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Racial and Ethnic Residential Segregation Across the United States

New Approaches to Understanding Trends and Patterns

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Mark A. Fossett

Preface

A full draft of the main text of this monograph was completed in April 2023. In June 2023, just a day after we received a preview of the book cover, Mark A. Fossett passed away in an intensive care unit in Houston, TX, due to complications following heart surgery. Before he passed, he spent weeks in the ICU battling infections and fighting to recover his strength. During that time, I did what I could to make edits, touch up tables and figures, proofread, and have the monograph ready for Mark to take one last look before we sent it off. I also needed him to write his acknowledgments, something he had talked about doing but did not start. I never stopped believing that he would recover, return home, and eventually get back to puzzling over his favorite demographic problems. That did not happen, and Mark is no longer on this earth to see this book published. But this book is a product of 15 years of working closely together and, more importantly, it is a product of the decades of work that Mark devoted himself to in order to solve problems in segregation research that would help all of us better understand the landscape of residential segregation across the United States. The technical solutions to those problems can be found in his 2017 monograph, *New Methods for Measuring and Analyzing Segregation*, which was published by Springer and is open access. Those solutions are also integral to this book. So, in the way that his work lives on, so too he lives on and is still here.

When Mark and I started working together on the analyses that would eventually become this book, I was a PhD student and he was a professor and my mentor in the Department of Sociology at Texas A&M University. I had at that point been working with him for four years and over that time had spent countless hours listening to him explain, with both enthusiasm and careful attention to detail, the challenges of measuring residential segregation, and how they can be overcome. He was at the time working on his monograph that covered these topics. He spent hours every day meticulously refining the formulas, simulations, graphical demonstrations, Stata code, and language he used to explain his innovations in segregation measurement.

Sometimes all I could be was a sounding board as he did this work, but over the months and years, "through osmosis" as he would say, I began to deeply understand what he had accomplished and why it was so important. So much so that I was beyond eager to write this book with him, write papers with him, and give as many presentations as possible to teach others how to apply these methods and to appreciate how much it mattered.

The main problem with segregation measurement that he focused on was known, but obscure in its origins. Popularly used measures of segregation were prone to a sometimes very problematic upward bias that would inflate scores and make it challenging to understand segregation at a single point in time, follow segregation patterns over time, and compare segregation patterns across groups and communities. This problem was worse under conditions where small spatial units were needed to observe segregation, when the groups in the analysis were severely imbalanced in size, and when dealing with small population counts. Thus, much of what we knew about segregation was centered on urban metropolitan contexts, where conditions were most ideal for conventional segregation measurements. In the preface to his 2017 monograph, Mark named four concerns that troubled him and motivated him to do the methodological work that is featured in this book. First, there was no clear understanding of how segregation scores represent group differences on a residential outcome. Second, nobody could draw a direct quantitative link between household locational attainments and the overall segregation patterns that are produced. Third was the long-standing issue of segregation index bias, which limited studies of segregation to metropolitan contexts to the detriment of any research focusing on nonmetropolitan communities or smaller populations. And finally, during his work he developed a fourth concern, which is that the most popular measure of segregation, the dissimilarity index, is not always a trustworthy indicator of when prototypical segregation is occurring – that is, the pattern where two groups are living apart and are having very little residential contact with one another, and location-based inequalities are possible. For two decades, he confronted these problems and solved all of them with precision.

The primary purpose of this book, then, is not to focus on rehashing the technical details of the methods that solve these segregation measurement issues, but rather to put forward empirical applications of those methods to demonstrate how important it is to have accurate and trustworthy measurement tools for so many critical research questions about residential segregation across the United States. We spent years constructing datasets, conducting analyses, testing different ways to write about the discrepancies between what we found and what others had found using conventional and flawed methods, and sharing what we could with the academic community in the meantime. This book traveled a long way with us. It saw me advance to PhD candidacy, complete my PhD, begin a postdoctoral position, join the faculty at Fresno State, and earn tenure and promotion. It saw Mark reach the heights of his incredible career which included establishing the Texas Federal Statistical Research

Data Center and its consortium of universities at Texas A&M, being named a Cornerstone Faculty Fellow in the College of Liberal Arts, supervising a number of very excellent students, and eventually talking about retirement, which he was prepared to begin just before he passed. This book is, hopefully, a very helpful resource for benchmarking segregation patterns and trends and for improving research designs in the study of residential segregation moving forward. For me, it is also the manifestation of a long and deeply meaningful collaboration with a truly brilliant scholar.

This book would not have been possible without the groundbreaking and brilliant work that Mark did to bring solutions to segregation measurement that had eluded researchers for decades. His work over those decades was driven by an unshakable commitment to do good research. Mark was determined to uncover true answers, and he would not accept results that were not entirely "bullet-proof." Sometimes this led to projects carrying on for years as he tested a measurement or a model from hundreds of different angles, but the result was a quality of work that laid a solid foundation for others to build on. Those efforts are what culminated in his 2017 book, *New Methods for Measuring and Analyzing Segregation,* which provided the methodological framework for this book. His book laid out in great technical detail the flaws in most segregation index scores, and more importantly, the perfect solutions that he developed. Mark was an impeccable scholar and a brilliant sociologist. He was also generous. He never boasted, but I imagine what he would be most pleased about was not his own incredible intellect but rather how his work helped others. Nothing excited him more than an idea that would make research better for everybody else. This included his elegant solution to the problem of segregation index bias, his techniques for agent-based modeling of segregation, the establishment of the Texas Federal Statistical Research Data Center at Texas A&M University which he spearheaded, co-directing multiple cycles of an undergraduate summer research institute to build a pipeline to bring students of color and first-generation students into graduate school (first funded by the American Sociological Association and later by the NSF-Research Experience for Undergraduates program), and his extraordinary energy for students, who got to be an integral part of it all. Including me.

This book has also received a tremendous amount of support from many individuals, institutions, and organizations. We are grateful to the Department of Sociology at Texas A&M University, the academic home for this work for many years and which supported Mark as a faculty member and me as a graduate student. We also recognize the tremendous role that the Texas Federal Statistical Research Data Center had in supporting this work, where Mark was Executive Director and later Associate Director and I was first a graduate research assistant and later a postdoctoral research associate. Some of the analyses in this book were conducted at the Texas RDC and would not have been possible without the energy and competence of Dr. Bethany DeSalvo, who was the RDC Administrator of the Texas RDC at the time. We are also grateful to the Department of Sociology at California State University, Fresno, where I joined the faculty and completed writing this book. I am especially thankful for my good friends and colleagues at Fresno State who over many years offered encouragement and advice as I worked on this book with Mark. Dr. Jennifer Randles in particular took on the role of mentoring me, and I am fortunate to have been able to learn from one of the brightest and most thoughtful sociologists I have ever known. Additionally, Dr. Randles along with my other friend and colleague Dr. Justin Myers provided a wonderful support network for simultaneously accomplishing the equally arduous tasks of writing books and raising small children. It is no small thing to have that space as a new academic parent. I am also grateful to their partners, Craig Bailey and Shay Myers, for being a part of that village. Finally, I am thankful for the friendship and collegial support of Dr. Cristina Herrera at Portland State University, who has served as a model for how to do excellent scholarship and maintain a work-life balance.

There are specific people who were at Texas A&M University during periods of time that this work was being completed who we recognize for their support. Dr. Jane Sell, Dr. Dudley Poston, Dr. Walter Gillis Peacock, Dr. Rogelio Saenz, and Dr. Mary Campbell deserve mention for their extended support and companionship over the years. They were part of a community of friendship and scholarship that for some dates back to Mark's early career days and who remained his friends until the end. We must give special mention to Dr. Wenquan (Charles) Zhang, now at University of Wisconsin – Whitewater, who collaborated with Mark for many years on segregation measurement issues and later worked with both of us on empirical analyses employing the methods featured in this book.

We have been the benefactors of the amazing support of Evelien Bakker, Bernadette Deelen-Mas, Prasad Gurunadham, and Corina van der Giessen at Springer, who have very gently and patiently encouraged us to complete this book and were always responsive when we needed more time and more flexibility. In the acknowledgments that Mark wrote in his previous book, he said, “Apparently, it is impossible to exhaust their patience and goodwill.” I imagine he would say something very similar again today, and I would agree.

Other individuals whose contributions to this work we are grateful for include Luna Chandna and Nereyda Ortiz, who are currently graduate students at Texas A&M University and have been supporting an analysis that did not make it into this book but will be published as an article. Mark would also want to thank his many current and former students who have shared ideas with him, learned from him, and co-created space for him to refine the way he described and explained the methodological challenges that he was taking on. These individuals include, in no particular order, Dr. Warren Waren, Dr. Lindsay Howden, Dr. Gabriel Amaro, Warner Henson II, Dr. Bianca Manago, Dr. Jennifer Davis, Dr. Jessica Barron, Dr. Nicole Jones, Bo Hee Yoon, Brittany Rico, Dr. Marisa Sanchez, Dr. Xuanren Wang, Chiying Huang, Katelyn Polk, Bridget Clark, Dr. Danielle Deng, Dr. Nathanael Rosenheim, Cassidy Castiglione, Dr. Xinyuan Zou, Mary Jalufka, Megan Bodily, and Dr. Michael

Upchurch. If there are others that I left out, I sincerely apologize. I know Mark would have named every single student who gave him even a minute of their time to indulge him as he shared his latest thoughts on segregation measurement, because talking with students about research always delighted him. Mark would also want to thank his dissertation advisor, Dr. Omer Galle, for being a lifelong mentor and friend. There are many other colleagues across the discipline who have given us feedback, served as discussants, asked us questions, and spent time with us as we did this work. In no particular order, we recognize Dr. Michael White, Dr. Daniel Lichter, Dr. Matthew Hall, Dr. Ann Owens, Dr. Peter Rich, Dr. Daniel Powers, Dr. Tod Hamilton, Dr. Clark Gray, and Dr. Elizabeth Korver-Glenn, Dr. Eric Jensen, Dr. Angelica Menchaca, and Dr. Bryce Hannibal. We also extend gratitude to the Cornell Population Center for inviting us to give a workshop on segregation measurement in 2019, and to the U.S. Census Bureau for inviting us to present our work during the Summer at Census series in 2022.

We also recognize and appreciate the funding support we have received over the years from the National Science Foundation and the National Institutes of Health. The National Science Foundation has through multiple grants supported Mark's work on segregation measurement (SES #1024390), my training as an undergraduate and graduate student (SES #0649277), and the open access publishing of this book (SES #2222573). The National Institutes of Health supported Mark's work on agent-based modeling to simulate segregation dynamics (R43HD038199 and R44HD038199). In addition, we are thankful to the journal editors at *Sociology of Race and Ethnicity, Spatial Demography*, and *Demographic Research* for publishing work that came out of this project.

Finally, and most importantly, we give immeasurable gratitude and recognition to our families. I am fortunate to have the unwavering support of my husband, Zach, who kept on encouraging me as I worked on this book over the years, including during our very difficult 16-month isolation period of the Covid-19 pandemic, when we were both trying to work and care for our two small children at home at the same time. This is when Mark and I inexplicably made the biggest push on writing this book. We could not have done any of that without the selfless help of my mother-in-law, Debra, who flies out to California from Texas every few weeks and lived with us during our entire pandemic isolation period to help with our children. My father-in-law, Frank, has also been a major help over the years in this regard. I am also so very grateful to my parents, Gabriela and Brian, and my brothers, Marcelo, Garrett, Brandon, and Benjamin, for encouraging me through my academic career and cheering on every accomplishment, including the completion of this book. Finally, I am lucky to be mom to Ash and Peter, two amazing little humans who keep me focused on the adventure of life and remind me that there is more to be gained if I prioritize balance.

I am not capable of writing Mark's words to his wife, Betsy, or their children, Lane, Tyler, and Kate, and their families. I would not dare try. But I know he loved them completely and endlessly and would thank them for bringing him joy. I am also thankful, as Mark's friend, that he was surrounded by such a beautiful family.

A few days after Mark passed, our dear friend Dr. Walter Gillis Peacock at Texas A&M University told me that I am not publishing this book without Mark, but rather I have the honor of publishing it with him. He is very correct. I send all my gratitude out into the universe to Dr. Mark Fossett for giving me the opportunity to learn from him and to share credit with him on this very good and important work. It was the greatest honor, and one of the greatest experiences of my life, to be Mark's student, colleague, coauthor, collaborator, and friend. We shall declare a victory.

Fresno, CA, USA Amber R. Crowell
June 2023

Abstract

This monograph builds on innovations in segregation measurement and analysis, previously developed by one of the authors of this book, by conducting empirical analyses of racial and ethnic residential segregation across a wide and comprehensive selection of communities in the United States. Past studies of residential segregation have been limited by a well-known and difficult challenge, which is that most segregation indices are prone to a sometimes very problematic upward bias that inflates segregation scores and makes it difficult to measure segregation at a single point in time, follow segregation patterns over time, and compare segregation across groups and communities. These problems are worse when using small spatial units such as census blocks, when the groups in the analysis are extremely imbalanced in size, and when population counts are small. This has resulted in a literature that is heavily focused on segregation in a selection of the largest urban metropolitan environments, with only limited studies focused on nonmetropolitan communities or small racial and ethnic populations. Even so, restrictive case selections do not directly solve the problem of index bias. Fortunately, we have the solution to index bias, in addition to other solutions that address related problems with segregation measurement, which allow us to reanalyze residential segregation patterns and include more communities and contexts. In this book, we examine White-Black, White-Latino, and White-Asian residential segregation across metropolitan, micropolitan, and noncore county communities from 1990 to 2010, giving special attention to how our findings may differ from what previous studies have found with measures that were not corrected for index bias and other related issues. We find that under the conditions where index bias is less likely to be a problem, our results track those from previous studies. But these communities do not make up the majority of cases, and in most communities our findings deviate in substantial ways from previous findings. We also employ new methods for linking micro-level processes of locational attainments to overall segregation patterns and develop a more complex understanding of residential segregation dynamics. This leads us to conclude that it is important to use our findings as benchmarks for residential segregation patterns over this time period and to adopt the methods of measurement and analysis that we endorse throughout this book for residential segregation research.

Contents

Chapter 1
Introduction

1.1 Overview

The purpose of this book is to describe and analyze patterns and trends in racial and ethnic residential segregation across the United States over time and across communities. With new methods to expand our scope of analysis beyond what has been done before, we cover recent decades in a variety of settings including metropolitan and micropolitan areas and rural communities (i.e., noncore counties). We direct our primary focus to residential segregation between major panethnic racial groups – Non-Hispanic White, Black, Latino, and Asian households in 2010 – and to broad changes in segregation from 1990 through 2010. But we also give attention to several more detailed aspects of trends and patterns in residential segregation. While the literature in sociology, demography, urban planning, and geography is rich with studies of residential segregation patterns, we believe this book establishes an important baseline for placing recent segregation research in a new context and for informing segregation research going forward. The basis for this is that we apply new methods for measuring and analyzing segregation that can at times drastically alter results obtained using more traditional approaches. In particular, we argue that these new methods of measurement and analysis address and overcome important methodological problems that have limited past research and, as a result, allow us to expand the scope of segregation studies and the quality of measurement to obtain improved findings that more accurately capture and reflect the demographic reality we are seeking to document.

With the exception of Chap. 2, which reviews and explains our methodology and study design, the chapters in this book give attention to a set of important substantive concerns addressed in the broader sociological and demographic research literature on residential segregation. Even as we describe and analyze patterns of residential segregation between panethnic racial and ethnic groups, an area that has been heavily researched already, we bring significant improvements in strategies of

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measurement and analysis when covering this familiar territory. Additionally, we expand the analysis to give close attention to segregation trends in nonmetropolitan and rural settings that are less frequently studied. We also give special attention to segregation patterns in communities that are seeing new and increasing presence of racially and ethnically minoritized populations as the population of the United States steadily becomes more diverse, not only in immigrant gateway cities and areas with established minoritized group presence, but also in metropolitan and nonmetropolitan settings across all regions of the country. Finally, we take the analysis of segregation to a further stage of innovation, where we use new methods to conduct community-specific analyses of micro-level segregation dynamics that shape overall segregation patterns.

The common theme connecting all of the empirical chapters is that we are able to delineate the levels, patterns, and trends in segregation more clearly and accurately than has been possible in previous research by drawing on attractive new options for measuring and analyzing segregation. We necessarily provide an overview of these new methods and note the advantages we gain by using them in Chap. 2. But we do not intend this work to be primarily a study of segregation methodology. Indeed, this is not necessary because the methods we use have been previously introduced and reviewed in depth in a recent work by one of the authors of this book (Fossett, 2017) and we have previously empirically demonstrated the advantages of these new methods of segregation measurement and analysis in earlier work by both authors (Crowell & Fossett, 2018, 2020, 2022). Instead, we intend the main contribution of this study to be to demonstrate the value of applying new methods to help obtain improved answers both to basic questions that have been addressed in the empirical literature for decades and also to questions that have been neglected in past research due to the limitations of earlier methodological practices.

In some cases, as in the study of nonmetropolitan segregation, the previous research literature has been extremely limited in scope and in the conclusions that are drawn because conventional methods of segregation measurement are known to be untrustworthy and potentially misleading for the analysis of interest. This issue is crucially relevant, for example, when investigating segregation in nonmetropolitan settings where it is necessary to use units that are smaller in spatial scale and population size (e.g., census blocks) to measure segregation (Fossett, 2017; Lichter et al., 2010, 2016) and also when the groups in the analysis are imbalanced in size as is certain to be the case in new destination communities and in other communities where new groups are taking on an increasing presence in the population (Hall, 2013; Lichter et al., 2010; Saenz, 2010; Frey, 2018; Winkler & Johnson, 2016; Vásquez et al., 2008). The methodologies we use overcome the challenges that rendered previous measurement strategies untrustworthy and potentially misleading in these situations. This is all to say that we are not necessarily exploring or identifying new areas of segregation research, but rather we are revisiting established areas of research with new and improved methods for understanding the dynamics of residential segregation in a variety of demographic contexts.

Ultimately, this book provides a comprehensive overview of residential segregation in the United States from 1990 up to and through 2010. In addition to describing residential segregation patterns in all areas of the United States, including Latino and Asian new destinations, we test major sociological hypotheses about the mechanisms and dimensions of segregation, highlight new methodological approaches to measuring and analyzing segregation, and offer suggested paths to continue the work of understanding residential segregation in the United States in the twenty-first century. The phenomenon of racial residential segregation shows little sign of abating or becoming an object of backward-looking historical interest. To the contrary, it appears the study of residential segregation unfortunately will be a priority issue in demographic and social science research well into the future. We hope to help improve the efforts in this field by demonstrating the advantages of new methods of measurement and analysis and showing how they make it possible to expand the scope of feasible research on segregation. These efforts will make segregation research more comprehensive and inclusive of a broader range of group comparisons and community settings. Finally, we believe that improving the quality of measurement and the scope of analysis that is possible in segregation research will not only clarify patterns and trends in residential segregation but also contribute to better evaluation and refinement of existing theories that stimulate new insights into the social dynamics that produce residential segregation.

1.2 Brief Note on Measurement and Implications for Future Research

While we review the value of the methods we use in this study in detail in Chap. 2, we want to emphasize here that our approach to measuring segregation is the basis for one of the major contributions of this book. As far back as Winship (1977) it has been acknowledged that commonly used measures of segregation have inherent flaws that lead to upward bias of segregation index scores that can be concerning in general and deeply troubling under certain conditions, particularly when analyses involve small areas or groups that are vastly disproportionate in size. The most common approach in the literature since Winship (1977) has been to simply restrict the scope of segregation studies to avoid conditions where inherent bias in index scores is most worrisome. This has resulted in certain populations and communities being neglected in the broader literature, either directly through outright exclusion from analysis or indirectly by down-weighting segregation comparisons in empirical analyses, and it has resulted in foregoing research in smaller communities where it is necessary to operationalize neighborhoods at small spatial scales. However, the need to adopt broad restrictions on study design to avoid examining segregation in settings that pose challenges for conventional methodological approaches is no longer warranted. Fossett (2017) has introduced refined formulations of all popularly used segregation indices that eliminate the upward bias inherent in their original formulations. With these new formulas, we proceed in this book to reexamine segregation across the United States free of concern for those particular problems that plagued segregation research in the past.

Additionally, we pick up the conversation begun by Fossett (2017) on segregation indices that diverge from one another and demonstrate in each empirical chapter the care that is needed in deciding which segregation index is most appropriate for capturing the most important aspects of the dimension of uneven distribution in any particular scenario. We also take advantage of an innovation to Fossett's (2017) segregation index reformulations which is that they can now be easily disaggregated and understood as measuring the difference in group means on individual residential outcomes. Placing segregation indices in a conceptual framework where index scores correspond to group-level aggregations of individual-level residential outcomes opens up new and exciting opportunities to analyze segregation as a group-level outcome driven by micro-level dynamics and use the toolkit of methods popular in inequality studies. This in particular builds a bridge between two traditions in the segregation literature that are described in more detail in a later section of this chapter.

The final methodological innovation that we mention here is that we build on the work of Fossett (2017) to call attention to the finding that problems associated with measuring residential segregation using data for persons – which is by far the most common approach used in the research literature – are greater than is generally realized. We first establish that the problems are substantial, and we then review methods that deal with them successfully to permit more accurate and trustworthy measurements of segregation. Our findings on this point have important implications for future research including research using the newly released data files from the 2020 Census of Population and Housing. Specifically, our findings show that analysis of levels and trends in segregation based on index scores computed using tabulations of persons in combination with conventional formulas will consistently overstate levels of segregation by greater amounts than is currently appreciated.

Furthermore, since the impact of index bias, the technical problem that inflates levels of segregation above their true value, varies across cases in complicated ways, there are no easy ways to address the problems when following conventional practices of measuring segregation using data for persons. Happily, we show here that superior, trustworthy measurements of segregation can be achieved. But we also show that it requires using both different measurement approaches and different data. Specifically, it requires using methods for unbiased measurement outlined in Fossett (2017), and these measurement methods must be applied either in combination with data for households or with detailed data for persons by size of household. We review these and other methodological choices we adopt and encourage other researchers to consider in Chap. 2.

1.3 The Continuing Relevance of Residential Segregation

Residential segregation is a distinct and fundamental feature of urban areas across the United States (Fong et al., 2022; Frey, 2018; Iceland, 2014). It is of major interest to social scientists because it involves pronounced and enduring patterns of uneven spatial distribution of resources and opportunities tied to housing and residential location (Charles, 2003; Fong et al., 2022; Krysan & Crowder, 2017; Massey & Denton, 1993; Sharkey & Faber, 2014). Patterns of residential segregation are characterized by high levels of inertia at a macro level. Individual neighborhoods sometimes change dramatically over a relatively short period of time (e.g., one or two decades), but these changes typically occur on the margins of broader spatial patterns that generally are more stable and rarely change rapidly over short time intervals. This is why Fong et al. (2022) describe segregation as "both dynamic and durable" (6). Consequently, contemporary urban residential patterns are strongly shaped by and reflective of urban history extending back many decades (Charles, 2003; Frey, 2018; Massey & Denton, 1993).

The massive tide of urban and suburban development associated with the transition of U.S. society from predominantly rural to urban and metropolitan during the twentieth century occurred at a time when racism and discrimination directed toward racially minoritized populations were pervasive, were sanctioned by law, and were deeply embedded in institutional practices in housing and mortgage lending markets (Charles, 2003; Frey, 2018; Massey & Denton, 1993; Rothstein, 2017; Taylor, 2019). These conditions enabled White households to settle in new neighborhoods that were marked by their racial exclusivity and also served to protect established White neighborhoods from minoritized group entry. Segregation policies served to inflate the value of properties in White neighborhoods by enabling resource accumulation in contrast to properties in Black neighborhoods marred by public and private disinvestment in addition to predatory real estate practices (Taylor, 2019).

Black households bore the brunt of these policies as they were left behind in disintegrating urban neighborhoods with declining property values, unable to share in the benefits White households gained from federal support and subsidies for new suburban development (Glotzer, 2020). Later in the century, industrial restructuring that saw manufacturing jobs decline with only partial replacement by information and technology jobs reduced employment opportunities that had previously sustained many Black neighborhoods, first inducing and then accelerating the decline of economic opportunity and wellbeing for segregated Black families in larger industrial urban areas of the North and Midwest (Wilson, 1987). These multiple dynamics served to create structured residential patterns that have persisted long after the era of legally sanctioned, or *de jure*, segregation ended. In the post-Civil Rights era, low-income Black families encountered continuing barriers to entry in White neighborhoods not only because of ongoing overt and covert racial discrimination but also because of the complex web of suppressed wealth accumulation due to depressed housing values and deleterious consequences of concentrated poverty that White households rarely experienced (Massey, 1990). Today, segregation continues to determine and reproduce unequal access to opportunities and resources (Massey, 2020).

Latino and Asian households, while apparently experiencing lower barriers to entry into White neighborhoods, nevertheless also experience moderate levels of segregation from White households on average and evidence suggests these levels are stable or even rising for Latino and Asian households as segregation for Black households is falling very slowly, albeit steadily (Frey, 2018; Iceland, 2014). Although Latino and Asian households to varying degrees experience historically rooted patterns of segregation from White households and may experience significant housing discrimination, especially for those Latino residents who are racialized as Black, the combination of historical and contemporary dynamics are more complicated due to the role of immigration. Latino and Asian immigrant families also may at first segregate because of the initial practical attractions of existing ethnic immigrant enclaves, or neighborhoods defined by a supportive economic and social infrastructure controlled by the ethnic group that lives there (Charles, 2003; Iceland & Scopilliti, 2008; Portes, 1981). For example, some historical Chinatowns emerged in response to racial discrimination against Asian immigrants but have persisted and thrived as ethnic communities, providing positive human capital to their residents (Zhou & Logan, 1989). In similar ways, Latino enclaves today may exist to support new arrivals seeking protection from discrimination and in need of a welcoming community with shared language that can facilitate entry into the housing and labor markets (Xie & Gough, 2011). The relative impact of beneficial aspects of enclaves serving to attract and retain immigrant populations versus enclaves being areas of last resort and a refuge from discrimination for groups excluded from alternative locations continue to be debated in the literature, but it is nevertheless the case that concentrated immigrant communities are detectable and persistent and are affected by unique dynamics that are distinct from other historical structural causes of racial segregation.

Other than the fact that most areas are still to some degree segregated and in certain metropolitan areas continue to experience extreme levels of White-Black segregation in particular (Frey, 2018; Massey, 2020), there is also other substantial evidence that ongoing *de facto* mechanisms of segregation have carried on past the Civil Rights era to reinforce spatial residential separation by race and class into the twenty-first century. Research on behalf of the Department of Housing and Urban Development (HUD) has revealed that as recently as 2013 Black families seeking housing still experience discrimination in comparison to White families, although they, along with other recent research, also found that the extent of these occurrences is on the decline (Quillian et al., 2020; Turner et al., 2013). Home loan discrimination also still occurs, echoing the nation's history of redlining, with Black potential homeowners, especially those buying homes in predominately Black neighborhoods, less likely to be approved for bank loans or more likely to receive subprime loans. Quillian et al. (2020) found that although housing discrimination is on the decline, racial gaps in mortgage lending are persistent.

The hypothesis that segregation is solely a product of mutual preference is not credible. Preferences are a potential contributing factor. But racial and ethnic segregation is an over-determined outcome supported by multiple causes including not only preferences, as one contributing factor among many, but also overt and informal discrimination, group differentials in resources, and a variety of structural barriers. Each of these can independently foster segregation and they can operate in combination to create and maintain segregation at high levels with White neighborhoods continuing to enjoy more resources, better infrastructure and amenities, and higher home values. As Douglas Massey and Nancy Denton assert in their influential book, *American Apartheid* (1993), the persistence of segregation, in addition to the meaningful consequences of segregation for racial and economic equality, justify that social scientists maintain the conversation on segregation rather than let it slip out of the discourse on our present social conditions.

Though often associated with early- to mid-twentieth century laws and housing policies, residential segregation today is one of the more persistent visible manifestations of racial conflict, separation, and inequality in the United States. Both the causes and consequences of racial residential segregation have implications for racial and ethnic relations and disparate outcomes by race, class, and other sociologically meaningful group identities. In this book we do not directly explore the individual- and group-level outcomes that can result from residing in racially and economically segregated neighborhoods because the data needed for a comprehensive study are not available. But we note these disparate outcomes to highlight the sociological importance of accurately documenting levels, patterns, and trends in segregation and understanding the dynamics that give rise to them. A broad range of studies on health disparities, environmental exposures, educational opportunity gaps, wealth gaps, and housing stability find important correlations with neighborhood characteristics and residential segregation (Sharkey & Faber, 2014). In the case of health and environmental inequalities, segregation consolidates the power of White neighborhoods to block development that could undermine their health, wealth, and wellbeing, which means that industrial plants and freeways are more likely to be constructed in poor communities of color (Sharkey, 2013; Trounstine, 2018). Educational opportunities are largely tied to the quality of public schooling and other location-based enrichment resources. White wealthy children living in homogenous affluent neighborhoods have the privilege of attending well-funded schools, while racially minoritized children and poor children systematically encounter inferior educational opportunities in understaffed and under-resourced schools located in racially segregated areas of concentrated poverty (Kozol, 1991). Wealth and housing are also anchored to residential location as most families build wealth through homeownership. The value of homes in White, affluent neighborhoods are inflated due to subjective assessments of locational value that are grounded in historically racist practices in the real estate and banking industries of assigning less investment and more loan risk to neighborhoods where minoritized racial groups predominate (Howell & Korver-Glenn, 2018; Korver-Glenn, 2021; Quillian et al., 2020; Taylor, 2019). This practice, commonly known as "redlining," is often associated with the FHA underwriting rules that were used in the 1930s and 1940s during the New Deal Era. But those rules were widely adopted by the real estate and mortgage industries and live on today in informal practices and statistical discrimination embedded in risk and value projection models. Segregation contributes to creating and maintaining White wealth, much of which, especially for the middle-class, derives from the appreciation of the values of their homes and the neighborhoods where they are located (Shapiro, 2006).

