innovation: Determinants and effects. *Papers in Regional Science*, **80** (3), 337–356.
- OETTL, A. and AGRAWAL, A. (2008). International labor mobility and knowledge flow externalities. *Journal of International Business Studies*, **39** (8), 1242–1260.
- OHUALLACHAIN, B. and LESLIE, T. F. (2007). Rethinking the regional knowledge production function. *Journal of Economic Geography*, **7** (6), 737–752.
- OPENSHAW, S. (1984). *The Modifiable Areal Unit Problem (Concepts and Techniques in Modern Geography)*. Norwich: Geo Books.
- and TAYLOR, P. (1979). A million or so correlation coefficients: Three experiments on the modifiable areal unit problem. In N. Wrigley (ed.), *Statistical Applications in the Spatial Sciences*, London: Pion, pp. 127–144.

- ORSENIGO, L., PAMMOLLI, F., RICCABONI, M., BONACCORSI, A. and TURCHETTI, G. (1997). The evolution of knowledge and the dynamics of an industry network. *Journal of Management and Governance*, **1** (2), 147–175.
- OTTAVIANO, G. I. P. and PUGA, D. (1998). Agglomeration in the global economy: A survey of the 'new economic geography'. *The World Economy*, **21** (6), 707–731.
- and THISSE, J.-F. (2000). *On Economic Geography in Economic Theory: Increasing returns and pecuniary externalities*. Working paper.
- and — (2001). On economic geography in economic theory: Increasing returns and pecuniary externalities. *Journal of Economic Geography*, **1** (2), 153–179.
- and — (2004). Agglomeration and economic geography. In J. V. Henderson and J. F. Thisse (eds.), *Handbook of Regional and Urban Economics*, vol. 4, 58, Amsterdam: Elsevier, pp. 2563–2608.
- OVERMAN, H. G. (2003). *Can we learn anything from economic geography proper?* CEP Discussion Papers dp0586, Centre for Economic Performance, LSE.
- and PUGA, D. (2010). Labor pooling as a source of agglomeration: An empirical investigation. In *Agglomeration Economics*, NBER Chapters, National Bureau of Economic Research, Inc, pp. 133–150.
- OWEN-SMITH, J. and POWELL, W. W. (2004). Knowledge networks in the Boston biotechnology community. *Organization Science*, **15** (1), 5–21.
- PAAS, T., KUUSK, A., SCHLITTE, F. and VAURK, A. (2007). *Econometric analysis of income convergence in selected EU countries and their Nuts 3 level regions*. University of Tartu - Faculty of Economics and Business Administration Working Paper Series 60, Faculty of Economics and Business Administration, University of Tartu (Estonia), <http://ideas.repec.org/p/mtk/febawb/60.html>.
- and SCHLITTE, F. (2007). *Regional income inequality and convergence processes in the EU-25*. Tech. rep., HWWI Research Paper 1-11.
- and — (2008). Regional income inequality and convergence processes in the EU-25. *Italian Journal of Regional Science*, **7**, 29–50.
- PACI, R. and PIGLIARU, F. (2001). *Technological diffusion, spatial spillovers and regional convergence in Europe*. Working Paper CRENoS 200101, Centre for North South Economic Research, University of Cagliari and Sassari, Sardinia, <http://ideas.repec.org/p/cns/cnscwp/200101.html>.
- and USAI, S. (1999). *The role of specialisation and diversity externalities in the agglomeration of innovative activities*. Working Paper CRENoS 199915, Centre for North South Economic Research, University of Cagliari and Sassari, Sardinia, <http://ideas.repec.org/p/cns/cnscwp/199915.html>.
- and — (2000a). The role of specialisation and diversity externalities in the agglomeration of innovative activities. *Rivista Italiana degli Economisti*, **2** (2), 237–268.