1.4 Theories of Segregation

The sociological literature on residential segregation has traditionally organized discussion of segregation dynamics around three dominant theoretical frameworks which focus on different but potentially interlocking and simultaneously operating dynamics that shape the level, patterns, and trends in segregation in a given area. The first of these is the spatial assimilation framework, which emphasizes the role of group differences in cultural, social, and economic characteristics in contributing to patterns of racial segregation (Alba & Logan, 1993; Charles, 2003; Massey & Denton, 1985). The explanation for segregation at the center of the spatial assimilation framework is that minoritized racial groups and immigrants are segregated from U.S.-born White households because of group differences in language, culture, nativity, and citizenship, as well as differences in resources crucial for residential attainment and location such as education, occupation, income, and wealth. Especially for immigrants, differences in language and culture can combine with relations of mutual support based on kinship and common origin to create ties to enclave neighborhoods. Additionally, differences in language, culture, and social status increase social distance from U.S.-born White residents and can foster avoidance and exclusion. Deficits in attainment resources such as income and wealth also limit the ability to purchase or rent homes in predominantly White neighborhoods with higher housing costs. These multiple effects are predicted to fade as groups steadily assimilate on language, culture, education, and socioeconomic standing with the central assumption being that assimilation weakens ties to enclaves, reduces social distance from middle-class White households, and reduces deficits in resources relevant for locational attainment.

The spatial assimilation model has roots in the mid-twentieth century "classical" assimilation models of the Chicago School which were developed based primarily on observations of the experiences of White ethnic immigrants of the 1860–1920 era who, over time and across generations, became for the most part socially and spatially indistinguishable from one another and from third-generation White populations (Alba et al., 1997; Lieberson, 1962). The major shortcoming of this perspective is that it has had little value for understanding persistent high levels of White-Black segregation, which is observed regardless of income or educational differences (Crowell & Fossett, 2022). Thus, the model became less relevant to understanding segregation in the United States in the decades following World War II. However, the model has received renewed attention in recent decades following the resumption of sustained, large-scale immigration, especially from countries of Latin America and Asia, after the reforms of the Immigration and Nationality Act of 1965.

Competitive ethnic relations theory also emerged from the Chicago School urban ecology/race relations cycle tradition which identified group-level competition as a powerful factor in social dynamics (Hawley, 1944; Barth & Noel, 1972; Lieberson, 1961, 1980; Fossett & Cready, 1998). The views of this perspective offset what many perceive as undue "optimism" of spatial assimilation theory by stressing the harsh reality that assimilation sequences are not inevitable as inter-group stratification and inequality can and do arise and endure when group relations harden around group competition and conflict. In particular, these perspectives posit broad regimes of intergroup inequality are especially likely to emerge and persist when majority groups directly and indirectly benefit from racial and ethnic stratification and view the presence and growth of culturally and racially distinctive minoritized populations as a threat to the majority group's social and material advantages, who then discriminate broadly along group lines to preserve majority group position (Blalock, 1956, 1957, 1959, 1967; Frisbie & Niedert, 1977; Olzak & Nagel, 1986; Fossett & Cready, 1998). In recent decades the dynamics of discrimination that are central in competitive ethnic relations theory are more often explored in the context of a more general perspective that stands as an alternative to spatial assimilation theory.

The second dominant theory is often referred to as the *place stratification* model. The general premise of this approach as introduced by Logan (1978) and subsequently expanded by many others is that segregation is an outgrowth of group conflict and is the product of discriminatory behaviors at individual and institutional levels that function to preserve majority group advantages. For understanding racial residential segregation, this framework centers the role of racism which serves to create location-based disparities that privilege White neighborhoods through the exclusion of other racial groups while simultaneously fostering disadvantage, decline, and disinvestment in segregated neighborhoods for racially minoritized (Logan, 1978; Massey, 2007; Trounstine, 2018). This framework focuses attention on a wide range of well-documented discriminatory practices of local, state, and federal governments as well as discriminatory behavior by individual actors such as realtors, speculators, and homeowners. Public housing programs, suburban development, federal home-purchasing loans, and other subsidized housing efforts reached their height prior to the passage of federal fair housing laws and often were designed with explicit intentions to maintain racially segregated neighborhoods (Massey & Denton, 1993; Taylor, 2019). However, even after fair housing laws were enacted, research continues to document persistent racial discrimination in the housing market in addition to racist stereotypes and ideologies that continue to motivate White homeowners to express preferences to live in predominately White neighborhoods (Farley et al., 1994). The place stratification framework attempts to capture these dynamics that emerge from systemic racism within the housing market and how they contribute to ongoing segregation, especially White-Black segregation, which is most strongly reinforced by racism as it manifests as anti-Blackness.

Finally, the third major perspective receiving extended attention in the segregation literature emphasizes the role of preferences in shaping residential patterns in communities. This perspective directs attention to the implications and consequences of the choices individuals and families make when moving to a particular residential location which involves choosing not only a housing unit to serve as their home but also, and perhaps more importantly, choosing a neighborhood to reside in (Krysan & Crowder, 2017). Preferences are obviously strong drivers of residential sorting. Decisions to buy or rent a home are not made casually and families weigh many factors when making these choices, including the safety and orderliness (or lack thereof) of neighborhoods, the quality of the local schools, accessibility to work and shopping options, property values, and more. In the racialized social context of U.S. urban areas families typically are mindful of neighborhood racial composition both for its own sake and because it is often seen as a proxy for other characteristics of neighborhoods that are correlated with racial composition (Krysan & Crowder, 2017). With regards specifically to racial composition, preferences that do not align proportionately with the overall racial composition of the community can contribute to patterns of segregation. Relatedly, in a city that is predominantly White, minoritized group households that seek to live in "integrated" – or, more precisely, "diverse" – neighborhoods to avoid being "isolated" in predominantly White neighborhoods also will promote uneven distribution.[1]

The feature that distinguishes preference theory from general discrimination theory is the former's focus on consequences of unconstrained choice in contrast to the consequences of constraints on choice resulting from exclusion and other acts of direct discrimination. For example, if households prefer neighborhoods where their racial-ethnic group is present in proportions exceeding parity, their choice behavior can create and maintain racial segregation. Survey research indicates that households from all major racial-ethnic groups express preferences for levels of same-group and cross-group contact that are not compatible with even distribution (Clark, 1991; Fossett, 2006). Preference theory stresses that ethnic demography interacts with preferences in ways that often are not fully appreciated. For example, in most U.S. communities, preferences by minoritized racial groups to live in neighborhoods that are diverse would, if realized, produce many disproportionately White neighborhoods (Fossett, 2006, 2011). Similarly, preference theory is potentially relevant for explaining the moderate-to-high levels of segregation observed among minoritized racial groups while theories emphasizing exclusion and discrimination by White residents have limited relevance. Findings from hedonic price analyses suggest preferences are consequential and are reflected by price premiums households pay for housing located in areas with desired racial composition (Yinger, 2016). Preference theory is controversial in some quarters, but it is readily accepted in others and is not easily dismissed. It warrants more attention both as a matter of basic science and also because standard anti-discrimination laws and policies have no effect on the consequences of choice behavior.

It is standard for segregation studies to identify and draw on the three frameworks just noted (Crowder & Krysan, 2016). Sometimes the frameworks are presented as identifying and emphasizing competing, mutually exclusive forces but more nuanced presentations recognize that logically all three dynamics can operate simultaneously and thus all must be acknowledged and considered together to capture the

[1] The term "integration" is used to convey a variety of meanings that, unfortunately, are in some cases inconsistent and incompatible. Under the accepted tenets of segregation measurement theory, integration defined as even distribution holds when all neighborhoods exactly match the ethnic composition of the city as a whole. Consequently, diverse neighborhoods are compatible with integration in cities with diverse ethnic composition but substantial segregation must occur for such neighborhoods to exist in cities that are not demographically diverse.

full complexity of residential segregation (Fossett, 2006, 2011; Fossett & Crowell, 2018; Crowell & Fossett, 2022). However, as popular and dominant as it has become to frame segregation theory in relation to these three perspectives, Maria Krysan and Kyle Crowder (2017) make the case that segregation researchers must recognize the limitations of these lines of demarcation and be open to reconsidering and refining segregation theory.

In particular, Krysan and Crowder criticize the "big three" for relying on the same single assumption that families make rational residential choices with a complete set of information about all possible neighborhood options (Krysan & Crowder, 2017). Their contribution to the literature is packaged in their response to this critique, which is to develop a new framework that emphasizes the parameters of residential sorting, factoring in that stratified groups do not move around within the same housing market but rather are stratified into different and more often than not disparate markets. Thus, as White, Black, Latino, and Asian households seek out new places to live, they move within spheres that have varying degrees of overlap, with the least amount of overlap occurring between White and Black residents. This framework incorporates useful elements of the three traditional theoretical approaches including the way in which residential sorting is driven by racist animosity, the desire to maximize resources, and preferences influenced by perceptions of neighborhoods with different racial compositions, but it brings to the forefront the more dynamic churning of residential sorting at a micro level.

1.5 Segregation as a Multilevel Process

The study designs adopted by empirical studies in the research literature on residential segregation can for the most part be grouped into one of two traditions, each of which focuses on aspects of segregation that are separate and distinct but also clearly inter-connected. The first of these traditions is to conduct comparative analyses of segregation across communities using summary scores to measure segregation. This approach gained renewed popularity following work by Massey and Denton (1988) which brought greater clarity and coherence to discussing and measuring the different dimensions of segregation at macro-scales. For this reason, and also due to the increased computational power that became available to process large census summary files in the latter half of the twentieth century, this tradition in the segregation literature undertakes large-scale studies of cross-area and over-time variation in aggregate-level segregation patterns in communities. This work commonly involves analyzing the associations and relationships of overall segregation with characteristics of communities including factors such as population size, the percent of the population that is not White, and median income differences (Farley & Frey, 1994; Iceland & Scopilliti, 2008; Lichter et al., 2010). A significant contribution of these studies is to establish that, while segregation is an almost universal phenomenon in the metropolitan United States, segregation levels vary across group comparisons, across communities, and over time and this variation can be linked to a variety of social, economic, demographic, and political characteristics of communities.

Many of the chapters in this monograph focus on the first task that must be accomplished by studies in this research tradition; namely, accurately measuring segregation so it can be described well. It may seem unnecessary to state that this first task is essential to documenting variation in segregation across areas and over time. But the fact is, there is substantial room for improvement in accurately measuring segregation for particular group comparisons in particular communities at given points in time. Many of the concerns about the current state of measurement that we review are already known to researchers. Thus, the more valuable contribution we make is to identify and implement methods of measurement that overcome known problems to achieve superior measurements and understandings of segregation patterns. A related goal is to achieve measurements of segregation that can sustain close analysis of individual cases and micro-level patterns. To the non-specialist, this may seem a low bar to reach. In fact, however, much previous research in this area has necessarily had to draw on index scores that often cannot sustain close case analysis because the scores that summarize particular segregation comparisons are sometimes distorted by index bias. Close case analysis becomes difficult and often highly questionable because the impact on index scores can be non-trivial and can vary in complex ways across individual segregation comparisons. Until recently no proven methods were available for eliminating these problems. We implement recently developed methods for measuring segregation that yield unbiased index scores that are superior to scores used in past research. We confine ourselves here to primarily reporting descriptive analyses of patterns and trends. But the contribution is valuable because the results and findings we report are often fundamentally different from those one would obtain using past measurement practices.

The second major research tradition in segregation research gained popularity later in the history of the literature. It is to conduct micro-level locational attainment analyses that focus on the residential outcomes of households and relate those outcomes to characteristics of the household including, for example, race, income, education, language, and nativity (Alba & Logan, 1991, 1992, 1993; South et al., 2008). This approach is relevant for understanding segregation because segregation for the community overall must in a certain sense be determined by the aggregation of the locational attainment outcomes of individual households at a micro level. Until recently, however, it has not been possible to make clear and precise connections between segregation as observed in individual communities and the findings from micro-level attainment analyses. Most studies of micro-level locational attainments have used national-level, sample survey datasets that cannot sustain analysis in individual communities. Yet crucial measures relevant for computing segregation indices for communities – for example, the value of racial composition as measured by proportion White (P) in the community – vary across communities. Consequently, predictions for proportion White in a neighborhood for individual households (p) with particular characteristics based on a national-level regression analysis will not have the same implications for segregation across communities. The predicted value of p may well be above the level expected under even distribution in some communities and below the level expected under even distribution in other communities. So, implications for segregation must be teased out at a more general and abstract level of a mythical "average community" and cannot be applied effectively in individual communities that differ from the average.

What should become clear, especially as one understands and appreciates the insights gleaned from locational attainments research, is that we intuitively understand segregation to be the product of micro-level processes that determine where individual households reside. Yet the empirical study of micro-level locational attainments and the empirical study of macro-level segregation patterns, up until recently, could not be directly linked in any definite way. Many important studies, including for example the work of Alba and Logan (1991, 1992, 1993) and the work of South and colleagues (2008) made significant strides in this direction. But missing from this work and from the broader literature was a method for quantitatively joining research on individual locational attainments and research measuring segregation at the community level. Our previous work in this area (Crowell & Fossett, 2018, 2020, 2022) provides the missing link by drawing on methods set forth by Fossett (2017) that seamlessly join aggregate-level segregation measurement with micro-level locational attainment outcomes in a way that can directly establish the quantitative implications of micro-level attainment effects for the level of segregation measured in a given community. We continue that work in this book by building on our prior published work and going beyond by applying the new methods to a broader range of analyses.

1.6 Chapter Overview

This book is organized to give a broad overview of segregation trends from 1990 to 2010, followed by analyses of segregation in more specific and detailed contexts, which we selected by giving consideration to how segregation can vary by populations and community types. Thus, we examine segregation in metropolitan and nonmetropolitan areas and in areas of established immigrant settlement and new immigrant destinations. We also analyze the link between micro-level processes of locational attainment and overall segregation patterns in a selection of metropolitan areas. Throughout these analyses, we are able to go beyond previous research in significant ways by taking advantage of new developments in methods of measurement and analysis, by explaining the advantages of these methodological innovations and showing how they bring practical improvements to empirical studies, and by using new techniques to help us answer both new and longstanding questions about the connections between micro-level locational attainment processes and overall levels of segregation.

Before we delve into the substance of our empirical work, we first lay out the technical foundation of the methods that support the contributions of this book. Thus Chap. 2 reviews our research design and major methodological choices and, in particular, describes in detail how we measure and analyze segregation using the methods developed in Fossett's *New Methods for Measuring and Analyzing Segregation* (2017). In addition to presenting and explaining all relevant formulas, in this chapter we also exercise our methods through several small examples to highlight some of the problems that can arise using conventional methodological approaches and how they can be addressed with the methodology that we promote in this book. These methodological tools are essential for understanding the contributions of our book as a whole because while they are new and innovative in many ways, they also provide continuity with past approaches and thus lay out a clear way forward for segregation research. We hope that this chapter in particular will inspire new segregation research in understudied areas and encourage the reader to learn more in Fossett's, 2017 monograph, but we expect the empirical demonstrations in the chapters that follow to more clearly showcase opportunities for innovative analysis.

With our methodology established, Chap. 3 begins the presentation of our empirical studies with an overview of racial segregation patterns across the United States from 1990 to 2010. Our analyses cover the entirety of the U.S. including nearly all metropolitan areas, micropolitan areas, and noncore counties (i.e., counties that do not have a significant urban center or "core"). In this chapter we establish the basic format that we will adopt in most successive chapters by presenting findings for familiar majority-minority panethnic comparisons for White-Black, White-Latino, and White-Asian segregation and describing the implications of methodological choices for the results we obtain including the choice of segregation index, the unit of analysis used for assessing spatial distributions, and the very conception of segregation and group disparity in residential outcomes. Also in Chap. 3 we provide, for the benefit of the reader, comparisons between segregation measured using different indices that we describe in Chap. 2 and use moving forward.

Following the comprehensive overview of segregation across the United States given in Chap. 3, we direct special attention to segregation in micropolitan and noncore areas, which we refer to collectively as nonmetropolitan communities, in Chap. 4. Many of the issues that arise using conventional approaches for measurement and analysis become especially prominent in nonmetropolitan communities because they hold so many of the characteristics that raise red flags such as small population sizes and substantial imbalance in the size of groups. Each of these concerns is addressed in this chapter, allowing us to showcase what more is possible with improved methodology as well as contribute to the limited knowledge that we have on racial segregation in nonmetropolitan contexts.

Chapter 5 enters into a timely conversation about the migration of Latino and Asian immigrants into the interior of the United States that has been occurring over the last four decades. In the decades following the Immigration and Nationality Act of 1965 many Latino and Asian immigrants have tended to settle in certain areas, including major "gateway" metropolitan areas such as Houston, Los Angeles, Chicago, Miami, and New York and also other metropolitan areas near international borders, where new immigrants may, by some mixture of choice and necessity, settle in established ethnic communities and contribute to patterns of segregation in complex ways. A growing number of immigrants and their families have settled in what are referred to as "new destinations" that are primarily located in the Midwest and South and include not only many metropolitan areas but also a much larger number of nonmetropolitan communities encompassing both micropolitan areas and rural (non-core) counties which have historically been predominately White, with the exception of some Southern Black Belt communities. The settlement of new racial groups in these areas has raised questions about their reception, which can in part be reflected in where they residentially locate in relation to White households. In Chap. 5 we describe segregation patterns in new destinations for Latino and Asian groups and how these areas are spatially transforming over time in comparison to traditional areas of settlement, taking advantage of three decades' worth of census data that capture this phenomenon.

The analyses we present in Chaps. 3 through 5 generally follow many familiar conventions in the literature of approaching segregation at an aggregate level, with the major contributions being to implement significant improvements in measuring segregation that allow us to document levels and trends in segregation more fully and accurately than has previously been possible. The analyses we present in Chap. 6 build on the methodological innovations we review in Chap. 2 in a different way; namely, by working with detailed microdata for individual communities to take advantage of new opportunities to directly link aggregate-level segregation patterns to the micro-level locational dynamics of households. Specifically, we review results from a series of locational attainment analyses – that is, micro-level regression analyses predicting residential outcomes for individual households – where group means on the residential outcomes being predicted in the regression analyses exactly determine the values of aggregate-level index scores that summarize the level of segregation in the community. Thus, these particular locational attainment models create a quantitative bridge joining the two main empirical research traditions in the literature on residential segregation. This framework allows us to answer questions such as "How do group differences in characteristics and resources relevant for locational attainments contribute to creating the level of segregation observed in the community?" and, alternatively, "How much of the level of segregation observed in the community rests on group differences that remain net of controls for relevant characteristics and resources?" Moreover, we are able to answer these and other related questions separately for multiple group comparisons and for a sizeable sample of large metropolitan areas. As of this writing, we are the only researchers to use these methods, in part because using them effectively requires working with data that are restricted and not generally available to researchers. So, the analyses we present in this chapter have no parallel in previous research, other than our own, and provide new insights that cannot be gleaned from research by others.

In our seventh and concluding chapter we summarize the substantive and methodological contributions from the previous chapters and review their implications for future directions in segregation research. One point that we hope will become very clear is that the methodological approaches adopted have enabled us to set new, more trustworthy benchmarks for studying segregation trends over time and across communities. We also hope these methods will be adopted in future segregation research, as they are a clear improvement over traditional methods while also providing continuity with past approaches. In discussing the future, we also consider the timing of this book. We wrote this book while anticipating the release of 2020 census data products, which for a variety of reasons may pose significant challenges for demographers and other social scientists eager to document recent trends in segregation. The political climate at the time preceding the 2020 census in addition to the upheaval caused by the COVID-19 pandemic can be expected to affect the response rate of major populations discussed in this book including Latino immigrants and rural residents, potentially undermining success in meeting the decennial census goal of obtaining a full count of the population by their demographic characteristics.

One thing we do know is that racial and ethnic diversity will be increasing across communities as Asian and Latino populations increase in size nationally and diffuse across a wider range of communities, leading to the creation of more new destination communities and causing earlier new destination communities to transition toward areas of established presence. Additionally, we also believe that, due to the heightened social and political divergence between large metropolitan areas and nonmetropolitan areas, social scientists will be giving greater attention to nonmetropolitan communities which previously were largely neglected in segregation research. The findings here demonstrate that research investigating patterns and trends in segregation across communities that are increasingly diverse with respect to race and ethnicity will benefit from using the new methods we use in this study, especially in nonmetropolitan communities and smaller metropolitan areas where it is necessary to use smaller spatial units to measure segregation in a satisfactory manner.

In brief, the new methods we use here address and overcome difficult problems in measurement that have posed major challenges for segregation research. Some, like the previously intractable problem of inherent upward bias in index scores that varies in magnitude across different group comparisons and research situations, are well-known and have long motivated researchers to adopt a host of questionable ad hoc strategies for analyzing inherently flawed scores. The efficacy of ad hoc strategies used in past research has never been rigorously demonstrated and, candidly, is at best questionable (Fossett, 2017). Accordingly, there can be no dispute that the approach adopted here of obtaining unbiased scores at the point of initial measurement is clearly superior and renders the discussion of past practices moot, as the need to consider ad hoc practices for dealing with flawed index scores is entirely eliminated when one has the option of obtaining technically sound, unbiased scores.

Relatedly, the new methods we draw on lead to insights that increase the relevance of both the consequences of index bias and the benefits of being able to compute unbiased index scores. The relevant insight comes into focus when we adopt the difference-of-means framework for calculating segregation scores set forth in Fossett (2017). This framework establishes that a segregation index score can be understood not only as an aggregate-level summary measure indicating the level of segregation in a community, but also as a quantitative estimate of the impact of group membership on residential outcomes for households as shaped by a micro-level locational attainment process in which group membership is one among many potential predictors. From this vantage point it becomes clear that the residential outcomes in question – which are scored from area group composition – cannot be treated as independent across persons because most individuals locate in coordination with other individuals within a household that is homogeneous on racial and ethnic composition.

This new perspective leads directly to three technical insights about the measurement and analysis of segregation. The first is that locational attainment regression models relevant for analyzing segregation cannot treat individuals as independent observations. The second insight is that previous research, already profoundly influenced by concerns about the problem of index bias, had in fact significantly underestimated the magnitude of the problem by not recognizing the implications of the fact that individuals locate as part of ethnically homogeneous households. And, more happily, it also leads to the third technical insight that the problem of bias can be addressed and eliminated by applying refined formulas for unbiased index scores in combination with data for households instead of persons. We believe these insights must be acknowledged in research going forward and that studies of segregation that fail to consider these issues and take appropriate action will be open to question.

1.7 Final Thoughts: Why This Book Now?

Some readers may ask, "Why publish a study of trends and patterns in segregation in 2023 that reviews results based on data for 1990 to 2010 but does not also include results based on data from the 2020 Census?". It is a fair question. Our answer notes multiple reasons why our study has value and should be shared with the research community. First, and most importantly, we believe the findings our study presents make important contributions to the existing literature that should be shared as soon as feasible. Doing so accomplishes more than just improving our understanding of patterns and trends in segregation over the period 1990 to 2010. It also can influence research practices going forward in ways that we believe will bring important benefits for developing better assessment of the most recent patterns and trends in segregation when relevant data are available. This leads to a second reason for publishing our study. It is that, as of this writing, the kinds of data that are crucial to implementing our methods of measuring and analyzing segregation have not yet been released and distributed for the 2020 Census.[2] So, it was literally not possible for us to include these data in our study. Waiting for these data to be released would lead to delays in sharing important findings that demonstrate the benefits of using new methods for

[2]Our study reports findings based on aggregate tabulations of households for small geographic domains (e.g., census blocks) and also findings based on microdata for households that incorporates information about similar low-level census geography. As of this writing, the Census Bureau has not released aggregate tabulations of households by race for the low levels of geography we use in this study and, likewise, they have not yet released the relevant microdata for the years needed to replicate our analyses based on data for 2010.

measuring and analyzing segregation and in sharing results that challenge some past conclusions regarding levels, patterns, and trends in segregation. In light of this, we stress that the central contribution of our study is not the currency of the data. Instead, it is that our study applies new approaches to measuring and analyzing segregation that enhance our ability to document segregation in the recent past with greater accuracy and nuance. In doing so it provides examples to consider for research going forward. More specifically, we use new methods to obtain segregation index scores with superior technical properties. The resulting measurements often depart significantly from measurements obtained using past practices. When differences emerge, the results we obtain are more accurate and trustworthy because they implement refinements that eliminate multiple sources of bias and distortion associated with previous approaches measuring uneven distribution. Additionally, we demonstrate the value of carefully comparing findings obtained using multiple measures of uneven distribution. Accordingly, we argue our study makes valuable contributions to improving research focusing on segregation before 2020 and benefitting future research focusing on 2020 and beyond.

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Chapter 2
Measurement and Study Design

2.1 Overview

A major feature of our study is that we use new methods for measuring residential segregation that make it possible for us to assess levels and trends in segregation with consistent accuracy and across a wider range of measurement circumstances. This includes combinations of group comparisons and community settings where trustworthy measurements of segregation previously have not been possible. More specifically, we measure the dimension of segregation known as *evenness* using refined versions of two familiar and widely used measures, the dissimilarity index (D) and the separation index (S).[1] The versions of the measures we use are free of index bias, a problem that poses major challenges for measuring segregation in many situations, and thus yield index scores that are accurate and trustworthy in situations where scores obtained using conventional approaches to measuring segregation used in previous studies would be distorted by index bias. In the past, the problem of index bias forced researchers to choose between two undesirable options. One option is to measure segregation across a more comprehensive and representative range of circumstances but with an understanding that the index scores obtained are in many cases untrustworthy and potentially misleading because they are distorted by bias. The other option is to restrict the scope of the analysis to a much smaller and less representative set of combinations of group comparisons and community settings where index bias is likely to be negligible and scores for standard versions of segregation indices are trustworthy and can sustain close analysis of cases. The

[1] We follow Fossett (2017) in using the term "separation index" to refer to a measure that is known by many other names including eta squared (Duncan & Duncan, 1955), the segregation index (Zoloth, 1976), Coleman's r (1975), and the variance ratio (James & Taeuber, 1985) among others. When the population consists of only two groups, it is equivalent to Bell's revised index of isolation (Bell, 1954). We use the term "separation index" because that is more effective in conveying the aspect of uneven distribution the index measures.

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measurement methods we use make it possible for us to sidestep these difficult choices and avoid the undesirable consequences that accompany them. The benefit of using these new measurement methods is that we are able to obtain segregation index scores that are consistently accurate across a much broader range of measurement circumstances (e.g., combinations on group comparisons and community settings) than has been possible in previous research. The consistent accuracy of the unbiased measures enables us to draw conclusions about the levels and patterns of variation in segregation across group comparisons, across communities, and over time with greater confidence. Additionally, it allows us to selectively conduct close analysis of index scores for individual cases including, for example, tracking changes in segregation over time for a small subpopulation (e.g., Latino immigrants) in a small nonmetropolitan community, an analysis that cannot be sustained with conventional measurement practices used in past research. The task we seek to accomplish in this chapter is to first provide an overview of the conceptualization of residential segregation and the motivations for studying it and to then highlight the features of our study design that enable us to make new and important contributions to research on this topic.

We organize the discussion in this chapter as follows. We first review the broad concept of residential segregation, the research concerns that motivate our study, the aspects of segregation that are most relevant for our research concerns, and the implications this has for choices for measuring segregation. We then review the basic features of our study design including the community-level study units, the micro-level units, the group comparisons we examine, and our coverage of group comparisons across communities. Then we identify the sources of data we use to measure segregation and the spatial units we use for measuring segregation within individual communities. Finally, we review the issues of measuring residential segregation, focusing on two major points. First, we give attention to the details of how index scores are calculated. Second, we describe how we use new methods to obtain index scores that are superior to those used in past research because they are free of index bias and note how we use different indices to measure different aspects of segregation. Methods are crucial to any empirical study and, as the saying goes, the devil is often in the details. But thorough discussion of the details of measurement tends to be dry and tedious. So, we try to keep the discussion in this chapter relatively brief and refer readers to Fossett (2017) for more detailed reviews of the issues involved.

2.2 What Is Residential Segregation and What Motivates Us to Study It?

Massey and Denton characterized residential segregation as "the degree to which two or more groups live separately from one another, in different parts of the urban environment" but recognized that it is more complex on closer consideration because "groups may live apart from one another . . . in a variety of ways" (1988:282–283). Accordingly, researchers view residential segregation as having multiple dimensions that together encompass the variety of ways in which groups can be differentially distributed across spatial locations in a community, giving rise to varied patterns, potentialities, and consequences (Stearns & Logan, 1986; Massey & Denton, 1988). That said, it is safe to say that the literature on residential segregation of racial and ethnic groups is primarily motivated and guided by concerns about aspects of segregation that are directly and indirectly associated with group inequality across many domains. Thus, Massey (1990:333), Orfield and Lee (2005), Peterson and Krivo (2010), Quillian (2017), and many others have argued segregation warrants sustained attention from social scientists because it carries the potential to separate racial groups across different neighborhoods in a manner that produces racial inequality in neighborhood conditions including, but not limited to, differential exposure to poverty, quality of schools and learning environments, crime and violence, and access to resources and opportunities for life chances and social mobility.

We recognize that segregation can involve patterns that are sociologically interesting apart from their connection with stratification-related aspects of spatial distribution. But our study is not motivated by concerns about these more "benign" aspects of group differences in spatial distribution. Instead, we focus on residential segregation because the pronounced and enduring patterns of segregation seen in communities across the United States are often centrally implicated in social stratification processes and outcomes at the individual and group levels. We are hardly unique in this regard as concerns about stratification-related aspects of segregation motivate many, perhaps most, of the large number of empirical studies investigating residential segregation by race and class. But we call attention to this basis for focusing on segregation because some measures of segregation serve better than others for identifying when aspects of segregation that are most relevant for stratification and inequality are present. Specifically, of the dissimilarity index and the separation index, two of the most widely used measures of evenness, the separation index is clearly better for the purpose of identifying when group differences in distributions across neighborhoods create the potential for majority-minority inequality on advantages and disadvantages associated with neighborhood of residence.