- and — (2000b). Technological enclaves and industrial districts: An analysis of the regional distribution of innovative activity in Europe. *Regional Studies*, **34** (2), 97–114.
- and — (2009). Knowledge flows across European regions. *The Annals of Regional Science*, **43** (3), 669–690.
- PARTRIDGE, M. D. and RICKMAN, D. S. (1999). Static and dynamic externalities, industry composition, and state labor productivity: A panel study of states. *Southern Economic Journal*, **66** (2), 319–335.
- PATUELLI, R., VAONA, A. and GRIMPE, C. (2010). The German east-west divide in knowledge production: An application to nanomaterial patenting. *Tijdschrift voor Economische en Sociale Geografie*, **101** (5), 568–582.
- PERROUX, F. (1970). Note on the concept of growth poles. In D. X. McKee (ed.), *Regional Economics: Theory and Practice*, New York: The Free Press, pp. 93–103.
- PETRAKOS, G. and ARTELARIS, P. (2009). European regional convergence revisited: A weighted least squares approach. *Growth and Change*, **40** (2), 314–331.
- , DIMITRIS, K. and AGELIKI, A. (2007). *A generalized model of regional economic growth in the European Union*. Papers DYNREG12, Economic and Social Research Institute (ESRI).
- POLANYI, M. (1966). *The Tacit Dimension*. Garden City, NY: Doubleday.
- POLENSKE, K. (2007). Concepts and measurements in innovation: Introduction. In K. Polenske (ed.), *The Economic Geography of Innovation*, Cambridge: Cambridge University Press, pp. 3–13.
- PONDS, R., VAN OORT, F. and FRENKEN, K. (2010). Innovation, spillovers and university–industry collaboration: an extended knowledge production function approach. *Journal of Economic Geography*, **10** (2), 231–255.
- PORTER, K., WHITTINGTON, K. B. and POWELL, W. W. (2005). The institutional embeddedness of high-tech regions: Relational foundations of the Boston biotechnology community. In S. Breschi and F. Lissoni (eds.), *Clusters, Networks and Innovation*, 10, Oxford: Oxford University Press, pp. 261–296.
- PORTER, M. E. (1990). *The Competitive Advantage of Nations*. New York: The Free Press.
- (1996). Competitive advantage, agglomeration economies, and regional policy. *International Regional Science Review*, **19**, 85–94.
- (1998a). Clusters and the new economics of competition. *Harvard Business Review*, **76**, 77–90.
- (1998b). *On Competition*. Boston: HBS Press.

- (2000). Locations, clusters, and company strategy. In G. L. Clark, M. S. Gertler and M. P. Feldman (eds.), *The Oxford Handbook of Economic Geography*, Oxford: Oxford University Press, pp. 253–274.
- and STERN, S. (2000). *Measuring the "Ideas" Production Function: Evidence from International Patent Output*. NBER Working Papers 7891, National Bureau of Economic Research, Inc.
- POWELL, W. W. and GIANNELLA, E. (2010). Collective invention and inventor networks. In B. Hall and N. Rosenberg (eds.), *Handbook of Economics of Innovation*, Amsterdam: Elsevier, pp. 1–53.
- and GRODAL, S. (2005). Networks of innovators. In J. Fagerberg and R. Mowery, D. and Nelson (eds.), *The Oxford Handbook of Innovation*, Oxford: Oxford University Press, pp. 56–85.
- PRED, A. R. (1966). *The Spatial Dynamics of U.S. Urban Industrial Growth, 1800-1914*. Cambridge: Harvard University Press.
- PRESS, K. (2006a). *Divide to conquer? The Silicon Valley - Boston 128 case revisited*. Papers in Evolutionary Economic Geography (PEEG) 0610, Utrecht University, Section of Economic Geography.
- (2006b). *A Life Cycle for Clusters? The Dynamics of Agglomeration, Change, and Adoption*. Heidelberg: Physica-Verlag, A Springer-Verlag Company.
- PRO INNO EUROPE (2010). Proinno-Europe: homepage <http://www.proinno-europe.eu/eca>, accessed: 03.03.2011.
- PUGA, D. (1999). The rise and fall of regional inequalities. *European Economic Review*, **43** (2), 303–334.
- (2002). European regional policies in light of recent location theories. *Journal of Economic Geography*, **2** (4), 373–406.
- (2010). The magnitude and causes of agglomeration economies. *Journal of Regional Science*, **50** (1), 203–219.
- and DURANTON, G. (2000). Diversity and specialisation in cities: Why, where and when does it matter? *Urban Studies*, **37**, 533–555.
- QUAH, D. (1993). Galton's fallacy and tests of the convergence hypothesis. *Scandinavian Journal of Economics*, **95** (4), 427–43.
- (1996). Regional convergence clusters across Europe. *European Economic Review*, **40**, 951–958.
- RATANAWARAH, A. and POLENSKE, K. (2007). Measuring the geography of innovation. In K. Polenske (ed.), *The Economic Geography of Innovation*, Cambridge: Cambridge University Press, pp. 30–60.