2.3 Preliminary Comments on Index Choice

We explain our views on index choice in more detail later in this chapter. But, setting aside technical issues in segregation measurement for the moment, the heart of the matter is relatively simple and important to discuss now as part of understanding how segregation is conceptualized and operationalized. Separation of groups across different neighborhoods in the community is a necessary precondition for groups to experience systematic inequality on location-based outcomes. When separation is pronounced, groups live apart from each other in different parts of the residential environment of the community and group inequality on location-based outcomes becomes logically possible, and potentially empirically common and important. When separation of groups across neighborhoods is minimal, groups reside together in the same parts of the residential environment of the community and share similar neighborhood environments. Consequently, group inequality on location-based outcomes is not logically possible. We are interested in identifying when segregation takes the form where groups live apart from each other in different neighborhoods because this identifies communities where segregation creates the potential for group inequality on location-based outcomes to exist. The separation index provides a reliable signal of whether segregation involves this kind of pattern or not (Fossett, 2017).[2] The dissimilarity index does not.

We bring this point up early on in our discussion because the choice for how to measure segregation is highly consequential in this study. The findings we obtain using the separation index in some cases differ dramatically from the findings we obtain using the dissimilarity index. This is particularly true for findings regarding the level of segregation and nature of change in segregation over time in nonmetropolitan settings and also for Latino households in new destination communities. For example, analysis of scores for the dissimilarity index suggests White-Latino segregation initially emerges at medium levels when Latino households first begin to settle in communities where previously there was little or no Latino presence and then over time segregation begins to decline and converge on levels seen in communities where Latino presence is sizeable and well-established. Analysis of scores for the separation index suggest a fundamentally different story wherein White-Latino segregation emerges at very low levels when Latino households first arrive in new destination communities and then over time segregation increases and begins to converge on levels seen in communities with established Latino presence.

The literature on segregation measurement has for many decades noted that the dissimilarity index has significant conceptual and technical problems. But researchers have tended to overlook these problems for a variety of reasons. The measure has been widely used in empirical studies, so it is familiar and provides continuity with past research. It also is relatively easy to calculate, and many believe it has an appealing interpretation. Finally, researchers tend to not view the conceptual and technical limitations of the dissimilarity index as particularly concerning because some studies have reported that findings obtained using the dissimilarity index are often similar to findings obtained using other, technically superior measures. We consider these issues in more detail below. But we preview discussion relating to the last point by noting that there is no dispute regarding whether scores for dissimilarity can diverge from scores for other indices; they can and sometimes do. So, previous studies that reported obtaining results using the dissimilarity index

[2] Coleman et al. (1982) and Stearns and Logan (1986) make points that support the same conclusion. But the discussion in Fossett (2017) speaks to the point more directly.

that were similar to results obtained using other indices should be seen only as fortunate situations where index choice did not matter; they cannot be construed as establishing that index choice never matters. Fossett (2017) identifies both circumstances under which index choice is less likely to matter and circumstances under which index choice is more likely to matter. He also documents that the issue has practical importance by showing that in many sociologically interesting circumstances results obtained using the dissimilarity index can and often do differ dramatically from results obtained using other indices, particularly the separation index.

We find results for the dissimilarity index and the separation index often diverge in our study, sometimes by large amounts. When results for the dissimilarity index diverge from results for the separation index, we are hard pressed to see a basis for prioritizing results for the dissimilarity index over the separation index. To the contrary, our view is that, the more one understands about how it is possible for scores on the dissimilarity index and the separation index to diverge, the less confidence one will place in the dissimilarity index. We outline the basis for that review here. What we ask of researchers who have grown comfortable with relying on the dissimilarity index is this: Upon encountering the fact that other measures yield results different from those obtained using the dissimilarity index, please be open to reconsidering habits that, while familiar, are weakly justified. We believe doing so will lead to a better understanding of how results for the dissimilarity index and the separation index can and do vary and that in turn will provide a more informed basis for appreciating what we can learn about segregation using different measures.

2.4 Details of Study Design

As we noted earlier, segregation is a community-level phenomenon relating to how members of two groups are distributed across spatial subregions or neighborhoods within the community. Segregation indices provide quantitative scores summarizing particular aspects of group differences in residential distribution in the community. To support this study, we prepared a database of index scores to document the levels of segregation for particular group comparisons in individual communities at different points in time. We then performed statistical analyses to establish how segregation varies across group comparisons, across communities, and over time. As is necessary in any study of this nature, we had to make a variety of choices relating to research design and measurement. In this section we provide a brief summary and rationale for some of the most important choices.

Specifically, we review the main elements of our study design, including the data we use and the communities we examine. We devote a later section to an extensive discussion of measurement in order to provide a clear and thorough technical basis for justifying our choices. But we do not intend for this chapter to be a detailed technical introduction into new methodologies for segregation measurement. One of the authors of this work has published a monograph (Fossett, 2017) that provides a detailed review of the relevant technical issues. We will draw on the central points of those technical discussions and clarify how the issues matter for our goals of conducting a study of levels and trends in residential segregation. At certain points, however, we will refer readers to this earlier work for technical details, noting that it is published as open access and so can be obtained as a free download from the publisher's website.[3]

2.4.1 Measuring Segregation in Metropolitan Areas, Micropolitan Areas, and Noncore Counties

One of the contributions of our study is that we examine segregation across the full range of communities in the United States. Specifically, we measure segregation for nearly all metropolitan areas, micropolitan areas, and noncore counties which taken together covers all of the United States. Metropolitan areas and micropolitan areas are core-based statistical areas (CBSAs) as defined by the U.S. Census Bureau. Each CBSA is comprised of one or more contiguous counties whose populations are socially and economically integrated with an urban core of at least 10,000 inhabitants.[4] CBSAs with an urban core reaching or exceeding 50,000 in total population are designated as metropolitan. By definition, micropolitan areas are nonmetropolitan but they are not generally rural in character due to having a nontrivial urban core of at least 10,000 but less than 50,000 inhabitants. As the term implies, noncore counties are counties not associated with a CBSA. Not surprisingly, they often are rural in character since they do not have a significant urban core and generally have small populations and low population density. These three categories of communities – metropolitan CBSAs, micropolitan (nonmetropolitan) CBSAs, and noncore counties cover the entire land area and population of the United States. In all there are 960 CBSAs; 384 are metropolitan and 576 are micropolitan. We also measure segregation in the 1355 noncore counties that are not included in a CBSA.

Depending on researcher interest, residential segregation can be considered at various macro-level domains ranging from expansive spatial domains such as state and region, to intermediate-level spatial domains such as metropolitan and nonmetropolitan communities, and even down to subregions within communities (e.g., central city and suburban ring). Our interest is with relatively self-contained metropolitan and non-metropolitan communities where it is reasonable to view residential dynamics as playing out within a single broad housing market. We acknowledge that larger communities may have spatially segmented housing markets – central city and suburbs for example. But for our purposes, these lines

[3] A link for downloading the book is available at https://www.springer.com/gp/book/9783319413020

[4] We use CBSA definitions that applied for the 2010 Census of Population and apply them in 2000 and in 1990.

of balkanization in housing markets are part of the broader dynamics that produce segregation for the community overall. We agree that differential segregation within spatially segmented subregions (e.g., segregation in suburban sub-communities in a metropolitan area) in a community is a valuable focus of study. But our concern here is with overall patterns of segregation across the full housing market for the community.

Empirical studies of segregation tend to focus on metropolitan areas and many influential studies have focused on only the largest 50–60 or the largest 100 metropolitan areas. These communities are important and deserve close attention. But we believe it is equally important to examine segregation in smaller metropolitan areas, in micropolitan areas, and in noncore counties as patterns of segregation in the largest metropolitan areas are not necessarily representative of patterns across the rest of the country. It is relatively uncommon for empirical studies of segregation to include micropolitan areas and noncore counties. One methodological reason for this is that researchers must use small spatial units such as census blocks to measure segregation in smaller communities, and this raises concerns that index scores will be distorted by index bias. This concern may apply to past research, but not ours because we use refined methods to obtain index scores that are free of index bias even when using data for households in combination with small spatial units. Another reason segregation research has neglected examining segregation in micropolitan areas and noncore counties is that some audiences and perhaps also some researchers question whether residential segregation is substantively important in smaller communities. On this point we can acknowledge that the patterns documented for White-Black segregation in Chicago, Cleveland, Detroit, Milwaukee, Newark, and other notorious cases are qualitatively and quantitatively distinctive due to the scope and scale of segregation patterns in these large metropolitan areas. Thus, we note that the term "hypersegregation" coined by Massey and Denton (1988), the pattern where segregation reaches high levels on many dimensions of segregation simultaneously, has only been applied to segregation patterns seen in a small set of the largest metropolitan areas where regions of concentrated minoritized group presence span many square miles in a manner that cannot occur in smaller communities.

At the same time, however, we do not hesitate to assert that residential segregation is an important marker of racial inequality in smaller communities and it carries important consequences for life chances in both the short and long run. Thus, while residential segregation may be less consequential for school segregation in small communities where students in public schools sometimes attend a single school, segregation may be more consequential for a host of other things including, as a brief list of examples: exclusion from police, fire protection, and ambulance service zones; exclusion from public water and sanitation systems; exclusion from service zones for utilities and maintenance of safe roads and drainage systems; exposure to natural hazards such as flooding; exposure to disamenities based on proximity to stockyards, sewage treatment plants, garbage dumps and landfills; and exposure to industrial emissions and waste products affecting air and groundwater.

Segregation in smaller communities often relegates minoritized group populations to less desirable, administratively neglected areas where residents are subject to disamenities and hazards and do not benefit from basic social and municipal services and effective enforcement of protective regulations. A particular, but not necessarily exceptional, example is seen in the *colonia* communities of South Texas border regions. *Colonias* are small, usually predominantly Latino, low-income residential areas in rural portions of medium-sized metropolitan areas, micropolitan areas, and noncore counties. Their populations often reside outside of city and county administrative boundaries – in many cases due to selective annexation practices – and as a result often have no potable water, no public sanitation, no police and fire protection services, poor roads and infrastructure, no public transportation, or other social services. Many are subject to having flooded homes and washed out roads during ordinary thunderstorms due to neglect in public works for flood control and road maintenance. Census tracts are too large to capture the populations of these residential areas because they often mix the populations residing in individual *colonia* settlements with populations residing in incorporated places or in suburban and exurban neighborhoods. In contrast, census blocks typically do not mix the populations residing in *colonia* settlements with other populations.

The measures of segregation we use, particularly the separation index (S) establish whether minoritized group populations live apart from the White majority population in the residential areas in smaller communities. Scores on S provide a reliable marker for the structural potential for group inequality on the area-based outcomes just mentioned as separation of groups across spatial units is a fundamental logical prerequisite for group inequality on location-based outcomes. In sum, there is no question that segregation can be pronounced in small communities and can have important consequences for life chances in those settings. Thus, our study makes a valuable contribution by using improved methods to document segregation in smaller communities.

2.4.2 Coverage Spanning Three Decades

Our study spans the time frame 1990 to 2010. We adopt the CBSA designations used in the 2010 Census of Population and apply the county-based community definitions for 2010 in 2000 and 1990. In sharp contrast to cities, county boundaries are highly stable over time. So, county-based definitions maintain consistent spatial definitions of communities over the study period. We reviewed counties to identify those that changed boundaries over time in a way that could potentially lead to a significant change in the spatial definition of a CBSA or a noncore county. Only 5 noncore counties were affected. and we excluded them from our analysis. Our coverage of all U.S. communities extends back from 2010 as far as is feasible with available data. The limiting factor is that block-level data needed to measure segregation in smaller metropolitan areas and nonmetropolitan areas is not available in the full coverage form needed before 1990. As we completed this study, the 2020 Census of Population was conducted. But, for a variety of reasons, the 2020 data we would need to extend this study was not yet available. So, we must defer extending this analysis to include data for 2020 to a later study.

2.4.3 Group Comparisons

We assess segregation patterns for three White-nonwhite group comparisons that can be maintained consistently over the 1990–2010 timeframe using public census tabulations for small areas. The specific groups we study are broad panethnic groups routinely considered in empirical studies of residential segregation in the United States. They are identified based on responses to separate census questions on race and Hispanic identity and include: Non-Hispanic White (hereafter simply “White”) households, Black (African American) households, Latino (per census terms and of all races) households, and Asian (Asian American) households. While we would prefer to do so, it is not possible to identify Black and Asian households separately as Hispanic and Non-Hispanic in all three study years when using data for households at the block level. Due to this limitation of the data, it is logically possible to have the same household represented in the group counts for Black and Latino households and in the group counts for Asian and Latino households. This could in principle pose problems for measuring Black-Latino and Asian-Latino segregation in some communities, and so we give limited attention to examining these comparisons in our study. The potential impact on measures of White-nonwhite group segregation is much smaller. We identified communities where this issue was a potential concern (i.e., based on high percentages of Latino persons among Black and Asian persons) and performed robustness checks by comparing results of analyses with these White-Black and White-Asian comparisons included and excluded to assure our findings for White-Black and White-Asian segregation were not significantly affected by these cases.

2.4.4 Combinations of Group Comparisons Across Communities and Time

The absolute and relative size of each group’s presence in a community varies across communities and can change over time in any single community. Many communities are diverse, with all four groups considered here being present in non-negligible numbers, and many others are less diverse. We apply minimum population requirements to include particular segregation comparisons for a community in any of the three decades. The primary filters we apply are to require that both groups in the segregation comparison have a minimum of 50 households and 150 persons in the community overall and to constitute at least 0.5 percent of the households in the segregation comparison. These thresholds are much lower than those typically used in previous research. We are able to adopt these more inclusive (less restrictive) criteria because we use new methods for measuring segregation that can provide accurate and reliable results for small subpopulations and small, nonmetropolitan communities. This is significant because it allows us to track segregation of new populations from the onset of their initial appearance as a small subpopulation in a community and then on into later decades when they may or may not become a larger presence in the community.

Most studies of segregation adopt much higher thresholds for screening cases. For example, many adopt requirements that both groups have a minimum of 3000–5000 persons and represent at least 3–5 percent of the community population. The restrictions would preclude the study of segregation in most nonmetropolitan new destination communities and most metropolitan ones as well. Importantly, these screening criteria are not adopted based on substantive concerns. Instead, the primary motivation for adopting these restrictions is that researchers correctly fear conventional practices for measuring segregation will yield misleading index scores when one group in the analysis is small in absolute or relative terms. Similar concerns do not apply to the refined measures we use. This is possible because we measure segregation using Fossett's (2017) difference-of-means computing framework for computing segregation index scores which includes refinements that eliminate the problem of index bias when measuring segregation for small groups. A second advantage of this framework is that it formulates segregation index scores as a group disparity (i.e., a difference of means) on residential attainments, thus permitting calculation of standard errors and conventional tests of statistical significance of departure from the null hypothesis of no group difference. In principle, we could use even lower thresholds on population counts. But the limiting factor is that scores based on even lower counts would have high sample-to-sample volatility (large standard errors) under the null hypothesis of no group difference and thus low statistical power (i.e., limited ability to reliably detect true effects that are small-to-moderate in size). Nevertheless, we are able to use more inclusive criteria for screening cases and retain a much larger number of combinations of group comparisons across a larger number of communities.

2.4.5 Sources of Data and Microunits

The data we use for our study are drawn from census summary file tabulations of group counts across census blocks. More specifically, the main tabulations we use to obtain data on households and persons are taken from Summary File 1B and the PL-94 voter redistricting file from the 1990 Census, Summary File 1 for the 2000 Census, and Summary File 1 from the 2010 Census. These block-level tabulations provide complete coverage of the United States based on full (100%) counts, not sample data. The data sources for each year provide block-level counts of the number of persons and households for the groups considered in our study – White, Black, Latino, and Asian groups. We primarily focus on results obtained using data for households. But in a case study in Chap. 5, we also review results obtained using data for persons in order to establish methodological points and to have points of comparison with previous research which typically uses data for persons. We use these block-level data tabulations to calculate index scores that assess the level of segregation of households by race/ethnicity for individual communities in 1990, 2000, and 2010. In 2000 and 2010, the available data tabulations for households break counts for households out by household size. These data play an important role in methodological analyses we discuss later in this chapter. These methodological analyses establish that segregation index scores computed using data for households are superior to similar scores using data for persons because it is feasible to use methods for direct calculation of unbiased segregation index scores using data for households, while this is not feasible using data for persons. We provide a review of this issue later in this chapter.

Relatedly, the data sources we use also provide block-level counts of persons for the groups considered in our study. We use these data to calculate index scores that assess the level segregation of persons by race/ethnicity for individual communities in 1990, 2000, and 2010. To be clear, we computed and examined these scores for purposes of methodological analysis. We do not focus on results based on tabulations of persons in our main analysis chapters because segregation index scores calculated using person data are inferior to the index scores that we compute using data for households. Specifically, scores calculated using data for persons are distorted by inherent index bias to a much greater degree than is generally recognized by segregation researchers. Additionally, while it is technically possible to obtain unbiased segregation index scores calculated using data for persons under certain conditions, the methods for achieving this desirable result require detailed tabulations of persons by race and size of household that are not available for 1990. Additionally, even when requisite data are available, methods for obtaining unbiased index scores using data for persons are demanding and impractical for general adoption in empirical research. The procedures involve either applying complicated formulas to implement direct calculation methods per Fossett (2017) or they involve indirect norming procedures that require use of complex bootstrap simulation methods. Either approach is impractical because the scores obtained correspond closely to unbiased index scores that can be obtained by applying simpler calculations using data for households.

2.4.6 Spatial Units for Assessing Segregation Within Communities

We noted earlier in this chapter that we measure residential segregation using data for census blocks. Census blocks are the smallest spatial units for which relevant census tabulations are available. This brings a major advantage; namely, it makes it possible for us to measure segregation more accurately in nonmetropolitan communities such as micropolitan areas and noncore counties and also in smaller metropolitan areas. Many segregation studies in recent decades have used the much larger spatial unit of census tracts. This is probably not a concern in large metropolitan areas where segregation patterns play out across relatively expansive spatial domains that are adequately captured by census tracts. But census tracts are unacceptable units for studying segregation in smaller communities. For those who may have concerns about measuring segregation using census blocks, we offer the following reassurances.

- We calculate scores for segregation indices using data for households at the block level using new, refined methods that yield scores that are unbiased at the initial point of measurement. The resulting scores require no adjustment to be used as point estimates of the level of segregation in the community. Additionally, the scores can be used as is (without adjustment) to sustain close analysis of individual cases – including, for example, obtaining standard errors and confidence intervals for the point estimate – and direct case-to-case comparison of any two or more scores. Significantly, the claims we make here cannot be made for the segregation index scores used in previous studies.
- Segregation measured at the block level makes it possible for us to directly compare scores across all communities ranging from small noncore counties to the largest metropolitan areas. Index scores computed using block-level data and tract-level data will be similar for large metropolitan areas because segregation within tracts is a small fraction of the segregation in the community overall (Amaro, 2016). Index scores computed using tract-level data will be misleadingly and unacceptably low in smaller communities where the portion of overall segregation occurring within tracts is large and often exceeds the portion of segregation occurring across tracts (Amaro, 2016). Consequently, unbiased index scores based on block-level data are directly comparable across small and large communities. This is not true for scores based on data for tracts.
- Segregation at the block level is sociologically relevant for group differences on a wide range of location-based outcomes and associated life chances. Segregation at higher spatial scales – for example, segregation across school districts, across urban places within large metropolitan areas, between central city and suburbs, and across counties, states, and regions – all can be a legitimate focus of research (e.g., Fischer & Massey, 2004). This, of course, does not diminish the relevance and potential importance of segregation at the block level within communities.

2.5 Segregation Index Bias: Overview, Background, and Solutions

A relatively small number of indices are used to measure the *evenness* dimension of segregation in empirical studies. These include the Gini index (G), the dissimilarity index (D), the Hutchens square root index (R), the Theil entropy-based (or information theoretic) index (H), and the separation index (S) (which is known by many other names).[5] Of these, we present results for D and S, which we discuss in more detail below, because they are the two best known and most widely used measures. Additionally, they both have relatively simple computing formulas and they both have attractive substantive interpretations that are easy to convey to broader audiences. Also, when considered together, D and S are effective in capturing two distinctive aspects of segregation registered by measures of uneven distribution. The first aspect is group differences in distribution across neighborhoods ranked at the most basic level as simply being "below-parity" or "at-or-above-parity." The second aspect is whether displacement into non-parity neighborhoods involves group separation as occurs when uneven distribution is polarized, that is, when groups live apart from each other in different neighborhoods that are polarized on group composition.

The first aspect of uneven distribution is group inequality or disparity on the simple outcome of attaining parity-level contact with the reference group. The dissimilarity index captures this well because it is sensitive to all departures from even distribution whether large or small. More technically, D is equal to the index of net difference (ND), a measure of inter-group inequality on ordinal outcomes (Lieberson, 1976), applied to a three category neighborhood ranking of below-parity ($p < P$), parity ($p = P$), and above parity ($p > P$) where p and P are the reference group's proportion in the area population and overall population, respectively (Fossett, 2017). The relevant point is this; D registers living in below parity areas in the same way whether the area is below parity to the maximum possible degree (100% minoritized group) or merely 0.1 point below parity. Scores for D correlate very closely with scores for G and R ($r > 0.96$ in our data) which also respond strongly to this aspect of uneven distribution.[6] The separation index measures quantitative group inequality on p, not ordinal inequality (Fossett, 2017). Accordingly, S is more effective at capturing the group separation aspect of uneven distribution because S is more sensitive to the larger departures from even distribution that occur when areas are racially polarized. Scores for S also correlate relatively closely with scores for H ($r > 0.79$ in our data) which is the next best alternative for assessing this aspect of uneven distribution (Fossett, 2017).

In short, measures of uneven distribution fall into two groups; those that are sensitive to rank-order differences on area group composition and those that are

[5] A partial list of names for indices that are mathematically equivalent to the separation index (S) includes: the revised index of isolation (*ROI*) (Bell, 1954), the eta squared index (η^2) and the correlation ratio index (r) (Duncan & Duncan, 1955), Coleman's "r_{ij}" (Coleman et al., 1975), the segregation index (S) (Zoloth, 1976), the variance ratio index (V) (James & Taeuber, 1985), and the normalized exposure index (P) (Reardon & Firebaugh, 2002).

[6] G is also equal to the index of net difference, however, where D measures group inequality in distribution across only three ranked categories, G measures group inequality in distribution across all rank positions on p (Fossett, 2017). Thus, G is like D in that both respond to rank order differences, not quantitative differences, on p.

sensitive to quantitative differences. *D* represents the first group reasonably well,[7] while *S* represents the second group. We provide a more detailed review of how *D* and *S* register segregation patterns later in this chapter. Here we focus on a characteristic they both have in common with all measures of uneven distribution; they are inherently biased in the following sense – they have positive expected values under conditions where households are distributed randomly across residential locations. Significantly, the bias inherent in indices measuring uneven distribution is not "fixed" or constant; it varies in magnitude from one index to another and the magnitude of bias for any given index varies in complex ways across circumstances of measurement such as variation in the relative size of the groups in the comparison, variation in the size of spatial units, variation in the relative presence of other groups in the overall population, and variation in patterns of segregation involving groups not in the comparison of interest (Fossett, 2017).[8]

The problem of index bias was first identified in the 1960s and 1970s and gained wide appreciation following an influential study by Winship (1977) which established that index bias for *D* was very high when segregation was measured using small spatial units and groups were imbalanced in size. Prior to this time, many empirical studies of segregation used index scores calculated using block-level data for households (housing units) from tabulations published in the reports of the decennial census of housing (e.g., Taeuber & Taeuber, 1965; Roof, 1972; Van Valey and Roof 1976; Sørensen et al., 1975). Spurred in part by concerns about the magnitude of index bias when counts for groups by spatial units are small, researchers moved from using data for census blocks to using data for census tracts which are much larger. This change does provide some protection from the most severe problems of index bias, but it imposes a great cost on segregation research. It effectively precluded the possibility of studying segregation in all nonmetropolitan settings and even in many smaller metropolitan communities where spatial units that are the size of census tracts are too large to accurately capture segregation patterns.

The change from using block data to using tract data also was accompanied by a second change from using data for households (housing units) to using data for persons (individuals). This change resulted in much larger group counts for spatial units. On first consideration this might be seen as providing protection from index bias. In fact, it does not. To the contrary, as we discuss in more detail below, the shift to using data for persons provides no benefit on index bias over using data for households. Furthermore, it can potentially do more harm than good if it leads some researchers to have a false sense of security regarding the undesirable impact of index bias.

The problem of index bias is widely recognized, but for decades it defied a viable solution. As a direct consequence, segregation researchers began to adopt a variety

[7] *G* is technically superior to *D*, but in most empirical studies the two correlate closely and researchers choose *D* based on its ease of calculation and appealing substantive interpretation.

[8] The last three items affect bias through their impact on "effective neighborhood size", the average for the combined area count for the two groups in the comparison.

of ad hoc procedures for dealing with index bias by indirect means. Fossett (2017) reviews these procedures in detail and comes to a blunt conclusion. There is little rigorous evidence to indicate that the ad hoc procedures are effective in dealing with index bias. Evidence on this point would require methodological studies demonstrating that findings using biased scores with ad hoc procedures yield results comparable to those obtained using unbiased scores. But these studies do not exist. Instead, ad hoc procedures, while adopted with good intentions, are at best weakly justified. What the ad hoc procedures primarily accomplish is to restrict the focus of research to a subset of circumstances where bias is potentially kept to an acceptable if not negligible level. The most common ad hoc practices for dealing with bias are to exclude cases where scores are thought to be most distorted by bias and then to weight remaining cases differentially to give greater weight to cases whose index scores are viewed as less distorted by bias.

These procedures have three undesirable consequences. First, they dramatically restrict the scope of segregation studies because many research questions involve group comparisons that are typically excluded from consideration. For example, excluding cases prone to higher levels of bias precludes studying segregation in nonmetropolitan and rural settings where segregation must be measured using small spatial units and studying segregation of new groups that by their nature are small in absolute and/or relative size. The second negative consequence is that use of ad hoc case weighting procedures skews results of empirical analyses in the direction of results obtained for larger communities with larger minoritized group populations. This raises a concern that these cases are not representative of the much larger number of group comparisons that are excluded from empirical studies. Third, the ad hoc procedures create a false sense of security when in fact the index scores are subject to bias and, barring evidence to the contrary, are potentially untrustworthy for close analysis, thus making close comparison of scores across cases a questionable exercise.

Happily, concerns about the efficacy, or lack thereof, of ad hoc procedures can be set aside. New methods introduced by Fossett (2017) provide refined formulas for all popular indices of uneven distribution that yield scores that are unbiased across a broad range of measurement circumstances. The scores obtained using these refined unbiased formulas have many desirable properties. First and foremost, they have the crucial property of being unbiased; specifically, they have expected values of zero when groups are distributed randomly across residential locations. Second, because the scores are unbiased, scores for individual cases do not require screening or differential weighting to deal with distortions resulting from index bias. Third, unbiased scores can support close analysis of cases as comparisons across cases are no longer complicated by index bias. Fourth, the method for obtaining unbiased scores draws on formulas that express the indices as a simple group difference of means on the racial composition of a household's neighbors. This has the desirable consequence of placing segregation index scores in a group disparity analysis framework where any given index score can be evaluated using statistical methods that permit calculation of standard errors and confidence intervals for individual index scores and, if desired, tests of statistical significance for departure from the expected value of zero under a null hypothesis of independence of group membership and relevant residential outcomes.[9] Finally, the unbiased scores support substantive interpretations that are appealing and easy to explain.

We note only one caveat to these otherwise encouraging points. It is that unbiased scores are relatively easy to calculate when using readily available tabulations of households by race for blocks or other spatial units. But unbiased scores are not easy to calculate when using similar tabulations for persons. Instead, calculations using data for persons require data that are more detailed in combination with more complicated calculation formulas.

2.5.1 A Somewhat Technical Review of the Origins of Index Bias

Our discussion here summarizes points from Fossett (2017) regarding the origins of index bias. The first step in Fossett's analysis is to establish that all widely used measures of uneven distribution (i.e., G, D, R, H, and S) can be formulated in a simple difference-of-means disparity framework. In this framework the index score (IS) for any widely used measure can be obtained using a generic formula that computes a group difference of means on residential outcomes (y) experienced by the individual households in each group. The disparities formula for all popular indices is the following simple expression.

$$IS = \overline{Y}_1 - \overline{Y}_2 = (1/N_1) \cdot \Sigma\, n_{1i} y_i - (1/N_2) \cdot \Sigma\, n_{2i} y_i$$

To implement the formula one of the two groups is arbitrarily designated as the "reference group" in the comparison (indexed by "1" in the terms in the formula) and the other group is designated as the "comparison group" (indexed by "2" in the terms in the formula). In analyses of majority-minority segregation it would be conventional to adopt the majority group as the "reference group" in the comparison. But, ultimately, it is an arbitrary choice as the results of the calculation will be identical regardless of which group is designated as the reference group. The subscript i is an index for spatial units (e.g., census blocks); the terms n_{1i} and n_{2i} indicate the counts for the reference group and the comparison group in a given spatial unit i; and the terms N_1 and N_2 are the counts for the reference group and the comparison group in the community overall. To this point, all of the terms are the same regardless of which index is being calculated. The next term in the formula – y_i – has a generic interpretation but is obtained via a unique calculation specific to the index being used. The generic interpretation of y_i is that it is the value of a residential outcome related to area group composition (p_i) that is scored separately for individual

[9] Additionally, the disparity analysis framework can incorporate direct controls for non-group covariates when relevant microdata are available.

households. Fossett refers to this term as "scaled contact with the reference group" because y_i is scored as a positive, monotonic (sometimes rising, never falling) function of the relative presence (proportion) of the reference group (p_i) in area i obtained from the simple calculation $p_i = n_{1i}/(n_{1i} + n_{2i})$. In this framework, all measures of the uneven distribution dimension of segregation can be characterized as measures of group disparity on scaled contact with the reference group. The differences between particular measures trace to a single factor; namely, how values of "scaled contact with the reference group" (y_i) are scored from simple contact with the reference group (p_i).

Fossett (2017) derives the specific scaling functions – $y_i = f(p_i)$ – needed to generate the scores of any widely used index of uneven distribution using the difference-of-means computing formula. Here we focus only on the scaling functions that are relevant for the two indices we will consider in our study; namely, the dissimilarity index (D) and the separation index (S). The scaling function for D is: score $y_i = 1$ when $p_i \geq P$ and $y_i = 0$ when $p_i < P$ where P is the relative representation (proportion) of the reference group in the combined overall population of the two groups (i.e., $P = N_1/(N_1 + N_2)$). In substantive terms, the scaling function for D recodes continuous scores on p_i, the reference group proportion in the area where the household resides, into values of a dummy variable coded 0 or 1 based on whether the value of p_i equals or exceeds parity (i.e., $p_i \geq P$) for the relative presence of the reference group in the community overall. Accordingly, the value of D obtained from the difference-of-means group disparity formulation $D = \overline{Y}_1 - \overline{Y}_2$ registers the group difference in achieving parity-level contact with the reference group.

The scaling function for S is also simple. For S, the function is $y_i = p_i$. Thus, the value of S obtained from the difference-of-means group disparity formulation $S = \overline{Y}_1 - \overline{Y}_2$ registers the group difference in simple (unmodified) contact with the reference group. Comparison of the scaling functions for D and S clarifies the essential difference between the measures. Where S registers group differences on contact with the reference group in their "raw", unmodified form, D registers group differences in contact with the reference group after first collapsing them into two values, 0 or 1, based on whether contact reached parity. This reveals why D is less sensitive than S to whether the group differences in contact with the reference group are quantitatively large or small.

Winship (1977) notes it is peculiar that standard formulas for measures of uneven distribution such as D and S are calibrated to take values of zero (0) only under the condition of exact even distribution. There are multiple reasons why exact even distribution is a questionable baseline for integration. One is that in practice exact even distribution is often logically impossible to achieve, especially when counts of households for areal units are small.[10] Another is that exact even distribution is an unusual, precise pattern that would only be expected under structured residential

[10] Even under strategic assignment, it would be necessary to assign households and even persons to spatial units in fractional parts to achieve exact even distribution.

assignments (e.g., quota allocation), not under random distribution. Relatedly, and more importantly for our purposes, the reference point of even distribution is conceptually different from the reference point adopted in most research on group disparities in socioeconomic outcomes. Even distribution is a stylized pattern of outcomes for spatial units, not individuals and households. The conventional approach for evaluating group disparities is to examine whether an observed group difference on average attainment outcomes for households and individuals differ from zero, the value expected under conditions of the null hypothesis that group membership and attainment outcomes are statistically independent. In keeping with this perspective, Winship (1977) argues an unbiased segregation index should have an expected value of zero under random distribution. But this is not the case for any widely used measure of uneven distribution. Instead, they all have positive expected values under random distribution and this quality of upward bias makes standard measures of uneven distribution flawed for measuring group disparity in the residential outcome of group composition.

Placing segregation index scores in a difference-of-means, or group disparities, framework brings an important benefit; it helps identify both the source of index bias and also the relatively simple refinement that can eliminate index bias. The core issue is this. In the group disparities framework, an index will be unbiased if the expected value of the group disparity on location-based attainments (y_i) is zero (0) under random assignment. This is not the case for any index measuring uneven distribution; all take positive, sometimes large, expected values under random assignment. Fossett (2017) shows that index bias traces to a single source; the initial calculation of the value of a household's simple (unmodified) contact with the reference group (p_i). The problem is that the expected distribution of values on simple contact (p_i) under random distribution is not the same for households in both groups; it is systematically higher for households in the reference group and it is systematically lower for households in the comparison group. Since simple contact (p_i) is the "raw material" used in calculating values of scaled contact (y_i), it logically follows that expected values for scores on scaled contact (y_i) also must necessarily be higher for the reference group and lower for the comparison group, thus necessarily producing a positive expected value for the index score.[11]

The core insight is that the standard approach to calculating the value of simple contact with the reference group (p_i) for a given household has two components. The first component is the household's contact with the reference group resulting from *contact with neighbors* (p_{ni}). Under basic sampling theory the expected distribution of values for this portion of contact is the same for households from both groups so it does not create bias in the index score.[12] The second component is contact with the

[11] This conclusion is based on a more careful discussion in Fossett (2017) that reviews the form of the scaling functions – $y_i = f(p_i)$ – needed to place each index of uneven distribution in the difference-of-means "disparity" framework.

[12] Technically, there is a small negative expected difference across groups because random draws for households in the reference group will track $(N_1 - 1)/(N_1 + N_2 - 1)$ while random draws for households in the comparison group will track $(N_1 - 0)/(N_1 + N_2 - 1)$. But the difference is

reference group that results from *self-contact* (p_{si}); that is, contact determined by the household's own presence in the group counts for the area. Sampling theory is not relevant for the expected value of this portion of contact; it is fixed as same-race contact as determined by the group membership of the household in question. Accordingly, this portion of contact is systematically different for households in the two groups; it takes a positive value for households in the reference group and it takes a value of zero for households in the comparison group. The resulting positive difference across groups is the source of bias in measures of uneven distribution.

This can be stated more carefully as follows. First, start with the calculation of simple contact with the reference group for any given focal household (as noted earlier):

$$p_i = n_{1i}/(n_{1i} + n_{2i}).$$

Then re-express the count terms in the calculation as counts for neighbors (subscript "n") and self (subscript "s") as follows:

$$p_i = (n_{1ni} + n_{1si})/(n_{1ni} + n_{2ni} + n_{1si} + n_{2si}).$$

The terms n_{1ni} and n_{2ni} are the counts of the reference group and the comparison group among the household's neighbors. The terms n_{1si} and n_{2si} register the presence and group membership of the focal household; n_{1si} is set to 1 if the household is in the reference group and 0 if not, and, similarly, n_{2si} is set to 1 if the household is in the comparison group and 0 if not. Since the sum of the self-presence terms n_{1si} and n_{2si} is always 1, the expression can be simplified to:

$$p_i = (n_{1ni} + n_{1si})/(n_{1ni} + n_{2ni} + 1).$$

For convenience, the denominator can be designated as n_t – the number of households in the area. Then contact with the reference group (p_i) can be expressed as the sum of contact with reference group neighbors (p_{ni}) and contact with the reference group resulting from self-contact (p_{si}).

$$p_i = (n_{1ni} + n_{1si})/n_t$$
$$p_i = n_{1ni}/n_t + n_{1si}/n_t$$
$$p_i = p_{ni} + p_{si}$$

Under random assignment, a focal household's neighbors will be a random draw from the community so the expected distribution of values of p_{ni} will be identical for

quantitatively negligible except when N_t, the sum of total counts for both groups is small. For example, it is $\cong 0.0101$ when $N_t = 100$; $\cong 0.0020$ when $N_t = 500$; $\cong 0.0010$ when $N_t = 1000$; and $\cong 0.0002$ when $N_t = 5000$.

both groups and the expected mean for both groups will be equal to the relative presence of the reference group in the community (P). Consequently, this component of contact has no impact on the expected value of the group difference on contact with the reference group.

In contrast, the expected value of p_{si} is $1/n_t$ for households in the reference group and $0/n_t$ for households in the comparison group, resulting in an expected group difference of $1/n_t$. The expected distribution of values of contact associated with neighbors (p_{ni}) is identical for households from both groups. The addition of self-contact (p_{si}) systematically shifts the expected distribution of scores of simple contact (p_i) up for all households in the reference group but has no impact on the expected distribution of scores for households in the comparison group. As a consequence, expected values on scaled contact (y_i) scored from simple contact (p_i) are systematically higher for households in the reference group and thus the expected group disparity (difference of means) is positive and biased upward.[13]

2.5.2 *The Simple Refinement to Index Calculations that Yields Unbiased Index Scores*

Fossett's (2017) analysis of segregation index bias in the group difference-of-means framework not only pinpoints the source of bias, it also establishes how the formulas for calculating scores for indices of uneven distribution can be refined to eliminate bias. The solution for eliminating index bias is to exclude the impact of self-contact from the simple contact calculations. That is accomplished by revising the standard contact calculation

$$p_i = (n_{1ni} + n_{1si})/(n_{1ni} + n_{2ni} + n_{1si} + n_{2si}).$$

by subtracting out the terms associated with self-contact. This leads to the following expression for unbiased contact with the reference group (p_i'):

$$p_i' = (n_{1ni} - n_{1si})/(n_{1ni} + n_{2ni} - n_{1si} - n_{2si}).$$

As noted earlier, the sum of the terms n_{1si} and n_{2si} is always 1, so the expression can be restated as:

$$p_i' = (n_{1ni} - n_{1si})/(n_{1ni} + n_{2ni} - 1).$$

[13] This conclusion follows because the scaling functions – $y_i = f(p_i)$ – associated with G, D, R, H, and S are all positive, monotonic functions. Thus, incrementing all values of p_i for one group but not the other necessarily creates a positive difference of group means on y_i.

In practice, segregation index scores are computed using datasets that provide counts of households by group for spatial units. This supports efficient calculation of index scores. In this context the calculation formula can be applied to area counts as follows:

$$p'_i = (n_{1i} - 1)/(n_{1i} + n_{2i} - 1) \text{ for households in the reference group, and}$$

$$p'_i = (n_{1i} - 0)/(n_{1i} + n_{2i} - 1) \text{ for households in the comparison group}$$

When this measure of unbiased contact is used as the raw input to the difference-of-means computing formulas for the most widely used measures of uneven distribution – *G*, *D*, *R*, *H*, and *S*- the resulting scores for these indices are unbiased; they take expected values of zero (0) when households are distributed randomly across residential locations (Fossett, 2017).

Fossett (2017) reviews further mathematical and empirical analyses to establish additional findings regarding the nature of index bias. In Table 2.1 we note five findings that apply to *D* and *S*, the measures of uneven distribution we use in our analyses. The last point is the most important one: One is never worse off for using unbiased index scores. If standard scores are not distorted by bias, the scores obtained using the unbiased version of the index will match the scores obtained using the standard version of the index. If standard scores are distorted by bias, they will be untrustworthy, and scores obtained using the unbiased version should be preferred.

We will draw on these points in Table 2.1 and related factors to explain why findings obtained using the unbiased versions of *D* and *S* can, and in many situations do, differ from findings obtained using standard (biased) versions of *D* and *S*. For example, the results we obtain using the unbiased version of *D* indicate White-Latino segregation is stable or rising over time in new destination communities. In contrast, the results obtained using the standard (biased) version of *D*, suggest the opposite; they suggest White-Latino segregation is falling over time in new destination communities. The difference between results is due to the complex impact of index bias on scores obtained using standard computing formulas for *D*. By definition, Latino presence in new destination communities is initially low but it is rising over time. This means *P* – the relative presence of White households (the reference group) in the community – is initially close to its upper boundary of 1.0 but is falling and moving closer to 0.50 over time. All else equal, the value for the standard (biased) version of *D* will fall because the magnitude of bias in *D* will fall as *P* moves closer to 0.50. This is an important example of why it is important to use the unbiased versions of *D* and *S* to track trends in segregation and differences across communities.

Table 2.1 Selected Differences Between Standard (Biased) and Unbiased Scores for the Dissimilarity Index (*D*) and the Separation Index (*S*)

Properties of standard (biased) versions of indices of uneven distribution	Properties of unbiased versions of indices of uneven distribution
The magnitude of index bias in standard (biased) versions of *D* and *S* increases as self-contact becomes a larger portion of overall contact. Thus, all else equal, index bias is greater when spatial units have fewer households because the relative contribution of self-contact to overall contact is larger when spatial units are small.	The expected values of the unbiased versions of *D* and *S* do not vary with the size of spatial units. The expected values of $E[D^{'}]$ and $E[S^{'}]$ under random distribution are zero (0) regardless of the size of areal units.
The magnitude of index bias is greater for the standard version of *D* compared with the standard version of *S*.	The expected values of the unbiased versions of *D* and *S* are identical; under random distribution, both $E[D^{'}]$ and $E[S^{'}]$ are zero (0).
The magnitude of bias in the standard version of *D* varies with community racial composition (*P*); specifically, it increases at an increasing rate as the reference group proportion (*P*) departs from balance (0.50) and can become extreme when *P* is near the upper and lower boundaries of its logical range (i.e., when *P* is below 0.03 or is above 0.97).	The expected value of the unbiased version of *D* does not vary with community racial composition (*P*); $E[D^{'}]$ is zero (0) at all values of *P*.
The magnitude of bias in the standard version of *S* does not vary with community racial composition (*P*). Consequently, the expected *D*-*S* difference resulting from bias is greater when groups are unequal in size (i.e., when *P* departs from 0.50 and especially when *P* is near 0 or 1).	The expected difference of the unbiased versions of *D* and *S* does not vary with community racial composition (*P*); $E[D^{'} - S^{'}]$ is zero (0) at all values of *P*.
Bias in *D* and *S* can vary from being negligible in some situations to being very large in other situations.	When bias is negligible, scores for unbiased *D* and *S* will exactly equal standard scores for *D* and *S*. when bias is non-negligible, scores for unbiased *D* and *S* will be lower than standard scores for *D* and *S* and will be more trustworthy.

2.6 Households as the Microunits for Measuring Segregation

As we have mentioned already, we assess segregation using data for households. This makes households, not persons, the microunits in the calculations we perform to obtain the unbiased index scores we use in our analysis. This is not the most common practice in recent decades; most studies take persons as the microunits for computing index scores. But we not only hold that using data for households is an acceptable choice; we also argue it is a superior choice. We outline the basis for our conclusion in this and following sections of this chapter. The case we make has two main points. In this section we note that data for households provides better coverage of the subpopulations that are relevant to the study of residential segregation (e.g., includes households and excludes inmates of prisons and other institutions). In later sections we note that using data for households makes it possible to obtain unbiased index scores when this is not possible using data for persons.

Calculating index scores using households as the microunits was once a routine practice in the literature. Indeed, many of the most influential studies of racial residential segregation conducted from the 1940s through the 1970s drew on reports from the U.S. Censuses of Housing that tabulated occupied housing units by race for census blocks (e.g., Taeuber & Taeuber, 1965; Roof, 1972; Roof and Van Valey, 1972; Sørensen et al., 1975). However, in more recent decades it became more common for comparative segregation studies to measure segregation using data for persons instead of data for households. One methodological reason for this was that tabulations for persons provided more detailed breakdowns on race/ethnicity. For example, the block-level tabulations in the housing censuses for 1940, 1950, and 1960 were limited to a distinction between White and nonwhite households. The crudity of this classification was a major problem at the time. But it is not a problem for our study. The 1990, 2000, and 2010 censuses all have tabulations of households by categories of race at the block level that include the group distinctions – White, Black, Latino, and Asian – considered in empirical studies of segregation across communities in the United States.[14]

On the other hand, the data tabulations for households avoid multiple practical complications associated with the available data tabulations for persons. One complication is that data tabulations for persons often include several subpopulations that ideally would be excluded and whose presence can impact segregation index scores and distort their values.[15] Specifically, persons in group quarters in prisons, psychiatric institutions, military barracks, college dormitories, and other settings are often included in data tabulations for persons. These subpopulations can represent large fractions of one or both groups in the comparison and their spatial distribution is reflective of administrative practices and is not reflective of the social dynamics in the broader housing market. To protect against these problems, it is necessary to flag communities where these subpopulations are present and exclude cases where their impact on index scores is potentially important. This would lead to the exclusion of many dozens of cases in our study. Data for households do not include these subpopulations and thus they are not subject to these problems. Accordingly, we are able to retain most of the cases that would be excluded if we used tabulations for person data and achieve greater coverage of communities.

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[14] There are minor problems with these tabulations resulting from the fact that Black and Asian persons who also are Latino are counted in both the data for Black and Asian persons and also in the data for Latino persons. With only a handful of exceptions, which we identify and exclude from our analyses, this has little impact on scores for White-Black, White-Asian, and White-Latino segregation.

[15] Data tabulations for persons which avoid these problems (by being tabulated by size of household) use the same racial categories used with the tabulations for households and thus do not have any advantage on this issue.

A second complication associated with using data for persons to measure segregation is that the index scores obtained are impacted by bias to a greater degree than is generally appreciated and it is very difficult to obtain unbiased index scores using data tabulations for persons. This is the major reason why we use data for households; it is relatively easy to obtain unbiased index scores when using data for households and it is not possible to obtain unbiased index scores for all study years when using data for persons. This point is significant and rests on insights and observations that are new to the present study. In view of this, we provide a more detailed discussion of the issues in the next section.

2.6.1 Methodological Implications of Using Data for Households Versus Using Data for Persons

It is possible that studies in recent decades have used data for persons more often than data for households in part because some researchers may view index bias as a greater concern when using data for households. The potential justification for this view is that, all else equal, index bias is higher when group counts across spatial units are smaller and counts for households tend to be much smaller than counts for persons. However, any view that using data for persons instead of households provides useful protection from the distorting impact of index bias is misplaced on two important counts. The first is that, when considered carefully, the impact of index bias on segregation scores obtained using data for persons is inherently similar in magnitude to the impact of index bias on scores obtained using data for households. The second is that the available methods for obtaining unbiased index scores are easier to apply when using data for households and they are either difficult or infeasible to apply when using data for persons. Accordingly, measuring segregation using data for households is not only an acceptable practice, it is a clearly superior choice for the needs of our study.

Winship (1977) established index bias was greater in magnitude and concern when group counts in spatial units were small. The early literature examining segregation using block level data for households was thus open to legitimate concerns about index bias because the group counts for spatial units were indeed small. Following Winship's (1977) influential study, research practice shifted toward using the much larger spatial units of census tracts and using data for persons instead of households. As a result, the group counts for person data at the census tract level were much larger than group counts for households at the block level and thus could be seen as providing protection against the problem of index bias. This view was partly justified as, all else equal, the magnitude of index bias is smaller when segregation is measured using census tracts instead of census blocks. This is not an acceptable option for our study because we wish to assess segregation for smaller metropolitan areas and nonmetropolitan communities where it is necessary to use block-level data to accurately capture segregation patterns. This is not a concern for us, however, because the unbiased scores we use in our study can be calculated for blocks as easily as for tracts and the unbiased scores have the same desirable properties whether calculated using data for blocks or data for tracts.

To the extent that researchers believed empirical studies gained protection from index bias by using data for persons instead of households, they were mistaken. All else equal, data for persons do involve larger group counts than data for households. But these larger counts do not provide protection from index bias. To the contrary, the magnitude of the impact of index bias for scores computed using data for persons is similar, if not identical, to that for scores computed using data for households. Two factors account for this. One is that persons within households locate together in household-specific clusters of persons, not independently. The other is that persons within households are typically homogeneous on racial/ethnic status. These two factors combine to create fixed proportions of same-group contact – the source of bias in index scores – that are similar in magnitude whether scores are calculated using data for households or data for persons.

Earlier we noted index bias originates in the contribution of self-contact (p_{si}) to simple contact (p_i) because a household's self-contact is fixed and cannot, not even in principle, be randomly assigned and varies systematically by group membership. The situation regarding fixed contact that varies by group membership is fundamentally the same when considering data for persons instead of data for households. To illustrate, we consider the situation where all blocks have 10 households. The contact experienced by an individual household is comprised of contact with their nine neighboring households and the household's self-contact. Contact with neighbors can in principle be a random draw, in which case the contribution to expected contact with the reference group will follow the relative presence of the reference group in the community (P) based on $(9/10)P$. This expected value is the same for households from both groups, so the expected group difference on contact with the reference group from neighbors is zero (0).

In contrast, the contribution of self-contact is fixed and it varies systematically by race. So self-contact will increase contact with the reference group (p) by 1/10 for households from the reference group and will have no impact for households in the comparison group. Thus, the expected group difference in contact with the reference group resulting from self-contact is ten percent (10%) of total contact. This is based on taking the difference between the group-specific levels of expected contact with the reference group under random assignment as follows:

$$E[p]_1 = ((n_t - 1)/n_t)\, P + 1/n_t = (9/10)\, P + 1/10 \text{ for households in the reference group}$$

$$E[p]_2 = ((n_t - 1)/n_t)\, P + 0/n_t = (9/10)\, P + 0/10 \text{ for households in the comparison group}$$

where n_t is the number of households on a block (10 in this example). The expected difference ($E[p]_1 - E[p]_2$) will be $=1/n_t$, which in this example is 1/10. This difference in expected contact with the reference group resulting from the contribution of fixed same-group contact is the sole source of index bias (Fossett, 2017).

The basic character of this situation does not change when a researcher switches from using data for households to using data for persons. To illustrate why this is so we modify the example just considered by assuming the households in question all have four persons and thus the 10-household blocks all have 40 persons. We also assume persons within households are of the same race and locate together. From the point of view of an individual person, 36 of their neighbors (based on 9 households, each with 4 persons) can in principle be a random draw so also as before the expected contribution to contact with the reference group will follow the relative presence of the reference group in the community (P) and can be given as (36/40) P which reduces to (9/10) P, the same value just identified for households. As before, this expected value applies to persons from both groups, so the expected group difference in contact with the reference group from neighbors is zero (0).

If self-contact and contact with fellow household members were a random draw, its contribution to expected contact would be (4/40) P and the expected group difference would be zero (0). But both self-contact and contact with fellow household members cannot be a random draw; they are fixed same-group contact that varies systematically by race. So, the contribution of these sources of contact with the reference group (p) is 4/40 for persons from the reference group and zero (0) for persons from the comparison group. Thus, the expected group difference in contact with the reference group for persons is $4/40 = 0.10$, the same value seen earlier for households. To summarize, the difference between the group-specific levels of expected contact with the reference group under random assignment is given as follows:

$$E[p]_1 = ((n_t - n_h)/n_t)\ P + n_h/n_t = (36/40)\ P$$
$$+\ 4/40 \text{ for persons in the reference group}$$
$$E[p]_2 = ((n_t - n_h)/n_t)\ P + 0/n_t = (36/40)\ P$$
$$+\ 0/40 \text{ for persons in the comparison group}$$

where n_t is the number of persons on a block (40 in this example) and n_h is the number of persons in a household (4 in this example). Accordingly, the expected difference ($E[p]_1 - E[p]_2$) will be $= n_h/n_t$ which in this example is $4/40 = 1/10$, the same as for households.

2.6.2 *Difficulty of Correcting Index Bias When Using Data for Persons*

Our conclusion that the expected impact of bias on segregation index scores is fundamentally the same regardless of whether segregation is measured using data for households or data for persons has broader implications than may not be apparent on first consideration. We note three important implications here:

- The impact of bias on index scores calculated using data for persons is much greater than most researchers are likely to appreciate because it is greater than would be indicated by estimating index bias using either the analytic formulas introduced by Winship (1977) or the bootstrap simulation methods from Carrington and Troske (1997) in combination with data for persons.
- It is much more difficult to obtain unbiased index scores when using data for persons instead of data for households.
- In general, it is easier to obtain unbiased index scores when using data for households and, at least for U.S. communities, the results will be similar to results obtained using data for persons.

On the first point, Winship's (1977) analytic formulas for estimating index bias are explicitly formulated to be applied to households. The formulas are based on probability models that assume the locational outcomes for micro-level units are independent events. This assumption is reasonable for households. But it is not reasonable for persons. Most persons reside in racially homogeneous households and the locational outcomes for persons within households are strongly correlated. Spouses, partners, children, etc. do not locate independently; they locate in "clusters" and the clusters are homogeneous on race. This combination produces levels of bias in index scores that are much higher than would result if individuals within households located independently. A rough-and-ready rule of thumb is that, when compared to the level of bias estimated using data for persons in combination with an incorrect assumption that persons in households locate independently, the true level of bias will be higher by a multiple equal to the average size of households.[16]

In view of this, the analytic formulas outlined in Winship (1977) cannot be naively applied to data for persons. To be appropriate for use with data for persons, Winship's formulas must be modified to take account of the fact that persons locate in racially homogeneous household clusters. The same conclusion also applies to Carrington and Troske's (1997) method of estimating index bias using bootstrap sampling methods. Their methodology is explicitly crafted for use with data for persons, but the research context is measuring occupational sex segregation, a context where it is reasonable to assume a model of independence of events across persons. Their bootstrap method for estimating expected values for measures of residential segregation is appropriate to use with data for households but it is not appropriate to use with data for persons. To use the method with data for persons, the bootstrap simulation procedure must be modified to assign household-specific clusters of persons randomly to locations. We conducted a methodological study where we implemented this approach using detailed tabulations of race by size of household. The findings we obtained were simple and clear. Random assignment of persons in racially homogeneous household-specific clusters produces much higher expected values for index scores than random assignment of persons. And, the

[16]This is not to be taken literally. However, while the impact can be determined with fair precision using complex methods, household size is the dominant factor and a crude rule of thumb characterization is satisfactory for this discussion.

expected values for index scores obtained using complex methods needed for using data for persons were comparable to the expected values for index scores obtained using much simpler methods that can be used with data for households.

With this, the importance of the second highlighted implication comes into clear relief. There are no established methods for obtaining unbiased index scores when using simple (one-way) tabulations of persons by race for spatial units. We specify *simple*, one-way tabulations of persons by race because this is the kind of data used in most empirical studies of residential segregation. Additionally, while it is technically possible to obtain unbiased index scores when using data for persons, it requires that researchers work with detailed tabulations of persons by race and size of household. In many situations the requisite data are not available. Moreover, when the needed data are available there is little practical justification for going to the considerable extra time and effort because the results will be similar to results obtained by applying simpler methods to data for households.

Size of household varies considerably across households in general. Additionally, the central tendency and dispersion of the distribution of households by size varies over time, across racial/ethnic groups, across residential areas within communities, across metropolitan and nonmetropolitan settings, and more. Simple approaches to taking account of clustering of persons within households while working with data for persons – for example, dividing by average household size to convert person data to approximate household data – do not work well and are inferior to calculating unbiased index scores using simple tabulations of race by spatial units for households. This leads us to a simple and important conclusion. When data for households are available, unbiased index scores computed using these data are superior to all other feasible and practical options.

2.7 Contrasting the Dissimilarity Index and the Separation Index for Measuring Segregation

We measure segregation using two indices, the dissimilarity index (D) and the separation index (S). Both indices are well-established and have been used extensively since the earliest days of quantitative measurement of segregation. The dissimilarity index is the most commonly used measure of uneven distribution. It is popular in part because it is easy to compute.[17] Additionally, D has a substantive interpretation many researchers view as both appealing and easy to convey to nontechnical audiences. Namely, the value of D indicates the minimum proportion of households from either group in the comparison that would have to relocate to a different area to achieve even distribution – a pattern where the ethnic composition of every area matches the ethnic composition of the community overall. We also

[17] This was a very important consideration in the early decades of empirical segregation analysis. Even today, it is a big factor contributing to D's popularity.

note a disparity formulation of D has an appealing interpretation as well and is easy to convey to broad audiences. Under this formulation, the value of D is the group difference in the percentage of households that reside in parity areas; areas where the relative presence of the reference group (p) equals or exceeds the level seen for the community overall (P).

While D is a workhorse in empirical segregation studies, it has well-known technical deficiencies documented in methodological studies (Zoloth, 1976; Winship, 1977; James & Taeuber, 1985; White, 1986; Reardon & Firebaugh, 2002; Fossett, 2017). In particular, D is known for being sensitive to how groups are differentially distributed across below-parity areas and parity areas, distinguished by whether $p \geq P$, but insensitive to how groups are differentially distributed across areas on the same side of the parity line (White, 1986: 203; James & Taeuber, 1985: 13; Reardon & Firebaugh, 2002: 51; Fossett, 2017). Thus, it is fair to describe D as sensitive to group differences in the fraction of households displaced into below-parity areas but insensitive to whether non-parity areas are close to parity or far from parity. Alternatively, D is sensitive to group inequality in ordinal distribution across areas classified as below-parity, parity, and above-parity but insensitive to group inequality on quantitative outcomes on area group composition. Another characteristic of the dissimilarity index is particularly relevant for our study; D is especially prone to upward bias and the problem is acute when assessing segregation comparisons involving small populations and small spatial units (Winship, 1977; Carrington & Troske, 1997; Fossett, 2017). We used Fossett's (2017) refined formulation of D discussed earlier to overcome this problem.

Like D, the separation index (S) has been used extensively from the earliest days of quantitative research on residential segregation. But this fact is underappreciated because S has been used under a variety of different names over many decades including, in rough chronological order, the revised index of isolation (Bell, 1954), the correlation ratio or eta squared index (Duncan & Duncan, 1955; Stearns & Logan, 1986; White, 1986), the segregation index (Zoloth, 1976), the Coleman r_{ij} index (Coleman et al., 1975, 1982), the variance ratio index (James & Taeuber, 1985), the normalized exposure index (Reardon & Firebaugh, 2002), and the separation index (Fossett, 2017). The separation index consistently fares well in methodological studies (e.g., James & Taeuber, 1985; White, 1986; Reardon & Firebaugh, 2002; Fossett, 2017). For example, in contrast to D, S registers group differences in distribution across non-parity areas and thus, is sensitive not only to the extent to which groups differentially reside in non-parity areas but also to whether they reside in areas that are near or far from parity.[18] Additionally, in comparison to D, S is much less susceptible to distortion by index bias (Winship, 1977; Fossett, 2017).

[18] In more technical language, S, but not D, satisfies the measurement theory requirement that an index should properly register all integration-promoting residential exchanges including not only when the areas are on opposite sides of parity but also when both areas are on the same side of parity (James & Taeuber, 1985; Reardon & Firebaugh, 2002).

The separation index has multiple interpretations. Unfortunately, interpretations of *S* offered in earlier decades often highlighted the measure's correspondence with terms from analysis of variance and correlation.[19] These interpretations are, of course, technically correct. But they are not particularly effective in evoking the substantive relevance of segregation in a way that is intuitive and easy to convey to broader audiences. We favor a more appealing interpretation of *S* as a disparity measure; for example, in the context of majority-minority segregation, *S* reflects the majority-minority difference in average contact with the majority. This interpretation emerges naturally from the difference of means computing formula for *S* reviewed earlier.[20] It is attractive because it is easy to explain. If majority and minoritized group households live together, the contact households from both groups have with majority households will not differ. But, if majority households live apart from minoritized group households, the contact difference will grow and take the value 1.0 in the extreme where the two groups never reside in the same area.