- REY, S. J. and MONTOURI, B. D. (1999). US regional income convergence: A spatial econometric perspective. *Regional Studies*, **33** (2), 143–156.
- RICARDO, D. (1821). *On The Principles of Political Economy and Taxation*. London: John Murray, 3rd edn.
- RICHTER, H. M. E. W. and FREUND, M. C. (2008). Raumstrukturelle Aspekte der Wissensproduktion. In B. Luderer (ed.), *Die Kunst des Modellierens*, Wiesbaden: Vieweg und Tübingen, pp. 413–428.
- RIMA, I. H. (2004). Increasing returns, new growth theory, and the classicals. *Journal of Post Keynesian Economics*, **27** (1), 171–184.
- RIVERA-BATIZ, L. A. and ROMER, P. M. (1991). Economic integration and endogenous growth. *The Quarterly Journal of Economics*, **106** (2), 531–55.
- ROBERT-NICOUD, F. (2004). *The structure of simple 'new economic geography' models*. CEPR Discussion Papers 4326, C.E.P.R. Discussion Papers.
- (2005). The structure of simple 'new economic geography' models (or, on identical twins). *Journal of Economic Geography*, **5** (2), 201–234.
- RODRÍGUEZ-POSE, A. (2001). Is R&D investment in lagging areas of Europe worthwhile? theory and empirical evidence. *Papers in Regional Science*, **80** (3), 275–295.
- RODRÍGUEZ-POSE, A. (2010). *Economists as geographers and geographers as something else: On the changing conception of distance in geography and economics*. Working Papers 2010-22, Instituto Madrileño de Estudios Avanzados (IMDEA) Ciencias Sociales.
- RODRÍGUEZ-POSE, A. and CRESCENZI, R. (2008). Mountains in a flat world: Why proximity still matters for the location of economic activity. *Cambridge Journal of Regions, Economy and Society*, **1** (3), 371–388.
- and FRATESI, U. (2004). Between development and social policies: The impact of European structural funds in objective 1 regions. *Regional Studies*, **38** (1), 97–113.
- and FRATESI, U. (2007). Explaining the scarce returns of European structural policies from a new economic geography perspective. In B. Fingleton (ed.), *New Directions in Economic Geography*, Cheltenham: Edward Elgar, pp. 338–358.
- ROMER, P. M. (1986). Increasing returns and long-run growth. *Journal of Political Economy*, **94** (5), 1002–1037.
- (1987). Growth based on increasing returns due to specialization. *American Economic Review*, **77** (2), 56–62.
- (1989). Capital accumulation in the theory of long-run growth. In R. J. Barro (ed.), *Modern Business Cycle Theory*, Cambridge, MA: Harvard University Press, pp. 52–127.
- (1990a). Are nonconvexities important for understanding growth? *American Economic Review*, **80** (2), 97–103.

- (1990b). Endogenous technological change. *Journal of Political Economy*, **98** (5), 71–102.
- (1991). *Are nonconvexities important for understanding growth?* NBER Working Papers 3271, National Bureau of Economic Research, Inc.
- ROOS, M. (2002a). *How important is geography for agglomeration?* Ersa conference papers, European Regional Science Association.
- (2002b). *Ökonomische Agglomerationstheorien: Die Neue Ökonomische Geographie im Kontext*. Lohmar, Köln: Josef Eul Verlag.
- (2004). Agglomeration and the public sector. *Regional Science and Urban Economics*, **34** (4), 411–427.
- (2008). Die Neue Außenhandelstheorie und die Neue Ökonomische Geographie. *Wirtschaftsdienst*, **88** (11), 756–760.
- ROSENTHAL, S. S. and STRANGE, W. C. (2001). The determinants of agglomeration. *Journal of Urban Economics*, **50** (2), 191–229.
- and — (2003). Geography, industrial organization, and agglomeration. *The Review of Economics and Statistics*, **85** (2), 377–393.
- and — (2004). Evidence on the nature and sources of agglomeration economies. In J. V. Henderson and J. F. Thisse (eds.), *Handbook of Regional and Urban Economics*, *Handbook of Regional and Urban Economics*, vol. 4, 49, Amsterdam: Elsevier, pp. 2119–2171.
- RUKWID, R. (2007). *Arbeitslosigkeit und Lohnspreizung - Empirische Befunde zur Arbeitsmarktsituation gering Qualifizierter in Deutschland*. Violette Reihe Arbeitspapiere 24-2007, Promotionsschwerpunkt Globalisierung und Beschaeftigung.
- SACHS, J. D. and MCCORD, G. C. (2008). Geography of regional development. In S. N. Durlauf and L. E. Blume (eds.), *The New Palgrave Dictionary of Economics*, Basingstoke: Basingstoke: Palgrave Macmillan.
- SALA-I-MARTIN, X. (1996). The classical approach to convergence analysis. *Economic Journal*, **106** (437), 1019–1036.
- SALA-I-MARTIN, X. (2006). The world distribution of income: Falling poverty and ... convergence, period. *The Quarterly Journal of Economics*, **121** (2), 351–397.
- SAXENIAN, A. (1990). Regional networks and the resurgence of Silicon Valley. *California Management Review*, **33**, 89–111.
- (2006). *The New Argonauts: Regional Advantage in a Global Economy*. Cambridge, MA: Harvard University Press.
- (2007). Brain circulation and regional innovation: The Silicon Valley-Hsinchu-Shanghai Triangle. In K. Polenske (ed.), *The Economic Geography of Innovation*, Cambridge: Cambridge University Press, pp. 190–213.

- SCHERER, F. M. (1982). Inter-industry technology flows and productivity growth. *The Review of Economics and Statistics*, **64** (4), 627–634.
- (2005). Edwin Mansfield: An appreciation. *The Journal of Technology Transfer*, **30** (2), 3–9.
- SCHERNGELL, T. (2007). *Interregionale Wissensspillovers in der Europäischen High-Tech Industrie: Eine Empirische Analyse*. Wiesbaden: DUV Deutscher Universitäts-Verlag.
- , FISCHER, M. M. and REISMANN, M. (2007). Total factor productivity effects of interregional knowledge spillovers in manufacturing industries across Europe. *Romanian Journal of Regional Science*, **1** (1), 1–16.
- SCHINTLER, L. A., KULKARNI, R. G., GORMAN, S. P. and STOUGH, R. R. (2006). Power and packets: A spatial network comparison of the us electric power grid and the internet network. In A. Reggiani and P. Nijkamp (eds.), *Spatial Dynamics, Networks and Modelling*, Cheltenham: Edward Elgar, pp. 35–60.
- SCHMOCH, U., LAVILLE, F., PATEL, P. and FRIETSCH, R. (2003). *Linking technology areas to industrial sectors: Final report to the European Commission, DG Research*. Tech. rep., DG Research.
- SCHÜRMAN, C. and TALAAT, A. (2002). *Bestimmung von Peripheritätsindikatoren für Europa*. Tech. rep., Institut für Raumplanung Universität Dortmund (IRPUD).
- SCITOVSKY, T. (1954). Two concepts of external economies. *Journal of Political Economy*, **62**, 143–151.
- SCOTT, A. J. (1988). *New Industrial Spaces. Flexible Production Organization and Regional Development in North America and Western Europe*. London: Pion.
- (2000). Economic geography: The great half-century. In G. Clark, M. P. Feldman and M. Gertler (eds.), *Oxford Handbook of Economic Geography*, Oxford: Oxford University Press, pp. 18–44.
- and STORPER, M. (2003). Regions, globalization, development. *Regional Studies*, **37** (6–7), 549–578.
- SEITER, S. (1997). *Der Beitrag Nicholas Kaldors zur Neuen Wachstumstheorie: Eine vergleichende Studie vor dem Hintergrund der Debatte über den Verdoorn-Zusammenhang, Hohenheimer Volkswirtschaftliche Schriften*, vol. 27. Frankfurt a.M.: Peter Lang Verlag.
- (2005). Productivity and employment in the information economy: What Kaldor’s and Verdoorn’s growth laws can teach the US. *Empirica*, **32** (1), 73–90.
- SHEPPARD, E. (2000). Geography or economics? Conceptions of space, time, interdependence, and agency. In G. Clark, M. P. Feldman and M. Gertler (eds.), *Oxford Handbook of Economic Geography*, Oxford: Oxford University Press, pp. 99–119.
- SINGH, J. (2005). Collaborative networks as determinants of knowledge diffusion patterns. *Management Science*, **51** (5), 756–770.

- SJÖHOLM, F. (1998). *Productivity growth in Indonesia: The role of regional characteristics and direct foreign investment*. Working Paper Series in Economics and Finance 216, Stockholm School of Economics.
- SMIRNOV, O. and ANSELIN, L. (2001). Fast maximum likelihood estimation of very large spatial autoregressive models: A characteristic polynomial approach. *Computational Statistics & Data Analysis*, **35** (3), 301–319.
- SOLOW, R. M. (2007). The last 50 years in growth theory and the next 10. *Oxford Review of Economic Policy*, **23** (1), 3–14.
- SONN, J. W. and STORPER, M. (2008). The increasing importance of geographical proximity in knowledge production: An analysis of US patent citations, 1975–1997. *Environment and Planning A*, **40** (5), 1020–1039.
- SONOBE, T. and OTSUKA, K. (2006). The division of labor and the formation of industrial clusters in Taiwan. *Review of Development Economics*, **10** (1), 71–86.
- STABER, U. (2001). Spatial proximity and firm survival in a declining industrial district: The case of knitwear firms in Baden-Württemberg. *Regional Studies*, **35** (4), 329–341.
- STARRETT, D. (1978). Market allocations of location choice in a model with free mobility. *Journal of Economic Theory*, **17** (1), 21–37.
- STATA (2009). *Statabase Reference Manual Release 11*. Stata Corp.
- STEINMUELLER, W. E. (2000). Will new information and communication technologies improve the 'codification' of knowledge? *Industrial and Corporate Change*, **9** (2), 361–376.
- STEPHAN, P. E. (1996). The economics of science. *Journal of Economic Literature*, **34** (3), 1199–1235.
- STORPER, M. (1997). *The Regional World: Territorial Development in a Global Economy*. New York: The Guilford Press.
- (2000). Globalization, localization and trade. In G. L. Clark, M. S. Gertler and M. P. Feldman (eds.), *The Oxford Handbook of Economic Geography*, Oxford: Oxford University Press, pp. 146–165.
- and VENABLES, A. (2003). *Buzz: Face-to-face contact and the urban economy*. CEP Discussion Papers dp0598, Centre for Economic Performance, LSE.
- and VENABLES, A. J. (2004). Buzz: Face-to-face contact and the urban economy. *Journal of Economic Geography*, **4** (4), 351–370.
- SZÖRFI, B. (2007). Development and regional disparities: Testing the Williamson curve hypothesis in the European Union. *Focus on European Economic Integration*, (2), 100–121.
- TAYLOR, P. J. (2006). Jane Jacobs (1916–2006): An appreciation. *Environment and Planning A*, **38** (11), 1981–1992.