2.7.1 Segregation as Stratification and the Resonance of the Separation Index

Fossett (2017) advocates referring to *S* as the "separation index" because, among all measures of uneven distribution, values of *S* provide the most reliable signal of the extent to which groups are separated in their distribution across spatial units such that substantial portions of both groups live apart from each other in different spatial units that are highly polarized (homogeneous) on group composition. In this regard, we argue *S* resonates nicely with a definition of segregation offered by Massey and Denton (1988), which we recall again here:

> [R]esidential segregation is the degree to which two or more groups *live separately from one another, in different parts of the urban environment*. (Massey & Denton, 1988, emphasis added)

We endorse and highlight this definition of segregation for two reasons. The first is that this definition implies a logical connection of segregation and group inequality on location-based stratification outcomes. Specifically, when groups are residentially separated in the sense of living apart from one another in different spatial units or spatial domains, it becomes logically possible for the groups to have unequal social, economic, and health-related outcomes that are linked to area of residence. Additionally, if groups are not separated across spatial units, inequality on stratification outcomes linked to spatial location is not logically possible. Thus, separation is a

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[19] The dissimilarity index also has interpretations in terms of dispersion and variance in a distribution. In this regard, it is equivalent to the relative mean deviation statistic (Reardon & Firebaugh, 2002). But, advocates of *D* have emphasized other, more intuitive, interpretations.

[20] We also note a similar interpretation was offered by Becker et al. (1978).

necessary but not sufficient condition for segregation to have implications for group stratification on social, economic, and health attainments.

We believe most studies of residential segregation are like our study in being motivated by a fundamental assumption that segregation has important consequences for group inequality in life chances and a wide range of stratification outcomes. When this is true, the separation index is clearly superior to the dissimilarity index in ability to signal whether the pattern of segregation in a community creates the logical preconditions for inequality on location-based outcomes (Fossett, 2017). The separation index can take high values under only one condition, when groups are separated into different spatial units that are polarized on group composition, as occurs when the minoritized group is concentrated in enclaves, barrios, or ghettos (Stearns & Logan, 1986; Fossett, 2017). Thus, high values of *S* provide a strong, reliable signal that groups are separated across spatial units such that *both* groups live in neighborhoods where their group predominates and the other group is largely absent. Speaking of White-Black segregation, Stearns and Logan view this to be substantively important arguing, "The fact that some neighborhoods reach very high concentrations of black population has profound economic and political consequences for those neighborhoods" and noting that Black neighborhoods are subject to redlining, business disinvestment, siting of unwelcome developments (prisons, halfway houses, low income housing, garbage compacting sites, etc.) and avoidance of desirable developments (libraries, parks, universities, etc.) (Stearns & Logan, 1986:127–128).

Importantly, *D* does not provide a reliable signal regarding group separation across different spatial units. To the contrary, it is both logically possible and empirically common for *D* to take high values when groups are not separated and instead both groups live together in neighborhoods that are relatively close to parity (Fossett, 2017). The possibility for *D* to take high scores in the absence of group separation is due to the fact that *D* only registers group differences in distribution across the parity line and is insensitive to group differences in distribution across spatial units on the same side of the parity line. This is a serious flaw for measuring group separation because group differences in distribution across below-parity areas and/or across above-parity areas can vary widely with major consequences for group separation, creating the possibility for *D* and *S* to take different combinations of values which have different substantive implications.

2.7.2 Making Sense of D-S Combinations

We follow recommendations offered by Fossett (2017) and examine values of both *D* and *S*. Reporting and reviewing values of *D* helps maintain continuity with previous studies which often report only scores for *D*. It also is useful because different combinations of scores for *D* and *S* provide a basis for characterizing the pattern of segregation in a community for a given group comparison:

- When S takes high values, one can be certain that groups are separated in space in a pattern of prototypical segregation, or *polarized unevenness*, which establishes the logical preconditions for group inequality on location-based stratification outcomes. Since values of D cannot be lower than values of S, a high value on D will always occur when the value of S is high.
- When D takes high values, one cannot know with certainty whether groups are separated in space. It is a logical possibility and if this is the case S will also take a high value. But it also is logically possible and empirically common for a high value of D to result from a pattern of dispersed displacement from even distribution, or *dispersed unevenness*, which does not involve high levels of group separation and thus will occur in combination with a low value on S.

The potential for D and S to take different, potentially highly discrepant, values is not widely appreciated. As a result, researchers and broader audiences alike routinely, but incorrectly, assume that high values of D are a strong signal of an underlying pattern of segregation involving group separation and possibly substantial group inequality on location-based outcomes. This is not the case.

We use the chart in Table 2.2 to lay out the various logical possibilities for alignment of values of D and S in combination with possibilities for group inequality on location-based stratification outcomes.[21] The chart makes clear that the pattern of dispersed unevenness – characterized empirically by the combination of a high value for D and a low value for S, does not carry even the possibility of group inequality on location-based outcomes. In contrast, a high value on S does carry the logical possibility of group inequality on location-based outcomes, but only by signaling the necessary precondition of group separation across spatial units. If undesirable location-based outcomes are limited to areas where the minoritized group is the predominant presence and favorable location-based outcomes are limited to areas where the majority is the predominant presence, a pattern often approximated in communities across the United States, separation will in fact be associated with

Table 2.2 Logically possible outcomes on dissimilarity (D), separation (S), and group inequality on location-based stratification outcomes

Pattern of segregation and location-based inequality	Index score		Group inequality on location-based stratification outcomes	
	Dissimilarity	Separation	Possible	Actual
Logically possible scenarios				
No segregation	D Low	S Low	Low	Low
Dispersed unevenness	D High	S Low	Low	Low
Separation without inequality	D High	S High	High	Low
Separation with inequality	D High	S High	High	High

[21] Fossett (2017) reviews the basis for the conclusions presented here in more detail.

group inequality. But it is logically possible that separation can be high without inequality being high. This would result, for example, if all low-income households experienced similar undesirable location-based outcomes, and all high-income households experienced similar favorable location-based outcomes, but majority and minoritized group households lived apart in different spatial units. In this hypothetical example, inequality in location-based stratification outcomes is a strict function of income, not race. It is a logical possibility, but it is not widely observed in communities across the United States.

We conclude this section by noting that we view the separation index to be the best available measure for identifying when segregation patterns in a community involve groups living separate and apart from each other. If the value of *S* is low, we know that group inequality on stratification outcomes linked to residential location cannot be large because the two groups in the comparison are, to a substantial degree, residing in the same areas and necessarily experiencing similar location-based outcomes. If the value of *S* is high, we know the two groups are living apart and thus can potentially have unequal outcomes on attainments tied to residential location. We also occasionally report and discuss values of the dissimilarity index because it is familiar and widely used. So, we believe it provides a useful point of reference for readers who prefer *D* over *S* for their own reasons as well as to facilitate comparisons with other research that reports only scores for *D*. When *D* and *S* agree, interpretations and conclusions are relatively simple. When *D* and *S* do not agree, it will result because *D* is taking a high value under conditions of dispersed unevenness where most households reside in areas that are relatively close to parity. The possibility of this condition is not widely appreciated. Perhaps for that reason, the literature provides little basis for assigning substantive significance to a high-*D* low-*S* situation.[22]

2.7.3 Examining Empirical Examples of Selected D-S Combinations

Take the example of how groups are distributed across below-parity areas in the common situation of measuring majority-minority segregation in a community where the minoritized group is the smaller population. Separation will be maximized when minoritized group households are concentrated in below-parity areas that are

[22] The one example known to us concerns the implications of the volume of movement interpretation of *D* (i.e., minimum proportion that must change areas) for the amount of social disruption that would result if a policy were implemented to achieve exact even distribution. But this interpretation should not be taken literally because the consequence imagined is not necessary. A less disruptive reallocation scheme based on the “replacement index” can be used to achieve exact even distribution. The replacement index is given by $2PQD$ which indicates the minimum fraction of population movement required to achieve even distribution (Farley & Taeuber, 1968). Its value is always at least one-half *D* and in typical comparisons is substantially smaller than that.

homogeneous or near-homogeneous and separation will be minimized when all minoritized group households reside in below-parity areas that are as close to parity as possible. The first outcome occurs under a pattern Fossett (2017) terms "prototypical" segregation. The adjective "prototypical" is apt because it suggests the notion that comes to the minds of researchers and lay audiences when a community is characterized as being highly segregated. If *S* takes a high value, one can be certain segregation takes the form of prototypical segregation, which we have also referred to as polarized unevenness. The same cannot be said for *D*. Instead, while *D* will indeed be high whenever *S* is high, the value of *D* is not a reliable signal of separation and polarized unevenness because *D* also can take high values under the pattern of dispersed unevenness. Dispersed unevenness does not involve separation. Yet *D*, but not *S*, can take high values under this condition.

The contrast can be clarified using graphical representations of the residential patterns for a few communities. The first example we review is White-Black segregation in Chicago, IL in 1990 in Fig. 2.1. The case of Chicago has for nearly a century been seen as a distinctive pattern of polarized unevenness because it involves the two groups in question living in separate parts of the urban environment, here with a large proportion of Black households residing in predominantly Black neighborhoods located on the South side of Chicago and with a large proportion of White households residing in predominantly White neighborhoods on the North side and in the suburbs surrounding Chicago. The high level of separation is reflected by the high value of 79.7 for *S* and its close correspondence to the high value of 87.0 for *D*. The polarization chart in Fig. 2.1 visually depicts the extent of group separation by plotting each group's distribution across areas by level of percent White. The two frequency polygons form a distinctive combination of a left-peaked "L" curve for Black households registering the fact that more than 70%

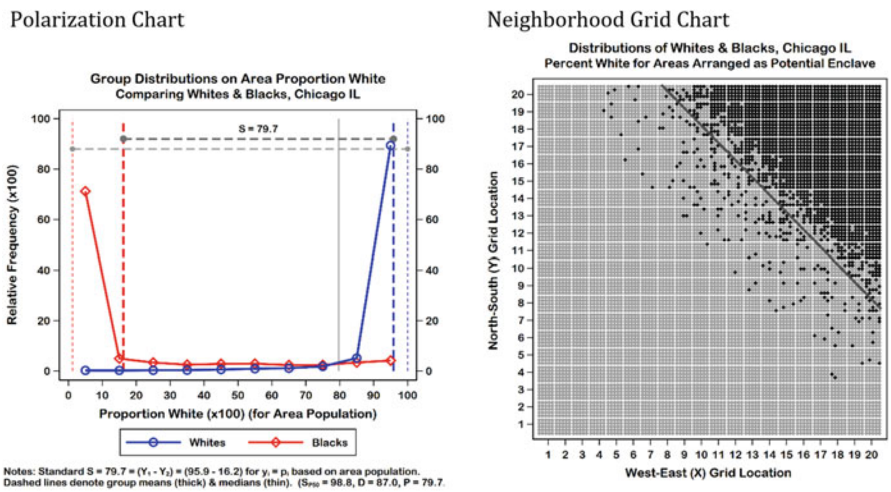

Fig. 2.1 Group distributions in Chicago, IL, 1990

of Black households live in areas that are at least 90% Black (less than 10% White) and a mirror image right-peaked "J" curve registering the fact that more 85% of White households live in areas that are at least 90% White.

Under even distribution the polarization chart would form a "JL" pattern, not an "LJ" pattern, with both curves peaking at 80 on the X-axis, the percentage of White households in the combined population, and falling away from there. The thick dashed vertical lines mark the respective group means for contact with White households at 95.6 for White households and 16.2 for Black households with the difference determining the value of 79.7 for the separation index. The polarization chart is so named because it clarifies that when values of S are high one can be certain that a large fraction of White households are residing in predominantly White neighborhoods and also a large fraction of Black households are residing in predominantly Black neighborhoods.

The neighborhood grid chart in Fig. 2.1 depicts this pattern using an alternative visualization approach. Specifically, the distributions of White households and Black households across areas is projected onto a stylized overhead view representation of the city as consisting of 400 neighborhoods arranged in a 20 × 20 neighborhood grid where each neighborhood has 25 households. This creates an abstract representation of a city with a total of 10,000 households. The chart is constructed by ordering the actual areas of the city on the basis of relative group presence – proportion White in this case – and then projecting the areas on to the neighborhood grid on a proportional basis. Homogenous White areas are filled in starting in the Southwest corner of the grid, then areas with mixed group presence are filled in in the middle portion of the grid, working from areas with greater White presence first and then areas with greater Black presence, and then finishing by filling in homogeneous Black areas in the Northeast corner.

A cross-diagonal line falling from left to right is superimposed on the grid to provide a visual reference for how the city would be divided into homogeneous White and Black regions under maximum segregation.[23] In Chicago, the housing grid chart depicts a striking visual pattern. The overwhelming majority of areas on either side of the diagonal line are either 100% White (on the southwest side of the diagonal line) or 100% Black (on the northeast side of the diagonal line). From this, it obvious that it is possible for White and Black households to have fundamentally different experiences on stratification outcomes that are tied to residential location including, for example, city services, schools, amenities, infrastructure, mortgage loan redlining, and more.

These patterns are not surprising because White-Black segregation in Chicago is perhaps the most widely known and studied empirical case in the broader literature on residential segregation. But is it representative? And, relatedly, is a high value of

[23] The diagonal is an approximation. The algorithm fills in whole areas on a one-by-one basis starting with the area in the upper-right corner, then to the two areas on the adjacent sub-diagonal running northwest to southeast, then to the three areas on the next adjacent sub-diagonal, and so on. Areas on any given sub-diagonal are filled in from the center of the diagonal, moving out to the end points.

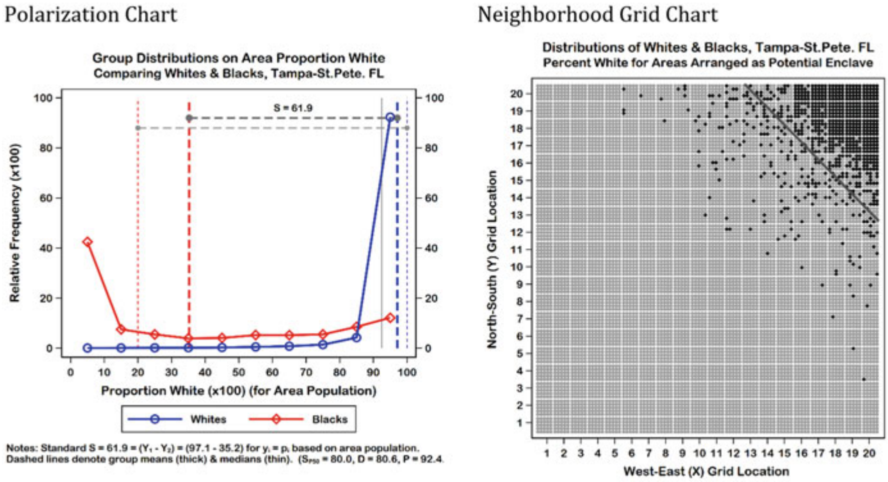

Fig. 2.2 Group distributions in Tampa-St. Petersburg, FL, 1990

D such as the one observed in Chicago always a reliable signal that a clear pattern of group separation is present as seen in Chicago? We have already tipped our hand regarding the answers to these questions. While Chicago is an important case, it is likely not representative because high values of *D* do not necessarily involve group separation as seen in Chicago.

We justify these conclusions by reviewing data for White-Black segregation in 1990 in four additional cities: Tampa-St. Petersburg, FL (Fig. 2.2); Lubbock, TX (Fig. 2.3); Topeka, KS (Fig. 2.4); and Erie, PA (Fig. 2.5). The results for Tampa-St. Petersburg and Lubbock are similar to the results seen for Chicago. Both cities have high levels of polarized unevenness, albeit not quite as high as in Chicago, with values of *D* and *S* being relatively close as is characteristic of the pattern of polarized unevenness; *D* and *S* are 80.6 and 61.9, respectively, in Tampa-St. Petersburg and 74.3 and 58.0, respectively, in Lubbock.[24]

In both cities the polarization chart has the "LJ" pattern associated with group separation and polarized unevenness, and, correspondingly, the neighborhood grid charts for the two cities depict clear separation of groups with a majority of areas on the southwest side of the diagonal being homogeneously White and the majority of areas on the northeast side of the diagonal being homogeneously Black. These visualizations of the segregation pattern make it clear that the separation of groups into different areas in the city creates the logical possibility for the groups to experience inequality in stratification outcomes linked to residential location.

[24] Our rule of thumb guideline for characterizing the pattern as polarized unevenness is $(S^{2/3} + 0.10) \geq D$ or, alternatively, $(D - 0.10)^{3/2} \leq S$. The guideline is met in Tampa-St. Petersburg based on $(0.619^{2/3} + 0.10) = 0.826 \geq 0.806$, and, alternatively, $(0.806 - 0.10)^{3/2} = 0.593 \leq 0.619$. Similarly, the guideline is met in Lubbock based on $(0.580^{2/3} + 0.10) = 0.795 \geq 0.743$, and, alternatively, $(0.743 - 0.10)^{3/2} = 0.516 \leq 0.580$.

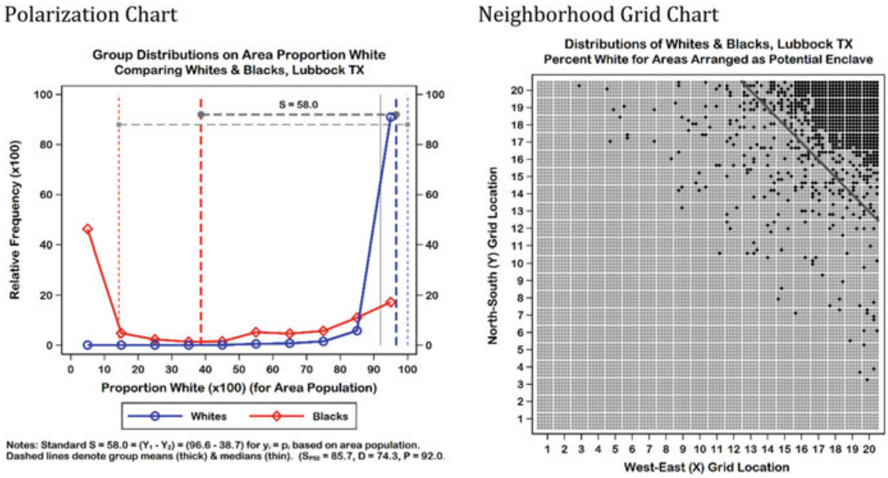

Fig. 2.3 Group distributions in Lubbock, TX, 1990

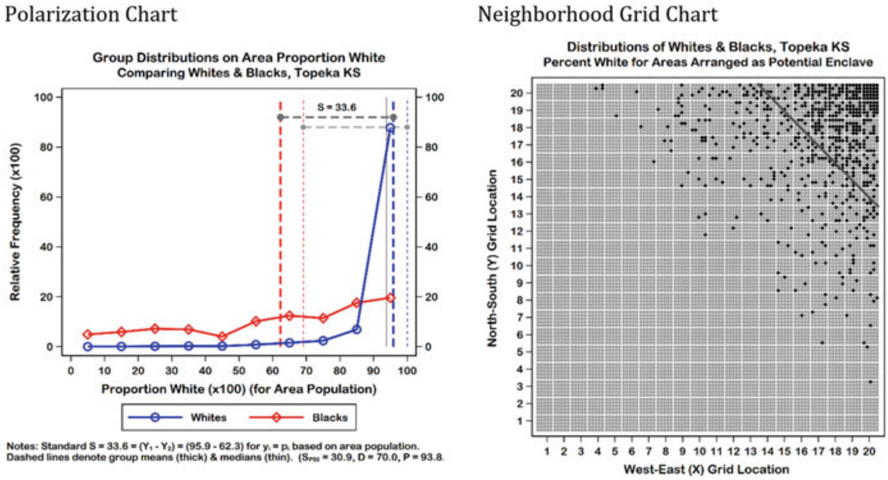

Fig. 2.4 Group distributions in Topeka, KS, 1990

The results for Topeka and Erie document a pattern of uneven distribution that is fundamentally different from polarized unevenness. Instead, they follow the pattern of dispersed unevenness. The hallmark of this pattern is that groups differ substantially on the outcome of residing in below-parity areas but at the same time they generally reside together in neighborhoods that are relatively close to parity and do not reside apart in areas that are polarized on group composition. A primary feature of the pattern is that values of *D* are high, as high as seen in Tampa-St. Petersburg and Lubbock, but values of *S* are markedly lower. The value of *D* for Erie is 75.2,

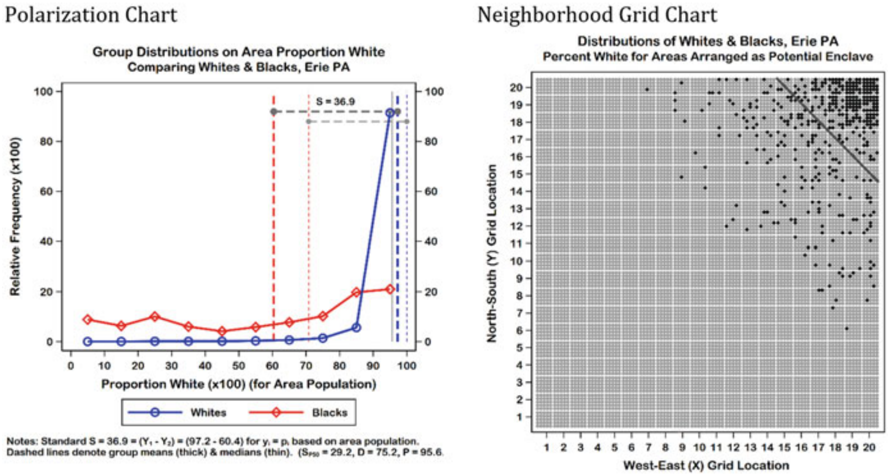

Fig. 2.5 Group distributions in Erie, PA, 1990

higher than the value of D for Lubbock, but the value of S is 36.9, not even half of the value of D for Erie and some 21.1 points lower than the value of 58.0 for S for Lubbock. Our quantitative guideline for polarized unevenness is not met and our quantitative guideline for identifying a pattern of dispersed unevenness is met.[25]

The polarization charts for Topeka and Erie depart dramatically from the corresponding charts for Tampa-St. Petersburg and Lubbock. In contrast to the first two cities, Topeka and Erie do not have the "LJ" pattern associated with group separation. The reason for this is that, while the Black populations in these cities do generally reside in below-parity areas (i.e., areas where $p < P$), the Black populations in these cities are not concentrated in predominantly Black areas, a necessary condition to form the "L" in the "LJ" pattern characteristic of group separation. Instead, the Black populations in these cities are dispersed across a wide range of neighborhoods with a clear majority living in majority White areas and with the two most common (i.e., modal) neighborhood results being areas that are 80–89% White and 90–100% White!

The pattern of dispersed unevenness is reflected in three obvious ways in the neighborhood grid charts for these two cities. The first is that, in vivid contrast to the same charts for Tampa-St. Petersburg and Lubbock, only a few of the areas above the diagonal are 100% or near-100% Black. Second, many of the areas above the diagonal are majority White! And, lastly, as a byproduct of the first two points, a large fraction of the Black population is dispersed across predominantly White areas

[25] Our "rule of thumb" guideline for characterizing the pattern as dispersed unevenness is ($S^{2/3}$ + 0.20) < D or, alternatively, $(D - 0.20)^{3/2} > S$. The guideline is met in Topeka based on ($0.336^{2/3}$ + 0.20) = 0.683 < 0.700, and, alternatively, $(0.700 - 0.20)^{3/2} = 0.354 > 0.336$. Similarly, the guideline is met in Erie based on ($0.369^{2/3}$ + 0.20) = 0.614 < 0.752, and, alternatively, $(0.752 - 0.20)^{3/2} = 0.410 > 0.369$.

in the region below the diagonal. In brief, few Black households live apart from White households in areas that are predominantly Black, and most Black households co-reside with White households in majority White areas that, while technically below parity, are relatively close to parity.

This pattern for group residential distributions has great substantive significance. When segregation takes this pattern, the potential consequences of segregation for group inequality on stratification outcomes linked to neighborhood location are blunted. White-Black differences in exposure to substandard city infrastructure, unfavorable treatment in mortgage lending, poor public services, food deserts, noxious odors and noise from industrial sites, hazardous wastes and emissions, and so on, cannot be large as under the pattern of polarized unevenness because most Black households are living in neighborhoods where more White than Black households are experiencing the same location-based outcomes. So, if one's interest in segregation is for its relevance for social inequality, the low values of the separation index are directly informative and readily distinguish between cities with polarized unevenness such as Chicago, Tampa-St. Petersburg, and Lubbock and cities with dispersed unevenness such as Topeka and Erie. In contrast, the high values of the dissimilarity index are unreliable and often misleading. The values of D are not low in any of these cities and, for example, D is higher in Erie (75.2) than in Lubbock (74.3), even though the segregation pattern in Lubbock is clearly fundamentally different from the pattern in Erie. The separation index readily distinguishes between the two patterns where the dissimilarity index utterly fails.

We chose examples featuring White-Black segregation in metropolitan areas in 1990 where P varies in a narrow range (92.0–95.6) to keep the differences between the cities considered to a minimum. But even within this relatively narrow scope, we are able to provide compelling examples of how D and S provide different insights into residential segregation. The separation index is clearly superior with regard to being able to identify patterns of segregation that contain the precondition of group separation across areas that creates the logically possibility for group differences in stratification on life chances and opportunities based on residential segregation.

We conclude this section by noting that the differences between D and S take on great importance in the findings we report in our analysis chapters. For example, we will see that the pattern of polarized unevenness, the pattern most closely linked to segregation and racial stratification, is much more common for White-Black segregation than for White-Latino segregation and White-Asian segregation, with the pattern of polarized unevenness in fact being quite rare for White-Asian segregation. We also show that White-Latino segregation generally follows the pattern of polarized unevenness in areas of established Latino presence but takes the form of dispersed unevenness in areas of limited Latino presence. Relatedly, we show that in general White-Latino segregation in new destination communities initially takes the form of dispersed displacement in the early stages of Latino settlement but as the Latino population becomes more established, segregation shifts toward the form of polarized unevenness. This leads to the seeming paradox where values of D are falling over time in Latino new destination communities while values of S are rising. The examples we review here illustrate how this can happen. Values of D are uninformative about group separation; they register the group difference in relative distribution across below-parity areas and parity areas but, since *D* is insensitive to how groups are distributed across below-parity areas, a high value on *D* can readily reflect either low or high separation of groups. Consequently, it is not only logically possible for group separation as measured by *S* to be rising while group differences in residing in below-parity areas are stable or falling, it is in fact a typical pattern for White-Latino segregation in new destination communities.

2.7.4 Dissimilarity, Separation, and Isolation Indices

Empirical studies of residential segregation often rely solely on the dissimilarity index to measure uneven distribution. But many studies also consider the "p-star" (P^*) isolation index (*I*) as a supplement to *D*. As a general practice we view this as perfectly fine because the isolation index provides potentially interesting information about the level of same-group contact a particular group experiences. At the same time, however, we also stress that this does not change the value and need to examine the separation index if one is interested in group separation. While the separation index and the isolation index both can be formulated in terms of same-group contact calculations, *S* is conceptually and mathematically distinct from *I* in two fundamental ways. First, following the standard practice adopted when measuring uneven distribution, contact terms relevant for the separation index are calculated using just the counts for the two groups in the comparison while contact terms relevant for the isolation index are calculated using counts for all groups in the population. This can lead the respective contact terms to take very different values depending on whether groups other than the two in the segregation comparison are present in the community. Second, even if the isolation index is computed using just the pairwise group counts, there is no necessary relationship between the scores for *I* and *S*. The isolation index registers the level of same-group contact, which is determined by the relative size of the two groups. This sets the "floor," or minimum value, for same-group contact and uneven distribution, which can raise the value of same-group contact to 1.0 under complete segregation. In contrast, *S* registers same-group contact in relation to its expected value and has no necessary relationship with relative group size. Thus, in the absence of uneven distribution, the expected value of *S* will be zero (0) regardless of the relative size of the groups. The value of *S* rises above zero only when (pairwise) same-group contact is higher than would be expected under integration and the value *S* takes will be a function of the degree to which groups reside in different areas and is not inherently related to relative group size. Accordingly, values of *S* can range from 0.0 to 1.0 at any given value of *I*. Thus, while values of the isolation index can be interesting in their own right, knowledge of *I* does not provide a reliable signal on group separation. The separation index is a direct reliable measure of group separation, while *D* and *I* are not.

2.7.5 Further Comments to Guide Interpretations of Values for Dissimilarity and Separation Indices

To this point we have only discussed *D*-*S* combinations that have distinctively different substantive implications. Here we provide guidance on how the wide range of possible intermediate *D*-*S* combinations can be characterized and interpreted. To begin, we note that it is always logically possible for scores of *D* and *S* to take the same values; this occurs under a condition of maximum polarization of non-parity areas on group composition, which is realized when all non-parity areas are homogeneous (Fossett, 2017).[26] This corresponds to the pattern of polarized unevenness where displacement of group distributions from uneven distribution maximizes group separation. The value of *S* will be lower than the value of *D* if any non-parity areas are not fully polarized (i.e., are not homogeneous). In empirical residential distributions, many non-parity areas will be less than homogeneous, even in high segregation situations like White-Black segregation in Chicago, due to a variety of idiosyncratic factors such as mixed areas that occur along the boundaries of transition between homogeneous portions of urban space. So, it is appropriate to characterize *D*-*S* combinations where *S* is lower than *D* as polarized unevenness – wherein displacement from even distribution involves a high degree of group separation – so long as values of *S* are fairly close to values of *D*.

On the other end of the continuum, the pattern of dispersed unevenness – uneven distribution without group separation – always involves a large *D*-*S* difference. In general, this occurs when no non-parity areas are homogeneous and instead most areas are quantitatively relatively close to parity. Fossett (2017) provides a technical review of the logical possibilities. The point most relevant for the present discussion is that when *D* is at a medium or higher level (e.g., $D \geq 40$) the pattern of maximal or near-maximal dispersed unevenness will produce a large *D*-*S* difference and the difference can be very large when the groups are imbalanced in size.[27] The potential for *D*-*S* divergence flows from the fact that they measure different aspects of uneven distribution. The separation index registers group separation which is greater when non-parity areas are quantitatively further from parity and polarized on group composition. In contrast, *D* registers group displacement into non-parity areas without regard for whether the areas are polarized or relatively near parity. Thus, a larger *D*-*S* difference is a sign that uneven distribution involves dispersed unevenness into near parity areas and low group separation while a smaller *D*-*S* difference is

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[26] This condition produces a symmetrical, trapezoid-shaped segregation curve Duncan and Duncan (1955) termed a "Williams" curve. In real cities it may not be possible to create this exact pattern due to the mathematical quirks of integer arithmetic (i.e., because household counts are integers, not fractions, the exact pattern many not be feasible). So, it is technically more accurate to say that, under maximum polarization of non-parity areas, the value of *S* will approach the value of *D* and equal it if maximum polarization of non-parity areas can be achieved with integer assignments.