- TÖDTLING, F., GRILLITSCH, M. and HÖGLINGER, C. (2010). *Knowledge sourcing and innovation in Austrian ICT companies? Does geography matter?* Tech. rep., Institute for Regional Development and Environment, Vienna University of Economics and Business.
- TERWAL, A. and BOSCHMA, R. (2009). Applying social network analysis in economic geography: Framing some key analytic issues. *The Annals of Regional Science*, **43** (3), 739–756.
- THISSE, J. (2011). *Geographical economics: A historical perspective*. ECORE discussion paper, ECORE.
- THÜNEN, J. v. (1966). *Der isolierte Staat in Beziehung auf Landwirtschaft und Nationalökonomie*. Jena: Fischer.
- THOMPSON, P. and FOX-KEAN, M. (2005). Patent citations and the geography of knowledge spillovers: A reassessment. *American Economic Review*, **95** (1), 450–460.
- TICHY, G. (1998). *Geography lost and found in economics*. ERSA conference papers ersa98p23, European Regional Science Association.
- TRIPPL, M. (2009). *Islands of innovation and internationally networked labor markets: Magnetic centers for star scientists?* Tech. rep., Department of City and Regional Development, Vienna University of Economics and Business Administration.
- UNITED NATIONS (2005). *Handbook on Poverty Statistics: Concepts, Methods and Policy Use*. New York: United Nations Statistics Division.
- USAI, S. (2008). *The geography of inventive activities in OECD regions*. OECD Science, Technology and Industry Working Papers 2008/3, OECD Directorate for Science, Technology and Industry.
- VAN DER PANNE, G. (2004). Agglomeration externalities: Marshall versus Jacobs. *Journal of Evolutionary Economics*, **14** (5), 593–604.
- and VAN BEERS, C. (2006). *On the Marshall - Jacobs controversy: It takes two to tango*. DRUID Working Papers 06-23, DRUID, Copenhagen Business School, Department of Industrial Economics and Strategy/Aalborg University, Department of Business Studies, <http://ideas.repec.org/p/aal/abbswp/06-23.html>.
- VAN LOOY, B., CALLAERT, J., DEBACKERE, K. and VERBEEK, A. (2003). Patent related indicators for assessing knowledge-generating institutions: Towards a contextualised approach. *The Journal of Technology Transfer*, **28** (1), 53–61.
- VAN OORT, F. and RASPE, O. (2007). Urban heterogeneity in knowledge-related economic growth. In J. Surinach, R. Moreno and E. Vaya (eds.), *Knowledge Externalities, Innovation Clusters and Regional Development*, Cheltenham: Edward Elgar, pp. 280–303.
- VAN ZEEBROECK, N. (2007). *The puzzle of patent value indicators*. Working Papers CEB 07-023.RS, ULB – Université Libre de Bruxelles.

- , STEVNSBORG, N., VAN POTTELSBERGHE DE LA POTTERIE, B., GUELLEC, D. and ARCHONTOPOULOS, E. (2008). Patent inflation in Europe. *World Patent Information*, **30** (1), 43–52.
- , VAN POTTELSBERGHE DE LA POTTERIE, B. and GUELLEC, D. (2009). Claiming more: the increased voluminosity of patent applications and its determinants. *Research Policy*, **38** (6), 1006–1020.
- VARGA, A. (2000). Local academic knowledge transfers and the concentration of economic activity. *Journal of Regional Science*, **40** (2), 289–309.
- VENABLES, A. (1996). Equilibrium locations of vertically linked industries. *International Economic Review*, **37** (2), 341–359.
- (2006). Shifts in economic geography and their causes. *Economic Review*, (Q IV), 61–85.
- VERSPAGEN, B. (1993). *Uneven Growth Between Interdependent Economies*. Cheltenham: Edward Elgar.
- (1997). Measuring intersectoral technology spillovers: Estimates from the European and US patent office databases. *Economic Systems Research*, **9** (1), 47–65.
- and DUYSTERS, G. (2004). *The small worlds of strategic technology alliances*. Open Access publications from Maastricht University urn:nbn:nl:ui:27-13048, Maastricht University.
- and SCHOENMAKERS, W. (2000). *The spatial dimension of knowledge spillovers in Europe: Evidence from firm patenting data*. ECIS Working Papers 00.07, Eindhoven Centre for Innovation Studies, Eindhoven University of Technology.
- and — (2004). The spatial dimension of patenting by multinational firms in Europe. *Journal of Economic Geography*, **4** (1), 23–42.
- , VAN MOERGASTEL, T. and SLABBERS, M. (1994). *MERIT concordance table: IPC - ISIC (rev. 2)*. Tech. rep., MERIT.
- VIEREGGE, P. and DAMMER, I. (2007). EU-Cluster- und Strukturpolitik 2007-2013: Ein Ausblick am Beispiel NRW. In T. Becker, I. Dammer, J. Howaldt, S. Killich and A. Loose (eds.), *Netzwerkmanagement*, Heidelberg: Springer, pp. 23–33.
- VILADECANS-MARSAL, E. (2004). Agglomeration economies and industrial location: City-level evidence. *Journal of Economic Geography*, **4** (5), 565–582.
- VON HIPPEL, E. (1994). Sticky information and the locus of problem solving: Implications for innovation. *Management Science*, **40**, 429–439.
- (2005). *Democratizing Innovation*. Cambridge, MA: The MIT Press.
- WEBER, A. (1922). *Über den Standort der Industrie: Erster Teil: Reine Theorie des Standorts*. Tübingen: Mohr, 2nd edn.

- (1929). *Theory of the Location of Industries*. Chicago: The University of Chicago Press, [translated by Carl J. Friedrich from Weber's 1909 book].
- WERKER, C. (2006). *An assessment of the regional innovation policy by the European Union based on bibliometrical analysis*. Papers on Economics and Evolution 2006-11, Max Planck Institute of Economics, Evolutionary Economics Group.
- WILHELMSSON, M. (2009). The spatial distribution of inventor networks. *The Annals of Regional Science*, **43** (3), 645–668.
- WILLIAMSON, J. (1965). Regional inequality and the process of national development. *Economic Development and Cultural Change*, **13** (4), 3–45.
- WILLIAMSON, O. E. (1975). *Markets and Hierarchies*. New York: The Free Press.
- (1979). Transaction-cost economies: The governance of contractual relations. *Journal of Law and Economics*, **22**, 233–261.
- WORLD BANK (2009). *Reshaping Economic Geography*. Washington, DC: World Bank Publications - The International Bank for Reconstruction and Development / The World Bank.
- YOUNG, A. A. (1928). Increasing returns and economic progress. *The Economic Journal*, **38**, 527–542.
- ZIMMERMAN, D. (2003). Geographically weighted regression. Book review of A. Stewart Fotheringham, Chris Brundson, and Martin Charlton. *Journal of the American Statistical Association*, **98**, 765–766.
- ZUCKER, L. G., DARBY, M. R. and ARMSTRONG, J. (1998). Geographically localized knowledge: Spillovers or markets? *Economic Inquiry*, **36** (1), 65–86.

HOHENHEIMER VOLKSWIRTSCHAFTLICHE SCHRIFTEN

- Band 1 Walter Deffaa: Anonymisierte Befragungen mit zufallsverschlüsselten Antworten. Die Randomized-Response-Technik (RRT). Methodische Grundlagen, Modelle und Anwendungen. 1982.
- Band 2 Thomas Michael Baum: Staatsverschuldung und Stabilisierungspolitik in der Demokratie. Zur neoinstitutionalistischen Kritik der keynesianischen Fiskalpolitik. 1982.
- Band 3 Klaus Schröter: Die wettbewerbspolitische Behandlung der leitungsgebundenen Energiewirtschaft. Dargestellt am Beispiel der Fernwärmewirtschaft der Bundesrepublik Deutschland. 1986.
- Band 4 Hugo Mann: Theorie und Politik der Steuerreform in der Demokratie. 1987.
- Band 5 Max Christoph Wewel: Intervallararithmetische Dependenzanalyse in der Ökonometrie. Ein konjekturaler Ansatz. 1987.
- Band 6 Heinrich Pascher: Die U.S.-amerikanische Deregulation Policy im Luftverkehrs- und Bankenbereich. 1987.
- Band 7 Harald Lob: Die Entwicklung der französischen Wettbewerbspolitik bis zur Verordnung Nr. 86-1243 vom 01. Dezember 1986. Eine exemplarische Untersuchung der Erfassung der Behinderungsstrategie auf der Grundlage des Konzepts eines wirksamen Wettbewerbs. 1988.
- Band 8 Ulrich Kirschner: Die Erfassung der Nachfragemacht von Handelsunternehmen. Eine Analyse der ökonomischen Beurteilungskriterien und der wettbewerbsrechtlichen Instrumente im Bereich der Verhaltenskontrolle. 1988.
- Band 9 Friedhelm Herb: Marktwirtschaftliche Innovationspolitik. 1988.
- Band 10 Claus Schnabel: Zur ökonomischen Analyse der Gewerkschaften in der Bundesrepublik Deutschland. Theoretische und empirische Untersuchungen von Mitgliederentwicklung, Verhalten und Einfluß auf wirtschaftliche Größen. 1989.
- Band 11 Jan B. Rittaler: Industrial Concentration and the Chicago School of Antitrust Analysis. A Critical Evaluation on the Basis of Effective Competition. 1989.
- Band 12 Thomas März: Interessengruppen und Gruppeninteressen in der Demokratie. Zur Theorie des Rent-Seeking. 1990.
- Band 13 Andreas Maurer: Statistische Verfahren zur Ermittlung von oligopolistischen Strukturen. 1990.
- Band 14 Peter Mandler: Zur ökonomischen und politisch-institutionellen Analyse öffentlicher Kredithilfen. 1992.
- Band 15 Heinrich J. Engelke: Die Interpretation der Rundfunkfreiheit des Grundgesetzes: Eine Analyse aus ökonomischer Sicht. 1992.
- Band 16 Thomas Fischer: Staat, Recht und Verfassung im Denken von Walter Eucken. Zu den staats- und rechtstheoretischen Grundlagen einer wirtschaftsordnungspolitischen Konzeption. 1993.
- Band 17 Stefan Elßer: Innovationswettbewerb. Determinanten und Unternehmensverhalten. 1993.
- Band 18 Reinhard Scharff: Regionalpolitik und regionale Entwicklungspotentiale. Eine kritische Analyse. 1993.
- Band 19 Karin Beckmann: Probleme der Regionalpolitik im Zuge der Vollendung des Europäischen Binnenmarktes. Eine ökonomische Analyse. 1995.