[27] For those who are interested, Fossett provides formulas that establish the logical maximum for *D*-*S* differences under the pattern of maximally dispersed unevenness from even distribution for any value of group composition (*P*).

Table 2.3 Guidelines for categorizing values of dissimilarity and separation (×100) from low to very high under conditions of prototypical segregation (*D-S* agreement)

Index		Low	Medium	High	Very high
Dissimilarity index		0–29	30–49	50–69	70–100
Separation index		0–15	16–34	35–58	59–100

a sign of prototypical segregation wherein uneven distribution involves group separation into non-parity areas that are polarized on group composition.

In empirical analysis, residential distributions in even the most highly segregated communities typically include some non-parity areas with intermediate (non-homogeneous) group composition. Consequently, values of S in empirical studies approach, but do not equal values of D even in exemplars of extreme segregation such as White-Black segregation in Chicago, Cleveland, Detroit, and Milwaukee, which come the closest to embodying a $S \approx D$ combination characteristic of polarized unevenness. Our analysis of the empirical relationship of D and S over thousands of group comparisons suggests polarized unevenness follows the pattern $D = S^{2/3}$, or, alternatively, $S = D^{3/2}$, as reflected, for example, in the combinations of $D = 0.90$ and $S = 0.85$, $D = 0.75$ and $S = 0.65$, $D = 0.55$ and $S = 0.40$, and $D = 0.45$ and $S = 0.30$. These empirical relations provide a basis for classifying patterns of prototypical segregation on a continuum from low to high as suggested in the chart in Table 2.3.

The empirical relationship of D and S in situations of dispersed unevenness and situations that are intermediate between polarized unevenness and dispersed unevenness cannot be summarized as easily, but we offer the following guidelines below.

- When $S \geq D^{3/2}$, the pattern of segregation can be characterized as prototypical segregation wherein displacement from even distribution produces polarized non-parity areas and a near maximum level of group separation.
- When $S < D^{3/2}$, the pattern of segregation can be characterized as near-prototypical segregation wherein displacement from even distribution produces both polarized and non-polarized non-parity areas and thus a high, but well-below maximum, level of group separation.
- When $S < (D - 0.10)^{3/2}$, the pattern of segregation can be characterized as dispersed displacement from even distribution producing many non-parity areas that are relatively close to parity and only a moderate level of group separation.
- When $S < (D - 0.20)^{3/2}$, the pattern of segregation can be characterized as highly dispersed displacement from even distribution producing non-parity areas that are close to parity and a low level of group separation.

Next, the purpose of Table 2.4 is to provide a concrete frame of reference for some of the important findings and conclusions we will offer in the analysis chapters to come. For example, we will conclude that White-Black segregation is exceptional in comparison to segregation involving other groups because uneven distribution is much more likely to take the form of polarized unevenness and creates the logical prerequisite conditions for group inequality on stratification outcomes linked to

Table 2.4 Rules of thumb for characterizing *D-S* combinations (×100) as reflecting uneven distribution involving patterns ranging from dispersed displacement to prototypical segregation

	Low	Medium	High	Very high
Dissimilarity values	20	40	60	80
Separation index ranges for suggested characterizations of D-S combination				
(a) Prototypical	9–20	25–40	46–60	72–80
(b) Near-prototypical	3–8	16–24	35–45	59–71
(c) Dispersed displacement	< 3	9–15	25–34	46–58
(d) Highly dispersed	---	< 9	< 25	< 46
Calculations for characterizations: (d) $S < (D - .20)^{3/2}$, (c) $S \geq (D - .20)^{3/2}$, (b) $S \geq (D - .10)^{3/2}$, and (a) $S \geq D^{3/2}$.				

spatial location of residence. In contrast, we will conclude that White-Asian segregation almost never takes the form of prototypical segregation but instead usually involves a pattern of dispersed or highly dispersed unevenness across non-parity areas that are close to parity and thus creates little to no group separation and minimal possibilities for group inequality on location-based stratification outcomes. Similarly, we will conclude that Latino households in new destination areas initially experience segregation from White households in the form of dispersed displacement into non-parity areas that are near parity, not homogeneous Latino areas, and thus the segregation pattern does not produce high levels of separation from White households. But as Latino households in new destinations become established and their presence grows, the pattern of segregation changes and begins to take on the form of near-prototypical segregation with higher levels of residential separation of White and Latino households. These and other important conclusions are not offered in previous research. The table provides a clear guide to our basis for characterizing these patterns and trends in segregation. They are not subjective assessments; they are conclusions guided in an explicit and clear framework for characterizing segregation patterns.

2.8 Summary and Overview

We conclude this chapter by acknowledging that study design and methods are not the most scintillating of topics. But these aspects of a study are crucially important to the potential for our study to advance understanding of segregation in U.S. communities beyond its current state. Our study's contribution is based in substantial degree on incorporating these recent advances in methods for measuring and analyzing segregation. This is most important in the following areas: distinguishing whether group differences in distribution into below-parity areas produces uneven distribution involving group separation or merely dispersed unevenness; whether values of segregation index scores are unbiased and trustworthy or biased and untrustworthy to some greater or lesser degree; and whether assessments of segregation using unbiased indices take proper account of the fact that locational outcomes for persons residing in households are linked and not independent. These and other issues may not make for exciting reading, but they are important to our ability to document patterns and trends in segregation across U.S. communities more thoughtfully and accurately than has previously been possible. Now, with these crucial issues covered, we turn next to applying these methods to generate empirical findings.

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Chapter 3
National Trends in Racial and Ethnic Residential Segregation

3.1 Overview

In this first chapter of empirical findings, we provide an overview of trends and patterns in the residential segregation of households by race and ethnicity from 1990 to 2010 across metropolitan areas, micropolitan areas, and noncore counties. Metropolitan areas are identified as a cluster of one or more counties associated with at least one urban core with a minimum population of 50,000. These areas include the most populated cities in the United States such as New York City, Los Angeles, Chicago, and Houston along with their associated suburbs and exurban regions as established by commuting patterns and other criteria. Micropolitan areas are defined in a manner similar to metropolitan areas but on a smaller scale, having urban cores with a population of at least 10,000 but less than 50,000. Finally, noncore counties consist of counties that are not associated with an urban core and thus are not included as part of a metropolitan or micropolitan area. Noncore counties are generally considered to be rural in character with no or only limited commuting patterns to urban areas. These three community types give our analysis wide geographic coverage across the United States. We examine segregation between White, Black, Asian, and Latino households across all areas over the two decades bracketed by the three decennial census years of 1990, 2000, and 2010.

The purpose of this chapter is twofold. While many studies have provided broad descriptive analyses of segregation patterns over time for large metropolitan areas, a comprehensive analysis of all communities in the United States, additionally including all smaller metropolitan areas, all micropolitan areas, and all noncore counties, does not exist. Studies by Lichter and colleagues (2007, 2010) have reported analyses for place-based areas including urban, suburban, and rural contexts and stand as the best previous efforts to document segregation in rural and nonmetropolitan communities as well as in large metropolitan communities. We acknowledge and build on these important contributions. Importantly, however, we

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take advantage of new developments in segregation measurement to more effectively address and overcome the problems and challenges that have complicated the measurement and analysis of segregation in nonmetropolitan communities and smaller metropolitan areas.

Previous empirical studies of trends and patterns in segregation, for reasons that we review in more detail here and anticipated in our discussions in Chap. 2, have generally focused on describing and analyzing segregation in larger metropolitan areas and even there only for groups that are fairly large in size. This somewhat narrow focus has not necessarily been by choice. Instead it reflects researcher concerns about the problems associated with measuring segregation in a wider and more representative set of communities and group comparisons. In the past, these concerns were well-founded and have led most researchers to view it as necessary to be selective and limit the scope of research designs to exclude communities and group comparisons where scores for conventional segregation indices are susceptible to distortion by index bias. We overcome the limitations of previous research by drawing on new methods for segregation measurement that allow us to obtain valid and reliable unbiased index scores across a much wider range of communities and group comparisons than could be considered in previous research. Thus, the analyses we report in this chapter provide a more comprehensive descriptive analysis of changes in racial and ethnic residential segregation over time across the United States than has previously been possible because we obtain measurements of segregation that are free of index bias and therefore are more accurate and trustworthy for sustaining comparisons of segregation across nearly all communities, ranging from the largest metropolitan areas to the smallest noncore counties and for group comparisons involving both large and small group populations. In doing so, we also establish benchmarks against which anticipated analyses of segregation using the 2020 census can be compared.

Because a portion of this chapter involves reanalyzing segregation in large metropolitan areas that have already been widely studied and analyzed, we anticipate the patterns that we document in those communities may not deviate much from previous findings even though we are using new improved measurement methods that will sometimes lead to changes in index scores. This is largely because, as mentioned previously, most past studies have been careful to restrict the scope of their analyses to include only communities and group comparisons where they do not see a high risk of conventional measures being significantly distorted by the problem of index bias. For example, a common practice in segregation research is to impose restrictions on the set of communities in the analysis sample by including only the largest 50 or 100 metropolitan areas or group comparisons where both groups meet a combination of minimum absolute size and minimum population share (e.g. Frey, 2018; Iceland, 2014; Massey & Denton, 1988). These restrictions, particularly the focus on large metropolitan areas, exclude a significant portion of communities across the United States from segregation analysis.

Two other related practices include avoiding measuring segregation using neighborhood geography (spatial units) smaller than census tracts (e.g. Iceland et al., 2002) and differentially weighting cases to deemphasize the impact of cases more susceptible to index bias. The choice to measure segregation by operationalizing neighborhoods using census tracts for spatial units leads to underestimation of segregation outside of large metropolitan areas because large spatial units cannot accurately capture segregation that is manifest at smaller spatial scales in nonmetropolitan communities and smaller metropolitan areas. There are a few prior studies that have measured segregation using smaller spatial units at the census block level (e.g., Lichter et al., 2010; Allen & Turner, 2012), who also go beyond metropolitan contexts to study segregation in small towns and rural counties. However, these studies have faced an unavoidable dilemma with no good choices. Researchers are left with the strategies that we have previously described, which include working with segregation index scores that in some, perhaps many, cases are likely to be inflated by index bias at nontrivial levels that vary in magnitude across different communities and different segregation comparisons or excluding communities and group comparisons to minimize these problems. Tending toward the second choice has the severe practical consequence of essentially foregoing the possibility of studying segregation in nonmetropolitan communities and smaller metropolitan areas. Thus, in the past, researchers wishing to study segregation in nonmetropolitan settings have had to hope for the best and cope with higher levels of index bias than they would otherwise wish to, or otherwise avoid studying segregation in nonmetropolitan communities altogether.

Because researchers most often choose to avoid the problem by studying segregation of large subgroups in large metropolitan areas, we anticipate that many general patterns of segregation in large metropolitan areas that have been reported in previous studies will generally, though not necessarily always, be replicated in this chapter. Even so, our choice to measure segregation using data for households rather than persons, and including a larger range of group comparisons, may yield results that will expand and refine what we know about segregation in metropolitan contexts and potentially lead to new findings and insights. In contrast, we strongly anticipate that the findings we report for nonmetropolitan communities – namely, micropolitan areas and noncore counties – will be significant new additions to knowledge about segregation outside of large metropolitan contexts. This will be the case regardless of what we find because currently concerns about the challenges of measuring segregation in nonmetropolitan settings are unsettled. If findings of previous research are largely replicated, it will be valuable to know that concerns about measurement are resolved in a way that leaves previous research findings intact. If findings of previous research are not consistently replicated, it will be valuable to know that concerns about measurement were justified in some degree and research going forward must use newer, more appropriate methods of measurement to accurately document trends and patterns in segregation.

3.2 Previously Observed Trends in White-Black, White-Latino, and White-Asian Segregation

Among the major nonwhite panethnic populations in the United States, Black households have been the most highly segregated from White households across the nation on all major dimensions of segregation and thus experience conditions of hypersegregation (high levels of segregation on several of the five dimensions of segregation identified by Douglas Massey and Nancy Denton (1988)) in many of the large metropolitan areas of the Midwest and Northeast (Massey, 2020; Massey & Denton, 1989; Massey & Tannen, 2015; Wilkes & Iceland, 2004). Black segregation, particularly in urban areas, is a deeply entrenched pattern that has been molded by over a century of overt and covert discriminatory practices to exclude Black households from White neighborhoods and undervalue the neighborhoods where they reside (Massey & Denton, 1993). Although researchers in recent decades have documented steady, albeit small declines in White-Black segregation over time (Frey, 2018; Iceland, 2014; Iceland et al., 2002), patterns of White-Black segregation are still distinct and carry on serious consequences within and across generations that have resisted change to a greater degree than for any other group comparison (Sharkey, 2013). High levels of White-Black segregation enable other inequities to persist that restrict opportunity and negatively impact the well-being of Black people (Massey, 2020). According to the 2010 Census, 14 percent of the United States population identified as Black alone or in combination with one or more other races. This is a 12 percent increase from 2000, a growth rate faster than that of the U.S. population as a whole (U.S. Census Bureau 2010). The Black population is also overwhelmingly native-born, meaning that the dynamics of residential and other social outcomes play out differently than they do for non-Black Latino and Asian households because the role of ethnic enclaves supported by influxes of immigrants is less pronounced.

The Latino population is now the largest nonwhite racial-ethnic group in the United States, having grown by 43 percent from 2000 to 2010 to stand at 16 percent of the national population by 2010 (U.S. Census Bureau 2010). The majority of this rapidly growing, multicultural population is of Mexican origin, with the second largest portion of the Latino population being of Puerto Rican origin. Despite sustained and fast population growth, past research indicates Latino households have been and continue to be only moderately segregated from White households on the two most widely studied dimensions of uneven distribution and isolation (Charles, 2003; Frey, 2018; Iceland et al., 2014; Massey & Denton, 1987). However, holding uneven distribution constant, population growth resulting from both natural increase as well as immigration have necessarily led to higher levels of isolation and a decrease in exposure to White households (Charles, 2003; Massey & Denton, 1987). And while White-Latino uneven distribution has in general been moderate, overall the uneven distribution of the Latino population in metropolitan areas has not declined as observed for Black households but instead has at least remained stable and may in some cases have increased, particularly in metropolitan areas where there has been greater Latino population growth (Frey, 2018; Iceland, 2014; Iceland et al., 2014; Iceland et al., 2002; Logan & Stults, 2011). At the individual level, research suggests that group differences in social and economic characteristics may be a significant contributing factor in White-Latino segregation. These studies note that, particularly in comparison to Black households, Latino households often experience greater levels of residential contact with White households as they acculturate and assimilate on socioeconomic status (Alba & Logan, 1993; Charles, 2000; Chetty et al., 2020; Crowell & Fossett, 2018, 2020, 2022; Massey & Fong, 1990). A caveat here is that this may not hold true for Black Latino households.

While studies of Latino segregation most often give attention to "traditional" or "established" areas of Latino settlement along the Southwest border and in major metropolitan areas, Saenz (2004) and Vásquez et al. (2008) have reported evidence that Latino households in general are moving away from the traditional areas of Latino population concentration such as the Southwest and entering new areas of settlement and residence that previously did not have sizable Latino populations across the Midwest and the South. This movement has inspired a new direction in the Latino residential segregation literature as researchers have begun to examine the residential patterns of Latino households in these "new destinations" (Lichter et al., 2010). This situation is of great interest both because of the rapid growth of the Latino population nationally and the special methodological challenges involved in tracking White-Latino segregation over time in new destination communities. Accordingly, we give separate and focused attention to these trends in Chap. 5.

Although well short of approaching the absolute size of the Latino population, the Asian population in the United States also has been growing rapidly in recent decades and therefore has been receiving greater attention in studies of residential segregation. In 2010, persons who identified as Asian either alone or in combination with one or more other races comprised 5.6 percent of the total U.S. population, a 45.6 percent increase since 2000 (U.S. Census Bureau 2010). Over the past half century Asian immigration has transformed the overall U.S. Asian population from being predominately Chinese and Japanese to also including other groups who ethnically identify as Filipino, Korean, Asian Indian, Vietnamese, Cambodian, and Laotian. Still, as of the 2010 census, the majority of the Asian population was comprised of the Chinese, Asian Indian, and Filipino subgroups (Hoeffel et al., 2012). Like the Latino population, the Asian population is a fast-growing group, but this growth is primarily due to immigration and less to natural increase. In addition to a small set of immigrant "gateway" metropolitan areas and a few other areas of historical Asian presence, metropolitan areas in non-traditional areas such as the South have seen significant Asian population growth in recent decades, suggesting that there may also be an Asian new destination phenomenon emerging (Flippen & Kim, 2015; Hoeffel et al., 2012).

Past research has consistently reported comparatively low-to-moderate levels of White-Asian uneven distribution and minimal change over time, as well as relatively low, albeit rising, levels of Asian isolation with relatively high but slightly declining exposure to White households (Charles, 2003; Frey, 2018; Iceland, 2014; Iceland et al., 2014). Similar to Latino households, much of the documented change in overall contact patterns is primarily due to Asian population growth, since uneven distribution has been mostly stable over time (Iceland et al., 2014; Logan & Stults, 2011). The literature shows that among minoritized racial populations, the Asian population as a whole is generally the least residentially segregated from White households and also that Asian households experience greater residential contact with White households as they acculturate and make socioeconomic gains in comparison to other minoritized racial groups, which in turn may lead to less residential segregation (Crowell & Fossett, 2022; Massey & Denton, 1987; Massey, 2020; Sakamoto et al., 2009; Zhou & Logan, 1991). Of those who identify as Asian alone, approximately 70 percent are foreign-born, and the foreign-born Asian population makes up 28 percent of the total foreign-born population in the United States (American Community Survey 2007–2011). Because of the nature of Asian immigration to the United States, the Asian population is also highly selective on higher educational and socioeconomic standing, although certain nationalities represented in the United States such as the Cambodian and Hmong populations, who arrived in the United States in the context of violent political conflict, exhibit lower levels of socioeconomic standing on average.

Demographic trends in the Asian and Latino populations pose special problems for tracking trends in segregation over time and variation in segregation across communities. In particular, these subpopulations vary considerably in absolute and relative size across different communities and within given communities over time. These demographic patterns create the possibility that segregation comparisons using standard index scores may be impacted by index bias in complex and unwelcome ways. National and local changes in the size of the Black population have been more modest in recent decades, especially in comparison with changes that took place during the Great Migration era from 1910 to 1940. But the Black population has diffused in some degree in recent decades to areas which previously had minimal Black population presence. Our use of new methods for obtaining unbiased index scores will allow us to examine these trends and patterns with greater confidence that the variation observed is real and not artifactual, thus providing more clarity in understanding these trends and patterns. These brief demographic descriptions of the minoritized racial populations included in our analysis serve two purposes. The first is to provide context for understanding variations in segregation patterns across areas and over time. Understanding the populations involved and their characteristics allow us to go a step beyond descriptive analysis to speculate on the underlying reasons for any changes we observe. The second purpose is to acknowledge previous segregation studies of these populations which have set the basis for received wisdom regarding trends and patterns in the segregation of minoritized racial groups in the United States. Because our approach to measuring segregation differs from the approaches used in prior empirical studies in the segregation literature, we will be interested to see whether our findings track or differ from the previously established baselines regarding the level and nature of segregation and how it varies across group comparisons, across communities, and over time.

3.3 The Historical Context of Segregation

Many factors are relevant to observed variations in levels of racial and ethnic residential segregation. These include the particular groups included in the comparison and basic demographic characteristics such as the population size of the community and the relative size of the groups in question. White-Black segregation is deeply woven into the fabric of urban spatial distributions from a history of formal, legal, and institutional segregation policies operating alongside informal, extra-legal behaviors, with both being driven by overt racial prejudice against the Black population. White-Black segregation in rural areas also has a distinct character shaped by the historical role of Black Americans in the agricultural economy of the rural South and the legacy of centuries of slavery, sharecropping, and Jim Crow segregation. White-Latino segregation has been impacted by the significant increases in immigration that began in the 1960s, bringing in large numbers of new arrivals with distinctive differences in language, culture, socioeconomic status, and legal standing. This population often encounters formal and informal constraints when choosing their residential locations. In addition, the Latino population is highly heterogeneous with wide diversity in racial identity, ethnic identity, and national identity across regions and among recent immigrant populations. For example, the highest levels of White-Latino segregation are found in the metropolitan Northeast where segregation looks similar to levels of White-Black segregation. One reason for this is that the Northeast has more Black Latino individuals, who identify as Latino but who also in many cases self-identify as, or are racialized by others as, Black. Latino individuals who racially identify as White or are perceived as White are likely to experience the lowest levels of segregation.

Similar observations apply regarding White-Asian segregation, as the Asian population in the United States has a unique and complex history. Prior to recent decades, the Asian population was small at the national level and was concentrated in a select number of communities in the United States where Asian communities were often subjected to overt legal and extra-legal discrimination from the middle–1800's up to the Civil Rights Era. But, following changes in immigration policy in the 1960s, the Asian population grew rapidly through primarily legal immigration that was highly selective in terms of socioeconomic status and skilled employment and also in some instances by refugee resettlement programs that often involved support and sponsorship. The scale of immigration was such that the Asian population shifted substantially toward having a high percentage of foreign-born and also having greater ethnic and national diversity. As a predominately foreign-born population, Asian residential settlement patterns are shaped by the economic and political conditions that contextualize immigration patterns for each Asian ethnic group that has immigrated to the United States, enclave formations, and the degree to which they experience social distance from White households. In general, but with important exceptions, the Asian immigrant population differs from the Latino immigrant population of recent decades in terms of having a higher socioeconomic profile, a smaller undocumented population, and a greater concentration in large and growing metropolitan centers with higher wages. In particular, in comparison with Latino and especially Black households of similar socioeconomic standing, high-income, high-education Asian households are likely to have greater residential contact with White households. Asian ethnic groups with lower socioeconomic resources, such as groups with a history of refugee resettlement, are likely to be more segregated from White households and less likely to reside in affluent neighborhoods.

3.4 Data

For our empirical analyses we draw on census block-level tabulations of households by race and ethnicity reported in the 1990–2010 decennial census summary files. We use these data to calculate pairwise segregation scores between White, Black, Latino, and Asian households for metropolitan and micropolitan core-based statistical areas (CBSAs) and noncore counties as defined in the 2010 census. White householders are defined as those who are non-Hispanic and who racially identified as White alone, while other racial groups include those who identify as Latino or Hispanic, as this is how household tabulations are constructed for public-use summary files. Latino householders are defined as anybody who indicated that they were "of Hispanic, Latino, or Spanish origin" (Census 2010 Questionnaire). These racial-ethnic categories were relatively stable over the 1990, 2000, and 2010 censuses with the exception that beginning in 2000 respondents could select more than one race to reflect multiracial identity, a change that resulted in less than 10% of the U.S. population identifying as two or more races in either decade.

As discussed in more detail previously in Chap. 2, we use data for households because this is the appropriate micro-level unit to use when calculating unbiased index scores. Data for persons are not generally appropriate for computing unbiased index scores for residential segregation because persons residing in multi-person households locate together, not independently. And, because households are overwhelmingly homogeneous on racial-ethnic group, the correlated locational outcomes of same-race members of households creates most of the bias in standard index scores. Basic tabulations of persons by race cannot sustain the proper calculations needed to obtain accurate unbiased index scores, but the proper calculations can be implemented using tabulations of households by race.[1] There is another side benefit of using data for households, which is that segregation scores based on tabulations of persons often include subpopulations not residing in households such as persons in

[1] Technically, valid unbiased scores can be calculated using person data if one has access to detailed tabulations of persons by race and size of household for the relevant spatial units. The calculations are not feasible for the study period considered here because relevant tables are not available in all years. We conducted methodological studies (not reported here) that confirmed, we would say not surprisingly, that unbiased index scores computed using data for households correlated near-perfectly with unbiased index scores computed using relevant detailed data for persons.

institutions and/or in group quarters that sometimes can distort segregation comparisons.[2]

The advantage of using county-based areas is that county boundaries are highly stable across time. For the handful of counties that changed boundaries across the three decennial census years considered in our analysis, we excluded the ones where boundary changes could not be reconciled to stable definitions over time. We also implemented the additional selection criterion of excluding CBSAs and noncore counties where the number of households for either group in the analysis is less than 50 households – which typically translates into 150–250 persons – or where the percentage share of the smaller group in the comparison is less than 0.5 percent. In comparison to selection criteria used in prior research, these restrictions are fairly liberal. This reflects the advantages of using new methods for segregation measurement. The unbiased indices we use can sustain valid, reliable measurement even when groups are small in absolute and/or relative size. In contrast, standard versions of indices of uneven distribution, and in particular the dissimilarity index (D), do not maintain acceptable behavior under similar conditions because their scores are distorted, often to a dramatic degree, by the impact of index bias.

The selection criteria, while liberal in comparison to those commonly used in previous research, still serve to screen out many logically possible combinations of group comparisons across communities. But this primarily reflects the demographic reality that for many communities the population in the community does not have the minimal numbers needed to sustain meaningful analysis of residential segregation for the excluded group comparison. After implementing these selection criteria, we are still left with a sizeable number of CBSAs and noncore counties for analysis for most segregation pairings (Table 3.1). The main exception is that very few noncore counties met the criteria for analyzing White-Asian segregation as the Asian population is overwhelmingly urban. As we review more closely below, the number of areas included varies depending on the year, area type, and the group comparison in question. Because the selection criteria we use are more inclusive, our analysis sample includes more communities and more segregation comparisons than would be the case if we used standard index scores and the more restrictive criteria needed when using standard scores. As a result, our analysis dataset is more representative of the full range of communities and group comparisons that could be considered.

[2]This is not an issue if tabulations for persons exclude persons residing in institutions, group quarters, and other settings that are not relevant to measuring residential segregation. But this is not the case in all decades. In that situation, cases must be reviewed, flagged, and excluded if index scores are potentially subject to distortion by the presence of these subpopulations.

Table 3.1 Areas included in analysis by year, area type, and pairing

Comparison	1990	2000	2010
White-Black			
Non-core	442	439	452
Micropolitan	366	383	428
Metropolitan	337	359	370
White-Latino			
Non-core	337	594	800
Micropolitan	357	511	565
Metropolitan	343	372	384
White-Asian			
Non-core	13	28	66
Micropolitan	110	199	284
Metropolitan	263	327	364
Black-Latino			
Non-core	131	284	375
Micropolitan	325	430	490
Metropolitan	371	379	383
Black-Asian			
Non-core	8	14	62
Micropolitan	161	275	378
Metropolitan	370	381	384
Latino-Asian			
Non-core	20	34	87
Micropolitan	204	316	405
Metropolitan	380	384	384

3.5 Measurement

In this chapter we rely primarily on the separation index (S), which measures the dimension of *evenness*, or the extent to which the racial composition of neighborhoods deviates from the overall composition of the area. For comparison we also include an analysis using the more widely used dissimilarity index (D). Both indices have a fairly straightforward interpretation, especially when conceptualized in the difference-of-means formulation discussed in Chap. 2 (and in more detail in Fossett, 2017). In the case of segregation from White households, the widely used dissimilarity index can be interpreted as the difference in the proportion of each group (e.g. White households and Black households) that lives in a neighborhood where the proportion White for the neighborhood equals or exceeds parity (i.e., is equal to or greater than the proportion of the population that is White for the community overall). The separation index has an even simpler interpretation; it is the difference in the average neighborhood-level proportion White between the two groups in the analysis.

In Chap. 2 we described scenarios where the separation index and the dissimilarity index can deviate from one another. In these situations, the value of S gives the more reliable signal regarding whether the two groups in the analysis in fact live apart from each other in different spatial domains within the community – the hallmark of "prototypical segregation" which is characterized by polarized displacement from even distribution, or *polarized unevenness,* that can sustain group differences in location-based outcomes. In contrast, D cannot provide a reliable signal on group separation because D inherently reacts strongly to neighborhood departures from parity that are quantitatively small and thus can take on high values even when the two groups in the comparison live together in neighborhoods that are similar on neighborhood group composition and have similar levels of contact with the reference group in the comparison – a condition Fossett (2017) terms dispersed displacement from even distribution, or *dispersed unevenness*. The situation of dispersed unevenness always involves a particular combination of index scores; namely, a high score on D and a low score on S. We call attention to these situations for three reasons. One is that the possibility of these situations, not to mention their relatively common occurrence, is not widely appreciated by segregation researchers. The second is that, bluntly, the high value of D in these situations can be highly misleading because many incorrectly assume that a high value of D will involve group separation and the potential for group inequality in area-based outcomes (e.g., pollution, crime, opportunities, amenities, services, etc.).

The third reason is that our analyses document important systematic patterns in the occurrence of segregation involving dispersed and polarized unevenness. For example, polarized unevenness – situations where D and S are similar – are typical for White-Black segregation. This means that Black households live apart from White households in different spatial domains in the community and thus have low contact with White households and can experience location-based disadvantages that do not affect White households. This fact, plus the fact that segregation studies from the 1940s to the 1980s typically considered only White-Black segregation, may partly account for why so many incorrectly assume that high values on D indicate that groups are separated across spatial units and thus can (and may be likely to) experience group inequality on location-based outcomes. In contrast, dispersed unevenness – situations where D is high and S is low – are typical for White-Asian segregation. This means that in general, Asian households live alongside White households in the same spatial domains in the community and thus experience high contact with White households and cannot experience location-based disadvantages that do not affect White households. We also find that the situation for White-Latino segregation is more complicated because both patterns of segregation – dispersed and polarized patterns of unevenness – are common. Dispersed unevenness is common in new destination communities where Latino households are a new and relatively small presence in the community and few Latino households live in neighborhoods that are predominantly Latino. Polarized unevenness is more common in established communities where Latino presence is larger and long-standing and where it is likely that a substantial fraction of Latino households will live in neighborhoods that are predominantly Latino.