- Band 20 Bernd Nolte: Engpaßfaktoren der Innovation und Innovationsinfrastruktur. Eine theoretische und empirische Analyse für ländliche Wirtschaftsräume in Baden-Württemberg. 1996.
- Band 21 Klaus-Rainer Brintzinger: Die Nationalökonomie an den Universitäten Freiburg, Heidelberg und Tübingen 1918 - 1945. Eine institutionenhistorische, vergleichende Studie der wirtschaftswissenschaftlichen Fakultäten und Abteilungen südwestdeutscher Universitäten. 1996.
- Band 22 Steffen Binder: Die Idee der Konsumentensouveränität in der Wettbewerbstheorie. Teleokratische vs. nomokratische Auffassung. 1996.
- Band 23 Alexander Burger: Deregulierungspotentiale in der Gesetzlichen Rentenversicherung. Reformnotwendigkeiten versus Reformmöglichkeiten. 1996.
- Band 24 Burkhard Scherer: Regionale Entwicklungspolitik. Konzeption einer dezentralisierten und integrierten Regionalpolitik. 1997.
- Band 25 Frauke Wolf: Lorenzkurvendisparität. Neuere Entwicklungen, Erweiterungen und Anwendungen. 1997.
- Band 26 Hans Pitlik: Politische Ökonomie des Föderalismus. Föderative Kompetenzverteilung im Lichte der konstitutionellen Ökonomik. 1997.
- Band 27 Stephan Seiter: Der Beitrag Nicholas Kaldors zur Neuen Wachstumstheorie. Eine vergleichende Studie vor dem Hintergrund der Debatte über den Verdoorn-Zusammenhang. 1997.
- Band 28 André Schmidt: Ordnungspolitische Perspektiven der europäischen Integration im Spannungsfeld von Wettbewerbs- und Industriepolitik. 1998.
- Band 29 Bernd Blessin: Innovations- und Umweltmanagement in kleinen und mittleren Unternehmen. Eine theoretische und empirische Analyse. 1998.
- Band 30 Oliver Letzgus: Die Ökonomie internationalen Umweltschutzes. 1999.
- Band 31 Claudia Hafner: Systemwettbewerb versus Harmonisierung in Europa. Am Beispiel des Arbeitsmarktes. 1999.
- Band 32 Jürgen Kulle: Ökonomie der Musikindustrie. Eine Analyse der körperlichen und unkörperlichen Musikverwertung mit Hilfe von Tonträgern und Netzen. 1998.
- Band 33 Michael Ganske: Intertemporale Aspekte von Staatsverschuldung und Außenhandel. 1999.
- Band 34 Margit Ströbele: Die Deregulierungswirkungen der europäischen Integration. Das Beispiel der Sondermärkte. 1999.
- Band 35 Marion Benesch: Devisenmarktinterventionen in Theorie und Praxis. Eine umfassende Analyse ihrer Zielsetzungen, Wirkungsweisen und wirtschaftspolitischen Bedeutung. 1999.
- Band 36 Torsten Gruber: Unterschiedliche geldpolitische Transmissionsmechanismen und Stabilitätskulturen als mögliche Ursachen geldpolitischer Spannungen in der Europäischen Währungsunion. 2000.
- Band 37 Bertram Melzig-Thiel: Arbeit in der Informationsgesellschaft. Chancen und Risiken neuer Informations- und Kommunikationstechnologien für die Beschäftigung. 2000.
- Band 38 Annette Fritz: Die Entsorgungswirtschaft im Spannungsfeld zwischen Abfallpolitik und Kartellrecht. Eine industrieökonomische Branchenstudie. 2001.
- Band 39 Harald Strotmann: Arbeitsplatzdynamik in der baden-württembergischen Industrie. Eine Analyse mit amtlichen Betriebspaneldaten. 2002.

- Band 40 Dietrich Benner: Qualitätsungewißheit bei Gütern mit Vertrauenseigenschaften. Entwicklung und Anwendung eines entscheidungstheoretisch fundierten Analyserahmens. 2002.
- Band 41 Jürgen M. Schechler: Sozialkapital und Netzwerkökonomik. 2002.
- Band 42 Kay-Uwe May: Haushaltskonsolidierung durch Ausgabekürzungen. Restriktionen und Strategien. 2002.
- Band 43 Peter Kühnl: Der Wechselkurs als Zwischenziel der Geldpolitik im Aufholprozess. Die monetärkeynesianische Entwicklungsstrategie der Berliner Schule vor dem Hintergrund der makroökonomischen Entwicklung ausgewählter Länder Mittel- und Osteuropas. 2003.
- Band 44 Steffen Wirth: Nichtparametrische Analyse von Bildungsertragsraten. Neuere Entwicklungen und Anwendungen. 2003.
- Band 45 Bernhard Holwegler: Innovation, Diffusion und Beschäftigung. Die ökonomische Theorie der Technologiediffusion und ihr Beitrag zur Erklärung technologischer Arbeitslosigkeit. 2003.
- Band 46 Guntram R. M. Hepperle: Zukunftsorientierte Industriepolitik. Möglichkeiten und Grenzen. 2004.
- Band 47 Udo Vullhorst: Stabilisierungspolitik bei supranationaler Geldpolitik und nationaler Fiskalpolitik. Eine spieltheoretische Betrachtung. 2004.
- Band 48 Matthias Rösch: Die Bedeutung von Investivlöhnen und Gewinnbeteiligungen für Einkommensverteilung und Beschäftigung. 2004.
- Band 49 Michael Bubik: Erfolgskriterien für Unternehmenszusammenschlüsse. Eine theoretische und exemplarische Analyse. 2005.
- Band 50 Jörg Weltin: Internationale Unternehmensbesteuerung. Allokation der Besteuerungsrechte unter veränderten Rahmenbedingungen. 2005.
- Band 51 Susanne Reichart: Zum Konvergenzprozess der mittel- und osteuropäischen EU-Beitrittsländer. 2005.
- Band 52 Daniel Hartmann: Geldpolitik und Beschäftigung. Die geldpolitische Strategie der Federal Reserve: Vorbild oder Auslaufmodell? 2005.
- Band 53 Marc Peter Radke: Explaining Financial Crises. A Cyclical Approach. 2005.
- Band 54 Katja Hölsch: Umverteilungseffekte in Europa. Eine Analyse für ausgewählte Länder. 2006.
- Band 55 Ulrike Lehr: Contingent Valuation Daten und Bayes'sche Verfahren. Ein Vorschlag zur Verbesserung von Umweltbewertung und Nutzentransfer. 2006.
- Band 56 Jutta Maute: Hyperinflation, Currency Board, and Bust. The Case of Argentina. 2006.
- Band 57 Michael Knittel: Geldpolitik und Stabilität des Bankensystems. Das Liquiditätsproblem aus Sicht der Theoriegeschichte und der gegenwärtigen Finanzmarktentwicklung. 2007.
- Band 58 Oliver Frör: Rationality Concepts in Environmental Valuation. 2007.
- Band 59 Jochen Gert Arend Wiegmann: Produktivitätsentwicklung in Deutschland. 2008.
- Band 60 Nicola Meier: China – The New Developmental State? An Empirical Analysis of the Automotive Industry. 2009.
- Band 61 Carsten H. Wander: Logistik und Wettbewerb. Zur Rolle logistischer (Re-)Organisation in einer wettbewerbsbasierten Marktwirtschaft. 2009.
- Band 62 Sven Wydra: Produktions- und Beschäftigungseffekte neuer Technologien. Am Beispiel der Biotechnologie. 2010.

- Band 63 Andreas Schaal: Die Relevanz von Venture Capital für Innovation und Beschäftigung. Theoretische Klärung und empirische Analyse. 2010
- Band 64 Sybille Sobczak: Geldpolitik und Vermögensmärkte. Volkswirtschaftliche Bedeutung von und geldpolitische Reaktion auf Asset Price Bubbles. 2010
- Band 65 Constanze Dobler: The Impact of Formal and Informal Institutions on Economic Growth. A Case Study on the MENA Region. 2011.
- Band 66 Tobias Börger: Social Desirability and Environmental Valuation. 2012.
- Band 67 Julian Phillip Christ: Innovative Places in Europe. Research Clustering, Co-Patenting Networks and the Growth of Regions. 2012.

www.peterlang.de