These are important distinctions because the pattern of polarized unevenness creates the maximum differences in group contact and the possibility of opportunity-hoarding and differential group disadvantage on location-based outcomes. The separation index will more reliably signal when segregation of this nature is occurring. Thus, towards the end of the chapter we comment on the empirical importance of index choice for generating findings and review how observing *S* and *D* together can be informative for describing changing patterns of unevenness between dispersed and polarized configurations. Under the sorts of conditions that we identified where index bias is prevalent and *D* can take high values at the same time that *S* does not, the two indices often do not change in the same ways over time. We are able to demonstrate in this chapter how this index divergence is not a flaw but rather is reflecting an observable pattern transition in the type of uneven distribution that is present. But even so, in situations where values of *D* and *S* differ in our empirical results, we assign priority to the value of the separation index for drawing substantive conclusions about trends and patterns in racial and ethnic residential segregation across the United States.

To interpret these scores, we use the schema shown in Table 3.2 (adapted from Fossett, 2017). The table shows the guidelines we will follow when characterizing scores for the separation index and the dissimilarity index as ranging from low to very high. One thing the table indicates is that for any given category the numerical range for *D* runs well above the numerical range for *S*. Scores for *D* inherently run higher than scores for *S* because *D* always responds more strongly than *S* when neighborhood departures from parity are not fully polarized (i.e., do not involve homogeneity of either group in the comparison). The boundary ranges for *D* make allowances for this. Thus, we do not characterize moderate *D*-*S* differences as indicating discordance. However, we do characterize step differences across categories – for example a high score on *D* (in the range 50–69) and a medium score on *S* (in the range 15–34) – as indicating *D*-*S* discordance, which signals the segregation pattern involves unevenness that is dispersed rather than polarized.

This chapter is also our first opportunity to empirically demonstrate the importance of using the unbiased formulations of segregation indices as described in Chap. 2 and developed by Fossett (2017). To review, nearly every commonly used measure of segregation that is based on some calculation of neighborhood-level composition is susceptible to an artificial upward bias when calculated using conventional formulas. Most segregation researchers are aware of this problem and avoid it by excluding cases where the bias is most likely to occur. The formulas we use to obtain unbiased index scores make case exclusion unnecessary as the formulas eliminate the source of upward bias that distorts scores obtained using standard formulas, thus yielding scores that can be treated as valid and reliable as given and

Table 3.2 Categorization schema for interpreting segregation scores (Fossett, 2017)

Level	Separation index	Dissimilarity index
Low	0–14	0–29
Medium	15–34	30–49
High	35–59	50–69
Very high	60–100	70–100

eliminating any need to consider post hoc adjustments or differential weighting of scores across cases.

As a brief reminder, we note again that the difference-of-means formulas for calculating index scores pinpoint the sole source of upward bias in standard index scores; it is the incorporation of self-contact in the calculation of an individual household's level of contact with the reference group in the comparison. The crux of the matter is that self-contact is fixed (it cannot be randomly assigned) and it varies systematically by group. Thus, if White households are designated as the reference group when calculating index scores for White-Black segregation, self-contact is always positive for White households and it is always zero for Black households. This creates an inherent value that is greater than zero for the group difference in average contact, even under random assignment. In contrast, contact with White households among others (excluding the focal household) will have the same expected value for White households and Black households under random assignment and thus has no impact on index bias. Revised formulas reviewed in Chap. 2 and in Fossett (2017) eliminate self-contact from index calculations and in so doing yield unbiased index scores (i.e., scores that have expected values of zero under random assignment). When unbiased scores differ from standard scores, the unbiased scores should be preferred. If bias is not a problem, the scores will not disagree. Therefore, the optimal choice is to use the unbiased indices.

3.6 Trends and Patterns of Racial and Ethnic Residential Segregation, 1990–2010

We begin by reviewing levels of White-Black, White-Asian, and White-Latino segregation as measured by the separation index (*S*), which are summarized in Table 3.3 and presented by decade and type of community alongside the more familiar dissimilarity index (*D*) in Table 3.4. While the separation index is our optimal index for measuring segregation and what we use to draw substantive conclusions about patterns and trends of residential segregation, we recognize that most readers are more familiar and comfortable with the dissimilarity index and that it has been the index behind much of what we know from the literature so far about residential segregation. Thus, we include it in Table 3.4 so that we can further explain why we prefer the separation index in comparison to the dissimilarity index and what impact that has on our findings and conclusions. Our choice to begin by examining Black, Latino, and Asian segregation from White households also warrants explanation. These three White-nonwhite group comparisons are a

Table 3.3 Descriptive statistics for distributions of scores for separation index

Comparison	Mean	S.D.	P_{10}	P_{50}	P_{90}
White-Black	36.24	21.30	5.63	38.56	62.95
White-Latino	12.33	11.17	1.22	8.72	28.73
White-Asian	7.73	7.40	1.49	5.10	18.33

Table 3.4 Segregation index (unbiased) by year, community type, and group comparison

Comparison	1990		2000		2010	
White-Black	S	D	S	D	S	D
Non-core	49.18	66.50	42.09	60.70	37.15	55.15
Micropolitan	38.95	59.84	31.09	54.03	24.60	47.91
Metropolitan	39.81	61.96	33.07	57.26	28.75	52.57
White-Latino						
Non-core	14.86	29.77	12.50	28.45	11.55	25.71
Micropolitan	10.43	30.53	10.64	29.79	11.18	27.99
Metropolitan	11.58	33.60	14.42	35.74	15.82	35.40
White-Asian						
Non-core	6.42	28.18	7.92	31.51	6.55	30.30
Micropolitan	8.91	36.77	6.99	36.44	6.62	33.66
Metropolitan	7.90	37.10	7.94	40.23	8.58	38.71

central focus in segregation research in the United States because residential segregation among racial-ethnic groups is a stratification outcome and is closely linked to group position and group inequalities across a wide range of location-based outcomes including basic living conditions, exposure to crime and social problems, amenities, social and economic opportunities, political influence, quality and responsiveness of government services, and more (Stearns & Logan, 1986; Massey & Denton, 1993; Firebaugh & Farrell, 2016; Krysan & Crowder, 2017). Given the White population's historical standing as the majority group in racial-ethnic relations in the United States, predominantly White neighborhoods have consistently been found to be advantaged on location-based outcomes, and residential separation from White households has consistently been found to be associated with related White-nonwhite disparities and broad systematic disadvantages for nonwhite groups, especially for Black households. This context for segregation theory and research makes the separation index an excellent choice for measuring uneven distribution because, among all widely used indices, *S* best indicates when groups occupy different residential spaces, thus creating the conditions that make group inequalities in location-based outcomes possible.

After reviewing White-nonwhite residential segregation patterns, we will next examine segregation between nonwhite groups including Black-Latino, Black-Asian, and Latino-Asian residential segregation patterns from 1990 to 2010. It is not common for segregation studies to focus on patterns between nonwhite groups for the theoretical reasons stated above and also due to the methodological challenges described in Chap. 2 as well as in the previous sections of this chapter. Finally, in this section we also include some discussion regarding the impact of our measurement approaches on our empirical findings and provide explanations to reconcile findings that may differ from what has been previously asserted in the literature on residential segregation patterns and trends over time. The two primary issues here are the extent to which index bias has affected previous studies and the inherent shortcomings of the dissimilarity index, which has been the workhorse of segregation research for many decades. Both issues, fortunately, are fairly simple to explain and resolve.

3.6.1 White-Black Segregation

Overall, we find segregation between White and Black households to be the highest among the three White-nonwhite comparisons considered in this analysis and by a large margin in both relative and absolute terms. The values of the separation index for White-Black segregation vary widely across the communities in our study with a mean of 36.2, a median of 38.6, a standard deviation of 21.3, and an inter-decile range of 57.3 points extending from 5.6 to 63.0 at the 10th and 90th percentiles, respectively. The typical level of White-Black segregation across all communities is at medium-to-high levels. Noncore counties in 1990 have the highest average level of White-Black segregation for the groupings of communities reported in Table 3.4 at 49.2 points on *S*. Based on the guidelines we presented in Table 3.2, this is a high level of segregation. Substantively, a value of *S* on the order of 49 means that, for the community in question, the relative presence of White households among neighboring households is 49 points lower for the average Black household compared to the average White household.

Values of *S* in this range provide a clear signal that White-Black segregation consistently involves polarized unevenness, which Fossett (2017) terms prototypical segregation because it is the pattern that immediately comes to mind for broad audiences and segregation researchers alike when they are told the level of segregation is high. In this prototypical pattern, White and Black households generally reside in different neighborhoods where their neighbors are predominantly from their own group. This then creates the structural precondition for White and Black households to experience substantial differences on location-based outcomes. However, while we find high and prototypical White-Black segregation in noncore counties, the more commonly experienced outcome across areas is medium levels of segregation, especially by 2010. The separation index for micropolitan and metropolitan areas in 2010 averages below 30, which is firmly within the moderate range. This finding would appear to be in conflict with what past research has found using the dissimilarity index, and indeed the dissimilarity index, even after correcting for index bias, remains at high levels for all areas in every decade. The discordance between the two indices grows larger over time. This finding has a simple explanation when it is understood that the separation index responds to patterns of displacement from even distribution in a way that the dissimilarity index cannot. As the separation index drops to medium levels while the dissimilarity index stays high, the underlying patterns driving this change are shifting from polarized to dispersed unevenness. Black households are still typically living in neighborhoods that are below parity on proportion White, but they are having more residential contact with White households in their neighborhoods over time.

The finding that White-Black segregation is highest among White-nonwhite comparisons holds across all three decades and all three community types. Regarding the level of segregation, we find that the average values of *S* for White-Black segregation are higher than the average values of *S* of other White-nonwhite comparisons by at least 25 points, a very large amount in both absolute and relative terms. Regarding changes over time, the average value of *S* for White-Black segregation declined substantially over the decades and falls by an average of 10 or more points from 1990 to 2010. Declines of this absolute magnitude are substantively important in their own right. They are equally if not more important when considered in relative terms as the average declines in raw scores represent relative declines of 20–25 percent over the two decades.

As for variation across types of communities, White-Black segregation as measured by *S* is highest in noncore counties compared to CBSAs by about 9–10 points. Among CBSAs, segregation is higher by 1–4 points in metropolitan areas compared to micropolitan areas. In 1990, the mean levels for all three areas were in the high range of 35–59 given in the schema in Table 3.2, with noncore counties in the top half of this range and CBSAs near the lower end of the range. Even after sizeable declines over the decades, White-Black segregation in noncore counties remained in the high range in 2010. In contrast, the similar declines of 10 or more points for White-Black segregation in metropolitan and micropolitan areas dropped the averages for these communities to below 30 and into the medium range of 15–34 points.

Because of the widely studied and understood circumstances of White-Black segregation that we are familiar with, where polarized unevenness is more common even in smaller, nonurban communities, we did not expect to uncover a story about White-Black segregation that is much different from what past studies have shown. When the pattern of unevenness is polarized, the separation index and the dissimilarity index will be in closer alignment. What we can conclude is what others have found, which is that White-Black segregation is on the decline from initially high levels across all communities, although these two groups still remain the most segregated from one another. But by focusing on the separation index, we contribute an added detail to our understanding of White-Black residential segregation and its trends over time. It is that in addition to the groups gradually becoming more evenly distributed, their pattern of unevenness is also becoming more dispersed. This means that overall, Black households are having more equal levels of residential contact with White households.

3.6.2 White-Latino Segregation

White-Latino segregation is a more complex and surprising story given the findings consistently reported in the literature of moderate and persistent White-Latino segregation with levels of segregation a bit below White-Black segregation. Therefore, this section warrants a more extended discussion. In contrast to previous findings, we find values of the separation index for White-Latino segregation are at levels well below White-Black segregation and vary in a narrower range across the communities in our study with a mean of 12.3, a median of 8.7, a standard deviation of 11.2, and an inter-decile range of 27.5 points extending from 1.2 to 28.7 at the tenth and 90th percentiles, respectively. On average, we find White-Latino segregation to be generally low, only approaching medium levels for noncore counties in 1990 and for metropolitan areas in 2000 and 2010. Previous reports measuring segregation of persons using conventional formulas have often reported medium and sometimes even high levels of White-Latino segregation, which understandably may raise questions about the low scores we produce here.

To address this likely concern, we note the following points. The first is that most previous descriptive studies of segregation have focused on the largest metropolitan areas in the United States, whereas our analysis extends beyond the large metropolitan context to include smaller metropolitan areas, micropolitan areas, and noncore counties because our methods can sustain meaningful analysis of segregation patterns in communities not considered in previous studies. In that regard, our analysis sample is more representative of the full range of White-Latino segregation across communities where Latino populations are present. Many of the communities that are often excluded in previous studies are less segregated than the large metropolitan areas that are more likely to be included in most previous studies. However, the inclusion of more communities, especially communities with Latino populations that are smaller in absolute and relative size, is a contributing factor, but not the overriding factor because the average scores we report for metropolitan areas also are lower than previous studies might lead readers to expect. Several other measurement practices we reviewed in Chap. 2 are more relevant. Two are especially important. The first is that we find White-Latino segregation is especially susceptible to distortion by index bias. The second is that, to a much greater degree than we expected, White-Latino segregation in many communities involves a pattern of dispersed unevenness instead of polarized unevenness as seen more commonly in White-Black segregation.

Regarding index bias, we highlight the following points. Many communities have relatively low levels of Latino presence in the local population. All else equal, this factor leads to higher levels of upward bias in the standard version of the dissimilarity index used in most previous research. In addition, Latino households tend to be larger than White, Black, and Asian households. Thus, the impact of bias on standard index scores for the communities in our study is much greater for White-Latino segregation than for White-Black segregation. And, conversely, the consequence of using unbiased index scores calculated using data for households instead of persons reduces the average scores for White-Latino segregation to a greater degree than for White-Black segregation. For example, for metropolitan CBSAs in 2000 (as a subset of cases included in many previous studies), the reduction in D based on eliminating index bias averages 13.7 points for White-Black comparisons and 26.9 points for White-Latino comparisons.

As for the greater prevalence of dispersed versus polarized displacement from even distribution, most previous studies do not acknowledge this aspect of segregation, so it is not surprising that its prevalence in White-Latino segregation is not appreciated. This leads to a situation where multiple factors contributed to the adoption of understandable, but unfortunately incorrect, assumptions about White-Latino segregation patterns. Didactic discussions of segregation measurement leading to high index scores invariably feature patterns characterized by polarized unevenness which produces clear group separation and prototypical segregation. In this situation, all index scores, including both *D* and *S*, take high values. Landmark studies such as Duncan and Duncan (1955) and Massey and Denton (1988) suggest *D* correlates closely with alternative indices and do not stress that *D* and *S* markedly differ. The few studies that did note the possibility that scores for *D* and *S* can diverge (e.g., Stearns & Logan, 1986) did not make the point as forcefully as might have been possible and thus had limited impact on segregation measurement practices. Thus, it was not until Fossett (2017) that a methodological study provided comprehensive evidence that scores on *D* and *S* not only can diverge, but also frequently do in studies that consider a wider range of communities and group comparisons than were considered in previous methodological studies.

This leads us to the present study where we report the finding, surprising to many for the reasons just reviewed, that divergence of scores for *S* and *D* characteristic of dispersed unevenness is much more common in White-Latino comparisons than in White-Black comparisons. Consequently, our use of the separation index to identify the extent to which groups occupy different neighborhoods in the community yields scores that are much lower than the scores of *S* we found for White-Black segregation. One reason why this finding is important, other than what it says about previous analyses of White-Latino segregation, is that it complicates analyses of trends in White-Latino segregation in new destination communities where Latino presence is relatively recent but is growing rapidly. We review the topic of new destinations in more detail in Chap. 5 and show that index choice turns out to be highly consequential for understanding segregation trends in new destinations, as *S* and *D* can lead to opposite conclusions if not understood correctly.

While While-Latino segregation was low across all three decades and across all community types, the trends over time varied by community type. White-Latino segregation slightly declined in noncore counties, remained stable in micropolitan areas, and increased in metropolitan areas. The highest levels of White-Latino segregation in 1990 are observed in noncore counties, many of which were experiencing the arrival of Latino migrants and immigrants in predominately White rural communities across the Midwest and South, which are more likely to be new destinations – again explored further in Chap. 5. By 2010, the average level of White-Latino segregation is highest in metropolitan areas due both to rising segregation in those areas and declining average segregation in noncore counties.

While White-Latino segregation is generally low across the communities in our study, segregation does reach medium levels ($S \geq 15$) in many communities and high levels ($S \geq 35$) in a smaller subset of communities. Not surprisingly, this includes large well-known metropolitan areas with $S > 45$ (e.g., Chicago, IL, Los Angeles, CA, and New York City, NY), smaller, less well-known metropolitan areas with $S > 45$ (e.g., Bakersfield, CA, Brownsville, TX, McAllen, TX, and Salinas, CA), micropolitan areas with $S > 35$ (e.g., Del Rio, TX, Dodge City, KS, Liberal, KS, Lumberton, NC, Nogales, AZ, and Uvalde, TX), and noncore counties with $S > 35$ (e.g., dozens of counties across states such as Arizona, Colorado, Georgia, Nebraska, New Mexico, North Carolina, and Texas). We point this out as reassurance that many basic patterns from past research carry forward when segregation is measured without bias and using S instead of D. And, of course, the much higher scores for White-Black segregation reviewed earlier also reinforce this point. In sum, our study finds White-Latino segregation to be lower than past studies might suggest because scores reported in past studies, especially outside of large metropolitan areas, are substantially inflated by index bias and because a pattern of dispersed unevenness, where scores for S are much lower than scores for D, is much more common for White-Latino segregation than for White-Black segregation.

The Latino population was growing rapidly at the national level from 1990 to 2010 and diffusing into areas of the country where Latino presence had previously been limited or absent altogether. This often played out as dramatic growth in new destination communities that met the criteria for inclusion in 1990 and it also led to new communities first meeting inclusion criteria in 2000 or 2010. This was most common in noncore counties where the number of communities meeting our minimum household count criteria more than doubled from 1990 to 2010. This raises the question of whether the addition of new qualifying cases in 2000 and 2010 impacts the findings we reviewed earlier. We addressed this question by performing our descriptive analysis using only the set of communities that met criteria for inclusion over the full time period from 1990 to 2010. We present these results in Table 3.5 and find that White-Latino segregation in noncore counties remained stable over the time period. This indicates that the newer areas of Latino settlement that emerge over this time frame appear to be driving the declines in White-Latino segregation in noncore counties seen in Table 3.4. Thus, Latino new destination communities that emerged most recently have lower levels of segregation than is seen in new destination communities where Latino migrants and immigrants began arriving in significant numbers at an earlier point in time. This suggests that segregation in the most recently emerging new destination communities will rise to the levels observed in the

Table 3.5 Separation index by year, type, and pairing in areas included in 1990

Comparison	1990	2000	2010
White-Black			
Non-core	50.07	42.95	39.10
Micropolitan	39.15	32.40	27.67
Metropolitan	39.81	34.96	30.99
White-Latino			
Non-core	15.00	15.20	15.64
Micropolitan	10.43	12.65	13.65
Metropolitan	11.61	15.21	16.94
White-Asian			
Non-core	6.16	8.42	9.00
Micropolitan	8.92	9.02	9.24
Metropolitan	7.90	8.99	10.39

Latino new destinations that are further along in the process of transitioning to areas of established Latino presence. Patterns for micropolitan and metropolitan areas are more consistent between communities that were included in all three decades of analysis and communities that joined the analysis in later decades due to population growth.

We conclude our descriptive findings for White-Latino segregation by noting that there is a much larger set of communities outside of the most urban-populated metropolitan areas which have markedly lower levels of segregation with weaker spatial boundaries, particularly for non-Black groups. Thus, in the case of White-Latino segregation, the typical community does not reflect the levels of White-Latino segregation observed in metropolitan areas like Chicago or Los Angeles, where the separation index hovers between 40 and 50 and would indicate high levels of segregation. By moving beyond the context of segregation in a selective group of large metropolitan areas, which has had a major influence on how we think about residential segregation in the United States, we can develop a new narrative of the reality of Latino segregation patterns across the United States.

3.6.3 White-Asian Segregation

Previous studies consistently report that Asian households experience the lowest levels of segregation from White households, and this result is replicated in our findings with the stipulation that, as with our findings for White-Black and White-Latino segregation, the levels of White-Asian segregation we find are lower than those reported in the literature. Some, but not all, of the reasons for this pattern are the same that we noted earlier for White-Latino segregation. First, moving to using unbiased index scores leads to lower measured levels of segregation. Second, moving from using D to using S leads to lower measured levels of segregation as well because for White-Asian segregation, more so than any other of these group comparisons, the underlying pattern involves dispersed rather than polarized unevenness. This pattern produces high-D, low-S combinations as the norm, not as an exception. Thus, while average values of D for White-Asian segregation are actually similar to average values of D for White-Black and White-Latino segregation when scores are calculated using standard formulas, average values of S for White-Asian segregation are much lower than average values of S for the White-Black and White-Latino comparisons and the divergence across group comparisons is even greater when scores are calculated using formulas that yield unbiased scores.

The consequence is that high values of D are particularly misleading for White-Asian comparisons because they rarely occur in combination with high values of S, as occurs frequently for White-Latino segregation and is the norm for White-Black segregation. Thus, values of unbiased S above 35 are rare in our data for White-Asian segregation. Of the communities in our analysis, only three have scores of at least 35, in two of the three decades. These communities are the micropolitan areas of Bay City, TX, Garden City, KS, and Morgan City, LA. Each one has an atypical history involving refugee settlement of a single Asian nationality subgroup. Dispersed unevenness is the norm for White-Asian segregation. The quantitative signature of the pattern is the combination of high-*D*, low-*S*. This is clear from the fact that, across all White-Asian comparisons in our analysis, the averages for the unbiased versions of *D* and *S* are 36.9 and 7.7, respectively. The unbiased scores are more accurate and meaningful. But we also note the averages for the standard (biased) versions of *D* and *S* are 74.0 and 14.3, respectively, to establish that the dramatic *D*-*S* difference is not specific to unbiased scores. The distinction between patterns of dispersed and polarized unevenness has been overlooked in past research. But it has important substantive implications. The occurrence of high values of *D* for White-Asian segregation rarely occurs in combination with a high level of group separation wherein White and Asian households occupy different neighborhoods that are polarized on group composition, such that the two groups could experience systematically different location-based outcomes. Instead, higher values of *D* for White-Asian segregation result because Asian households generally live in neighborhoods where they have contact with White neighbors at levels that are quantitatively close to parity, but technically are below parity. The dissimilarity index is highly sensitive to these near misses on parity. But, since this pattern does not create the level of group difference in contact that can create prototypical segregation where neighborhoods are polarized on group composition, the separation index takes very low values.

The prevalence of the pattern of dispersed unevenness in White-Asian segregation is evident in other findings. One is that, across most communities where *D* is high, *S* is low. Consequently, few neighborhoods are predominantly Asian – a requisite for group separation and group disparity on location-based outcomes. This is true when assessed in relation to total population and even when assessed on just the combined pairwise White and Asian populations. This stands in stark contrast to the pattern of polarized unevenness that is the norm in White-Black segregation. This pattern involves a substantial portion of Black households residing in predominantly Black neighborhoods as occurs when groups occupy different neighborhoods, which can create the structural potential for group disparity on location-based outcomes. Additionally, in our review of micro-level attainment processes across selected metropolitan areas in Chap. 6, we document that Asian households attain contact with White households at near-parity levels because the average levels on relevant resources for attainment are similar across White and Asian households and, equally importantly, Asian households convert these resources into contact with White households at much higher rates than Black households.

In comparison to White-Black and White-Latino segregation, we find that White-Asian segregation is more uniform across community types and over time. Across all community types, White-Asian segregation on average remains at very low levels with slight fluctuations that do not suggest any important trend over time. Similarly, there are only very small and inconsistent differences in levels of White-Asian segregation between noncore counties, micropolitan areas, and metropolitan areas, although the dynamics that drive these patterns may be quite different. Large metropolitan areas are more likely to be home to established Asian enclaves that contribute to residential separation, while micropolitan and noncore counties may be experiencing new enclave formation but also potentially more conflict dynamics if they are predominately White areas that are adjusting to the arrival of new minoritized racial populations.

Our major finding that White-Asian segregation based on households is very low is markedly different from past research. Previous reporting on White-Asian segregation has often reported that White-Asian segregation, while the lowest in comparison to segregation between other groups and White households, is still at moderate levels (Frey, 2018; Iceland, 2014). One reason for this seeming discrepancy is that past research is often only looking at metropolitan areas, but even in metropolitan areas we find that White-Asian segregation is quite low. We bring up two methodological points to explain these low scores. First, removing the upward bias from the segregation index can reduce scores dramatically, particularly when one group in the analysis is disproportionately smaller. Measuring White-Asian segregation is fraught with issues of index bias. Second, our choice to use the separation index means that we are more reliably capturing the extent to which the two groups are actually living apart from one another. As we explained in Chap. 2, uneven distribution does not necessarily mean that the two groups in the analysis are living in meaningfully different neighborhoods. Compared to the oft used dissimilarity index, which is the measure behind the most cited findings in the literature, the separation index is more likely to reflect polarized unevenness. Uneven distribution where the minoritized racial group is in fact living in neighborhoods that approach parity with the overall area on proportion White, dispersed unevenness, will not result in high scores on the separation index, as it might with the dissimilarity index.

The role of new destinations which plays prominently in our understanding of trends of White-Latino segregation is also relevant for our analysis of White-Asian segregation. We note a less pronounced but similar pattern to that found in our analysis of White-Latino segregation, which is that the number of counties that meet our criteria for inclusion increased from 1990 to 2010. As in the case for White-Latino segregation, this is also because of population growth and migration. While the trend of migration to rural communities observed in the Latino population is not as prominent for the Asian population, there is evidence of some dispersal away from metropolitan areas, as reflected in the significant increases of micropolitan and noncore areas eligible for inclusion in our analysis from 1990 to 2010. This trend emphasizes the increasingly important but understudied question of Asian residential patterns in nonmetropolitan communities.

For the few noncore counties that remained consistently in the analysis from 1990 to 2010, segregation remained low but increased over time. In contrast, when we look at all noncore counties, including areas that emerged as cases for analysis in 2000 or 2010, White-Asian segregation appeared to remain stable. This is also true for micropolitan and metropolitan areas, with one difference being that segregation on average is declining for micropolitan areas when all areas are included, whereas it is slightly rising in areas that are in the analysis across all decades. Similar to what we found in our analysis of White-Latino segregation in noncore counties, newly emergent sites of Asian settlement may initially experience relatively lower levels of segregation but see segregation increase over time. The story of rising White-Asian segregation in noncore counties is exemplified at the extreme when we look at maximum scores. The maximum observed White-Asian segregation score for noncore counties was 50 in 1990 but reached a high of 76 by 2010, while for metropolitan areas the maximum score was 49 in 1990 and 45 in 2010. Asian segregation in nonmetropolitan counties will be a subject of deeper investigation in Chap. 4 as well as Chap. 5, where we focus on nonmetropolitan segregation and segregation in new destinations for minoritized racial groups, respectively.

3.6.4 Segregation Between Minoritized Racial Groups

In this section of the chapter we review patterns of segregation between minoritized racial groups: Black-Asian, Black-Latino, and Latino-Asian segregation (Table 3.6). One remarkable finding from these results is that in general average levels of Black-Asian and Latino-Asian segregation are significantly higher than average levels of White-Latino or White-Asian segregation, reflecting medium segregation levels that we more often expect to find when looking at segregation from White households. Black-Asian and Latino-Asian segregation has remained low-to-medium and stable, with the exception of Black-Asian segregation in noncore counties where fluctuations are likely a result of the small number of cases included in the analysis. Generally, Black-Latino segregation has been on the decline across all areas, beginning at medium levels in 1990 and moving towards low levels by 2010. The overall declines in Black-Latino segregation fit with the patterns where Latino households have lower levels of separation from White households (albeit trending upward) than do Black households, and where White-Black segregation is trending down more strongly than any group comparison we consider.

Table 3.6 Separation index by year, type, and pairing, minoritized group-minoritized group

Comparison	1990	2000	2010
Black-Latino			
Non-core	44.56	36.97	32.40
Micropolitan	33.61	25.57	21.59
Metropolitan	28.37	22.89	20.53
Black-Asian			
Non-core	34.24	46.87	29.17
Micropolitan	32.18	31.52	29.42
Metropolitan	31.19	31.27	30.17
Latino-Asian			
Non-core	23.90	26.29	25.88
Micropolitan	29.81	29.71	27.16
Metropolitan	28.98	28.96	28.26

Previous research has largely neglected review of segregation among nonwhite groups. In part this has been due to concerns about index bias when measuring segregation of small subpopulations. This problem has been addressed and is no longer a constraint on research. Neglect of this topic also may have been due to the fact that until recent decades, most communities were closer to being mono-ethnic or bi-ethnic than multiethnic in group composition. However, as the Latino and Asian populations have grown in both absolute and relative size and as these populations have increasingly diffused spatially beyond an initially smaller set of regionally concentrated locations, multiethnic communities are more common and will steadily grow in prevalence.

We hope the patterns we document here will be incorporated into future research because they are potentially valuable for providing a more complete description of how spatial residential distributions vary by race and ethnicity. It also may be valuable for thoughtfully reviewing and potentially refining theories of racial-ethnic segregation. Simply put, the dominant prevailing perspectives guiding segregation research have not been applied to the analysis of segregation among nonwhite groups. The fact that our descriptive analysis documents levels of segregation among these subpopulations that sometimes approach or equal White-nonwhite segregation raises questions about whether theories of segregation primarily crafted to explain White-nonwhite segregation will need revision to explain a wider range of segregation patterns.

3.6.5 Where Is Segregation Rising? Where Is It Declining?

Because segregation is primarily shaped by the context of the given community, which includes migration patterns, local zoning and housing policies, patterns of residential development, dominant racial ideologies, and local history, changes in levels of segregation do not happen uniformly across the United States. To understand how segregation is shifting in any single community would call for a deeper and more qualitative analysis. But from a more macro-level demographic vantagepoint, we can ask a basic question: how are changes in segregation varying across the United States? In Tables 3.7, 3.8, and 3.9 we tabulate communities by community type and by broad categories of segregation change from 1990 to 2010

Table 3.7 Changes in White-Black segregation, 1990–2010

Area type	Declining >5 pts	Declining 2–5 pts	Stable |0–2| pts	Rising 2–5 pts	Rising >5 pts
Noncore	11.7%	77.7%	5.3%	2.7%	2.7%
Micropolitan	11.0%	67.1%	12.9%	4.2%	4.9%
Metropolitan	7.3%	67.3%	15.7%	5.1%	4.6%
All areas	10.2%	71.0%	11.0%	3.9%	4.0%

Table 3.8 Changes in White-Latino segregation, 1990–2010

Area type	Declining >5 pts	Declining 2–5 pts	Stable |0–2| pts	Rising 2–5 pts	Rising >5 pts
Noncore	10.5%	13.3%	27.4%	14.3%	34.6%
Micropolitan	9.2%	9.4%	34.5%	15.9%	31.0%
Metropolitan	3.4%	3.7%	30.2%	18.0%	44.8%
All areas	8.5%	9.9%	30.3%	15.6%	35.7%

Table 3.9 Changes in White-Asian segregation, 1990–2010

Area type	Declining >5 pts	Declining 2–5 pts	Stable |0–2| pts	Rising 2–5 pts	Rising >5 pts
Noncore	6.1%	4.6%	45.5%	15.2%	28.8%
Micropolitan	6.3%	9.2%	45.1%	21.8%	17.6%
Metropolitan	5.8%	4.1%	42.0%	27.5%	20.6%
All areas	6.0%	6.2%	43.6%	24.1%	20.2%

based on the unbiased separation index. Areas were categorized as "stable" if segregation changed by no more than 2 points in either direction.

For White-Black segregation, the vast majority of communities have experienced small but steady declines in segregation, regardless of community type. This includes two-thirds of micropolitan and metropolitan areas and over three-quarters of noncore counties. Less than 10 percent of areas have experienced increases in White-Black segregation. Given how high White-Black segregation typically is, these results are not necessarily surprising. With weakening effects of institutional discrimination in the housing market and an increasing amount of housing stock built after fair housing laws were enacted, and the emergence of a significant Black middle class in many communities, we would expect some reductions in White-Black segregation from levels that are initially very high. This is made most poignantly clear in Fig. 3.1, where we can see that White-Black segregation is declining across wide swaths of the United States. Increases in segregation are occurring in only scattered pockets along the Midwest and in the Northeast. Nevertheless, our previous results show that White-Black segregation is persisting at the highest levels, implying that these small reductions over time are indicators of slow progress toward White-Black integration.

Changes in White-Latino segregation are more varied, but one clear finding is that declining segregation is the least common scenario across all community types. Over a quarter of communities have had stable levels of White-Latino segregation from 1990 to 2010 while roughly a third of communities have seen large increases (over 5 points) in White-Latino segregation over the decades. White-Latino segregation as measured using the separation index, corrected for index bias and using data for households, is markedly lower than previous studies have suggested, but it is rising and, in many communities, it is rising quickly. This trend is most pronounced in metropolitan areas, where 45 percent have had separation index score increases by more than 5 points over the decades. Unlike White-Black segregation, which has

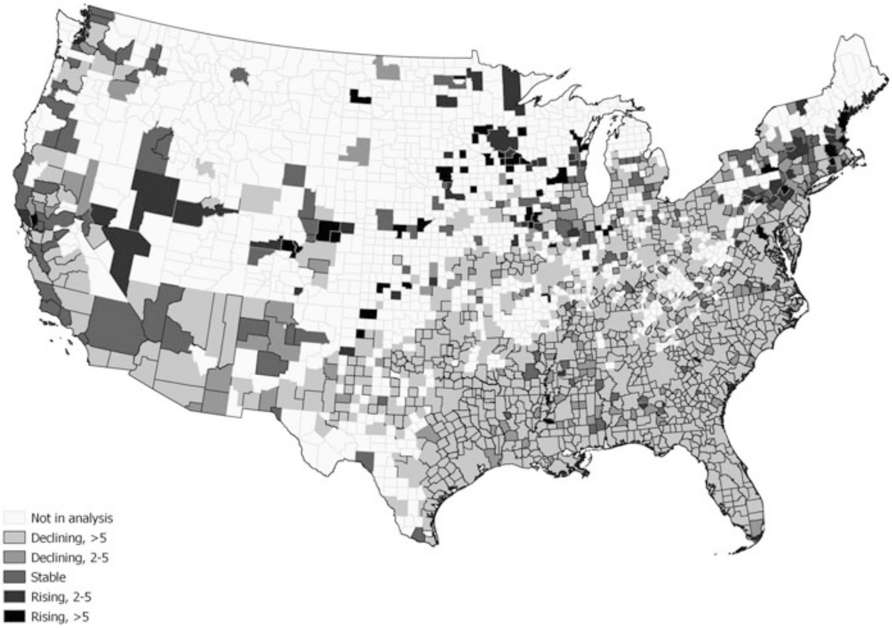

Fig. 3.1 Changes in White-Black segregation, 1990–2010

historically been high in metropolitan settings but declining, over half of metropolitan areas are seeing greater residential separation between White and Latino households. Furthermore, nearly a third of micropolitan areas and over a third of noncore counties are also seeing large increases (over 5 points) in White-Latino segregation. These communities may be less likely to have historically established Latino populations, but as Latino migrants and immigrants continue to spread outward across the United States to smaller, nonmetropolitan communities, segregation patterns are emerging. Indeed, Fig. 3.2 shows that areas of rising White-Latino segregation appear to be most concentrated in the South and parts of the Midwest. Declining White-Latino segregation is primarily occurring in the Southwest along the U.S.-Mexico border in Texas, New Mexico, and Arizona (Fig. 3.3).

Decline is also the most unlikely scenario for White-Asian segregation, with only 12 percent of all communities experiencing declines in White-Asian segregation from 1990 to 2010. Though, to be clear, this is partly due to the fact that White-Asian segregation is generally at such low levels it would not be easy for *S* to decline by 5 or more points in many communities. An equal portion of communities are experiencing either stable or increasing White-Asian segregation with a fifth of all communities seeing White-Asian segregation increase by more than 5 points in two decades. Although there is only a small number of noncore counties included in our analysis for White-Asian segregation, their patterns mirror those of micropolitan and metropolitan areas in that White-Asian segregation is most likely to be stable, with the second likely outcome being rising segregation. In sum, we find that

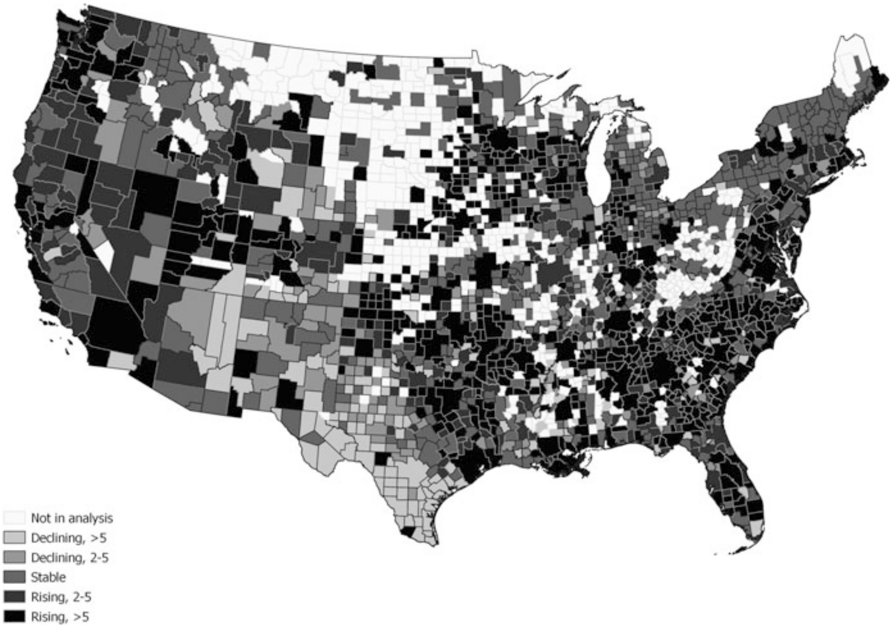

Fig. 3.2 Changes in White-Latino segregation, 1990–2010

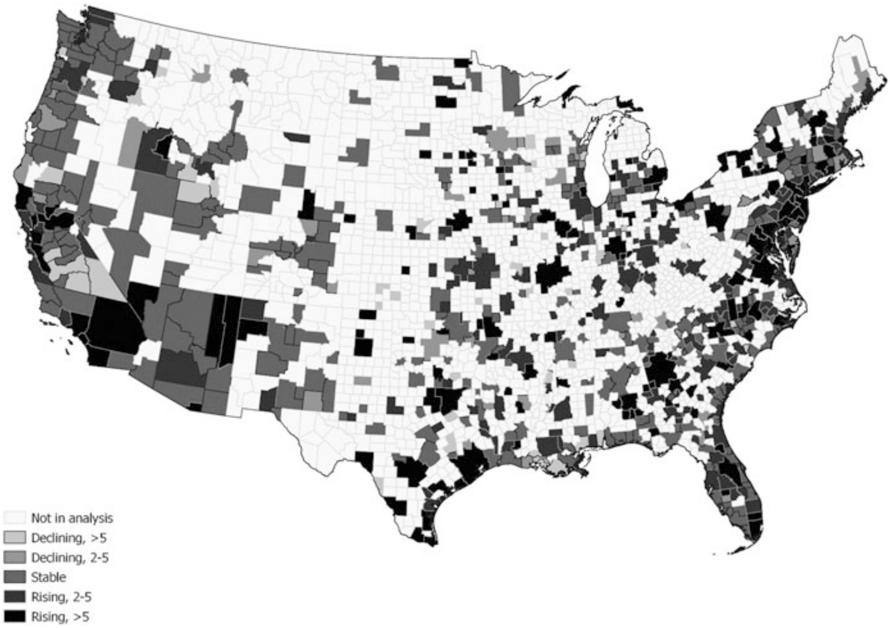

Fig. 3.3 Changes in White-Asian segregation, 1990–2010

White-Asian segregation is generally quite low, with Asian households on average having high levels of residential contact with White households, and these patterns appear to be either holding steady or trending towards increasing segregation.

3.7 Community-Level Analysis of Segregation Patterns

In this section of the chapter we attempt to further clarify the segregation patterns we have documented in the preceding descriptive analyses by reviewing community-level regression analyses we estimated to explore how variation in segregation across communities may correspond with variation in other characteristics of communities. We are cautious, for both methodological and theoretical reasons, in our approach to specifying community-level regressions predicting segregation. In particular, we have concerns about including aggregate-level predictors that measure group differences on characteristics that are relevant for segregation based on the role they are hypothesized to play in micro-level attainment models. Past research investigating community-level variation in segregation has sometimes tended in the direction of, perhaps inadvertently, framing segregation as an aggregate-level phenomenon. In part, this was due to the fact, noted as early as Duncan and Duncan's (1955) landmark article on segregation measurement, that the specific quantitative links between segregation indices and micro-level processes that gave rise to segregation were unclear. The introduction of the difference-of-means framework in Fossett (2017) changed this state of affairs. After first establishing that all popular segregation indices can be given as group differences on average levels of scaled contact with the reference group, Fossett (2017) then took the next logical step of pointing out that segregation index scores reflect group disparities and thus can be mathematically equated to the effect of (regression coefficient for) group membership in a micro-level regression predicting scaled contact with the reference group.

The difference-of-means formulation of segregation index scores clarifies how such effects can be directly estimated in micro-level analyses of the type we review in Chap. 6 and in Crowell and Fossett (2018, 2020, 2022). These analyses permit direct estimation of how group differences on micro-level characteristics ultimately impact segregation and the results document that the impact is often negligible even when the group disparity on the characteristic is large. Simply put, this is because the very communities where group differences on characteristics potentially relevant for locational attainment – for example, education, income, nativity, English-language ability, etc. – are largest also tend to be communities where minoritized racial groups are less able to translate these resources into more residential contact with White households. In such communities, eliminating inequalities in resources will have minimal to no impact on group differences in locational outcomes. The implication of this is that the correlation of group inequalities at the aggregate level is primarily a spurious relationship resulting from the multiple inequalities that are all shaped by a broad pattern of constrained and stratified opportunities (Fossett, 1988, 2017; Fossett & Crowell, 2018). Understanding this also opens the door to a wide range of analysis possibilities including detailed micro-level regressions investigating the factors contributing to segregation in a single community as we review in Chap. 6. Another new possibility is to estimate contextual and multi-level regression analyses exploring how the effect of group membership (race) on contact with the reference group varies across communities.

Given all this, we use conservative specifications of aggregate-level regressions that avoid including variables that should instead be taken into account in more complex multi-level models. And we also avoid drawing overly confident conclusions regarding how segregation patterns are determined by community-level factors based on aggregate-level regressions that cannot accurately control for the impact of group differences on individual characteristics. We estimated fractional regression models predicting community-level segregation measured by the separation index, pooling all communities, group comparisons, and years with dummy variables for community type, pairing, and time. For community-level covariates we draw on previous research and include the predictors of population size, region, percent Black, percent in armed forces, percent of housing units built in the last 10 years, and a set of workforce characteristics based on industry of occupation, including percent in government, percent in manufacturing, percent in retail, and percent in service. We studiously avoid including community-level predictors whose relevance derives from the hypothesized role individual-level characteristics play in micro-level attainment processes within individual communities. The covariates used in this model are described in Table 3.10.

The results from this pooled model in Table 3.11 indicate that segregation overall has dropped significantly from 1990 to 2010, although we know from our descriptive tables that White-Latino and White-Asian segregation outcomes are more varied

Table 3.10 Descriptive statistics for regression analysis, all communities in 2010

	Metropolitan		Micropolitan		Noncore County	
	Percent		Percent		Percent	
Region						
West	21.4%		15.8%		12.3%	
Northeast	13.5%		8.9%		4.7%	
Midwest	24.7%		29.8%		17.5%	
South	40.4%		45.5%		65.5%	
Demographics	Mean	SD	Mean	SD	Mean	SD
Percent black	10.7%	10.7	9.5%	14.4	12.5%	17.0
Population size	680,756	1,178,338	58,774	32,572	21,426	13,985
Industry						
% in government	5.3%	2.7	5.6%	3.5	6.4%	3.6
% in manufacturing	11.2%	5.4	13.6%	7.4	12.9%	7.6
% in retail	12.1%	1.4	12.2%	1.8	11.4%	2.6
% in service	18.3%	2.3	19.0%	3.1	18.7%	3.9
% new housing (<10 Yrs)	30.4%	10.9	27.5%	10.4	26.4%	9.8

Table 3.11 Fractional regression of segregation measured by the separation index

	Model 1		Model 2		Model 3	
	b	SE	b	SE	b	SE
Pairing (Ref: White-Black)						
White-Latino	−1.387***	0.059	−1.215***	0.060	−1.214***	0.060
White-Asian	−1.824***	0.101	−1.732***	0.103	−1.725***	0.103
Year (Ref: 1990)						
2000	−0.206**	0.067	−0.248***	0.068	0.064	0.175
2010	−0.342***	0.066	−0.369***	0.068	−0.409***	0.113
Community type (Ref: Metropolitan areas)						
Noncore counties	0.207**	0.066	0.194	0.130	0.145	0.133
Micropolitan areas	−0.164*	0.069	−0.090	0.099	−0.074	0.101
Population size (ln)			0.088*	0.035	0.103**	0.036
Region (Ref: Northeast)						
Midwest			−0.049	0.131	−0.002	0.134
South			0.484***	0.124	0.546***	0.133
West			0.101	0.138	0.141	0.146
% black			0.019***	0.002	0.019***	0.002
% armed forces			−0.039***	0.010	−0.032**	0.010
% government					−0.008	0.010
% manufacturing					−0.017***	0.005
% retail					−0.036**	0.014
% service					−0.017**	0.006
% new housing (<10 Yrs)					−0.006	0.004
Constant	−0.406***	0.067	−1.942***	0.483	−0.929	0.556

Note: *p < .05; **p < .01; ***p < .001

with many communities experiencing stable or rising segregation for these groups. We also find that segregation does not significantly differ by community type when population size, which has a positive effect on segregation, is included as a predictor. Taking communities in the Northeast as the point of comparison, we find that segregation is on average higher in communities in the South. This is perhaps surprising given the high levels of segregation often observed in metropolitan areas of the Northeast, but the South has seen widespread increases in White-Latino segregation as a result of increasing Latino migration to the South.

The results we report show several other factors have significant associations with levels of segregation when holding other contextual characteristics constant, including percent Black, which is a positive predictor of segregation, and percent in the armed forces, which is a negative predictor. The integrating effect of military presence is one that has been suggested in the literature before, particularly with regards to intermarriage. Communities with a larger military presence appear to also have more integrated neighborhoods even when looking specifically at household data (which excludes persons residing in military barracks). Our previous research on locational attainments, and our extensions of that work which we report in

Chap. 6, have also shown that nonwhite householders who have served in the armed forces are more likely to have greater residential contact with White households, while White householders who have served in the armed forces have less residential contact with other White households (Crowell & Fossett, 2018, 2020, 2022).

These findings together indicate that individuals who have served in the armed forces and therefore have been placed in more diverse settings are more likely to seek out and feel more comfortable in integrated neighborhood environments.[3] Finally we find that the percentages of the workforce who are in the manufacturing, retail, or service industries are negative predictors of segregation, with areas where the industrial composition of the workforce is more diverse perhaps being those that are likely to be included in our analysis of White-Latino and White-Asian segregation, which is often quite lower than White-Black segregation in large metropolitan areas where the manufacturing industry no longer dominates.

The purpose of these models is to identify the contextual characteristics of areas that are associated with cross-community variation in levels of segregation and describe the nature of those relationships. We find, as previous research has, that segregation is associated with community racial composition, population size, military presence, and industrial composition. This analysis should be seen as a step toward a more satisfactory analysis that investigates the impact of community characteristics in a modeling framework that can correctly take account of individual- and household-level characteristics that are relevant in micro-level processes of household locational attainments.

3.7.1 Aggregate-Level Predictors Not Considered

To elaborate on our point regarding how to model segregation outcomes at macro- and micro-levels, we add more discussion here on a category of variables that we intentionally excluded from the candidate list of community-level predictor/control variables we considered for inclusion in the aggregate-level regressions we estimated to explore cross-community variation in segregation. Specifically, we excluded predictors that measured group differences on resources (e.g., group inequality on income) and social characteristics (e.g., English language ability, foreign born status, etc.). Our reason for excluding these predictors is not because they are irrelevant to segregation. To the contrary, our own analyses presented in Chap. 6 document that these variables can in some cases be highly relevant to shaping the level of segregation in a community. Instead, we excluded these

[3]The theory here has both community-level and micro-level components. The community-level component is that military policies directly and indirectly exert influence on the local housing dynamics and systematically promote equal-status contact between groups across a wide range of social domains. The micro-level component is that serving in the military leads to changes in the behavior of the individuals who served. Taking our own advice, we must acknowledge that the aggregate-level regression is not ideal for evaluating the micro-level component.

predictors because their true impact on segregation cannot be accurately estimated using aggregate-level regressions. The practice of including such measures of this type in aggregate regressions predicting segregation is widespread. Accordingly, we could cite many examples, but we do not wish to call attention to a few studies when in fact the practice is common and in general is not seen as controversial. In light of this, we explain our basis for viewing this practice as flawed and likely to lead to erroneous conclusions about the determinants of segregation. We view the practice in question as a specific example of a broader flawed practice where researchers estimate aggregate-level regressions that use one or more measures of group disparity to predict a particular measure of group disparity of interest. In the interest of economy of discussion, we focus on the example of aggregate-level regressions that use measures of White-Black income inequality to predict measures of White-Black segregation.

The practice of estimating and "controlling for" the impact of income inequality on segregation in aggregate-level regressions is inherently flawed and prone to yield results that grossly overestimate the impact of income inequality on segregation. The core issue is that one cannot accurately estimate the impact of income inequality on segregation based solely on knowing the level of income inequality. An accurate estimate requires detailed knowledge of how locational attainments for each group vary with income separately in each community in the analysis. There are other methodological discussions which review the point in more careful detail (Fossett, 1988, 2017; Fossett & Crowell, 2018), but here we highlight two fatal problems with aggregate regression analyses of segregation that include measures of income inequality as predictors. The first is that the strategy implicitly assumes that co-residence with White households varies significantly for Black households by level of income, and that this relationship is uniform across communities. To put simply, these assumptions are untenable. Analyses of detailed microdata for individual communities indicates Black co-residence with White households tends to be low across all levels of income, and the pattern is consistent across communities. This fact leads to the inescapable conclusion that White-Black income differences on segregation are inconsequential.

The second fatal problem with the aggregate-regression specification is that there are compelling reasons to conclude that White-Black disparities across different domains of social and economic attainment will be spuriously correlated across communities. This is because theory predicts racial stratification dynamics in a community will have broad impacts across all attainment processes. As a result, measures of White-Black disparity across different domains of social and economic attainment will be strongly and spuriously correlated because they all have a common cause; their values rise and fall together depending on the intensity of the racial stratification system that constrains Black opportunities and attainments in the community. Thus, for example, it would be utterly implausible to suggest that White-Black residential segregation in a community in the Jim Crow South was due to White-Black income inequality. Income inequality and residential segregation would both be high under the Jim Crow racial caste system. But in this context, an intervention that increased Black incomes (but otherwise did not change the local racial stratification regime) would not lead to a reduction in White-Black segregation.

Once segregation is equated to a group inequality on a micro-level attainment outcome (per Fossett, 2017), it immediately follows that the correct way to take account of the effects of group differences on individual-level characteristics is within contextual or multi-level models that directly estimate the impact of the relevant covariate on the attainment outcome across individuals while allowing the effect to vary across communities (where it will be minimal in some and stronger in others) and also including community-level characteristics as predictors (Fossett, 1988, 2017). Unfortunately, the correct models are not easily implemented because they require large samples of detailed microdata across a large number of communities. Relevant data are available so the task is in fact feasible, but it is a major undertaking one or two orders of magnitude more difficult than estimating an aggregate-level regression. This is the unfortunate but hard reality of the situation.

In conclusion, we challenge researchers who include measures of White-nonwhite income inequality in aggregate regressions predicting White-nonwhite segregation to (a) specify and substantiate the assumptions that must be met for this method to yield correct estimates of the impact of income inequality on segregation and (b) provide a basis for setting aside the strong, theory-based presumption that White-nonwhite disparities across multiple domains of attainment will be spuriously correlated because they rise and fall together depending on the intensity of racial stratification dynamics in different communities. We do believe community-level regressions can provide useful insights, but we view the results as revealing community-level correlates of segregation, which is a preliminary, not definitive, step toward establishing the determinants of segregation. In Chap. 6 we use models of locational attainments to frame segregation as a form of inequality and demonstrate how segregation is driven by micro-level processes. In that chapter, we argue for a more methodologically appropriate modeling approach for understanding segregation as a product of micro-level factors.

3.8 Consequences of Index Choice for Understanding Trends in Segregation

In Chap. 2 we explained in detail the considerations that must be made when deciding which segregation measure to use for specifically analyzing the dimension of segregation known as evenness. The most widely used measure is the dissimilarity index, or *D,* which was first popularized by Duncan and Duncan (1955) many decades ago and continues to be the dominant choice in the literature on residential segregation. However, as we discussed in the previous chapter, methodological studies (e.g., Winship, 1977) have established that the dissimilarity index is especially susceptible to the problem of distortion by intrinsic upward bias in index scores and the problems can be alarming under certain conditions. Most notably, the issue arises when group counts for spatial units are small. This is the case with block-level data needed to study segregation in small communities and when one group in the comparison is disproportionately larger than the other group – a common occurrence in predominately White rural communities, micropolitan areas, and even many metropolitan areas.

Knowing that the conditions that create problems for using the dissimilarity index likely do occur in our comprehensive analysis of segregation across all areas of the United States, we chose in the previous sections to limit our substantive interpretations to the separation index, which is far less susceptible to the same issues that affect the dissimilarity index and more reliably reflects prototypical segregation, or patterns of polarized unevenness where the two groups in the analysis are living in substantively different neighborhoods with little residential contact with one another. In contrast, the dissimilarity index may react to uneven distribution but can register high scores even when the magnitude in the difference between the amount of residential contact that each group has with the reference group is small, i.e., dispersed unevenness. Over time, this may affect how we observe and interpret changing patterns of segregation within a community. In this final, brief methodological section of the chapter, we consider the separation index alongside the dissimilarity index to empirically demonstrate where *S* and *D* are most likely to deviate from one another over time.

Strictly speaking, one only needs to review the value of *S* to know whether the pattern of prototypical segregation and polarized unevenness is present. If the value of *S* is high, it is present; if the value of *S* is low, it is not. Since this is the aspect of segregation that motivates most concerns about segregation, one could stop at this point. However, when *S* is low, one must examine the value of *D* to know whether dispersed unevenness is present. If *D* is high while *S* is low, it is present; if *D* is low, it is not. Knowledge of the presence of dispersed unevenness might be of interest because it can be a precursor to the emergence of polarized unevenness, or it can be a vestige of declining polarized unevenness. The basis for characterizing the combination of high-*D*, low-*S* as a precursor to polarized unevenness is grounded in understanding how values of *D* and *S* can change in relation to each other when *D* and *S* are at intermediate and low levels and uneven distribution increases. When *D* and *S* are both low, all aspects of uneven distribution will be low. If uneven distribution increases, values of *D* and *S* will take paths at or between two possible extremes as follows:

- If emerging unevenness is maximally dispersed, values of *D* will rise and values of *S* also will rise but by much smaller increments.
- If emerging unevenness is maximally polarized, values of *D* and *S* will rise in equal increments.
- If emerging unevenness is intermediate on dispersal/polarization, values of *D* will rise and values of *S* also will rise but by smaller increments.

If *D* and *S* are at intermediate levels with $D > S$, the value of *S* can always potentially rise to match the value of *D* if unevenness shifts from being dispersed to being polarized. If uneven distribution increases while *D* and *S* are at intermediate levels with $D > S$, the value of S will lag behind D if increased unevenness is dispersed or, alternatively, it will move toward D if increased unevenness is polarized. As unevenness progresses from an intermediate level where $D > S$ to its maximum level, unevenness must eventually become fully polarized, so the value of S must eventually rise to match the value of D. From this, it is logically possible that the emergence of uneven distribution might start first with dispersed unevenness (high D, low S) and then continue and progress toward polarized unevenness (high D, high S) and prototypical segregation. In this scenario, the combination of high-D, low-S is a precursor to polarized unevenness.

The basis for characterizing the combination of high-D, low-S as a vestige of declining polarized unevenness is similarly grounded in understanding how values of D and S can change in relation to each other when both D and S are at intermediate and high levels. If both S and D are high, all aspects of uneven distribution will be high. If uneven distribution then declines, values of D and S will take paths at or between two possible extremes as follows:

- If declining unevenness involves shifting from maximum polarization to intermediate or maximum dispersal, values of S will decline rapidly, and values of D also will decline but by much smaller increments.
- If declining unevenness remains maximally polarized, values of S and D will decline in equal increments.
- If declining unevenness leads to an intermediate mix on dispersal/polarization, values of S will decline, and values of D also will decline but by smaller increments.

At any intermediate level of unevenness where values of D and S are concordant, the value of S can decline more rapidly than the value of D if unevenness transitions from being polarized to being dispersed. If unevenness progresses from an intermediate level to its minimum level, the value of D must eventually decline to match the value of S. Thus, it is logically possible that the elimination of uneven distribution might start first with polarized unevenness (high D, high S) and then progress toward dispersed unevenness (high D, low S) before ultimately going to zero on both D and S. In this scenario, the combination of high-D, low-S would be the last vestige of prototypical segregation going away.

Reviewing these scenarios calls attention to the possibility that trends over time can differ by index and it may be interesting to see whether D and S move in unison, or in different sequences. In Table 3.12, we describe initial and changing patterns of unevenness by area type and group comparison using both the separation index and the dissimilarity index as described above to identify the extent to which unevenness is polarized or dispersed. For White-Black segregation, the story is quite simple. In all area types, the typical initial pattern is one of polarized unevenness which is indicative of prototypical segregation. Both indices are initially at medium to high levels and White and Black households are largely living in different neighborhoods. However, we find that over time these levels of polarization are declining, leading towards more dispersed patterns of unevenness where Black households may still have less residential contact with White households than White households do, but

Table 3.12 Patterns of unevenness over time by pairing and community type

	White-Black	White-Latino	White-Asian
Noncore			
Initial pattern	Polarized (S ~ D)	Dispersed (S < D)	Dispersed (S < D)
Separation index change	Declining (−)	Declining (−)	Steady
Dissimilarity index change	Declining (−)	Steady	Steady
Pattern change	Dispersing	Dispersing	Steady
Micropolitan			
Initial pattern	Polarized (S ~ D)	Dispersed (S < D)	Dispersed (S < D)
Separation index change	Declining (−)	Steady	Declining (−)
Dissimilarity index change	Declining (−)	Steady	Steady
Pattern change	Dispersing	Steady	Steady
Metropolitan			
Initial pattern	Polarized (S ~ D)	Dispersed (S < D)	Dispersed (S < D)
Separation index change	Declining (−)	Rising (+)	Steady
Dissimilarity index change	Declining (−)	Steady	Steady
Pattern change	Dispersing	Polarizing	Steady

their overall residential contact with White households is increasing. Across all community types, White-Asian segregation has initial patterns of dispersed unevenness where the separation index is low in absolute terms and much lower than the dissimilarity index. For the most part, this pattern is holding steady with both indices changing in only negligible amounts.

While the dissimilarity index for White-Latino segregation remains relatively steady over time across all community types, the separation index shows more complicated patterns. In all community types, initial patterns of unevenness are dispersed because the separation index is considerably lower than the dissimilarity index. However, over time these communities are trending in different directions. In noncore counties, the separation index is declining, which indicates that these communities continue to shift towards more dispersed patterns of unevenness. In micropolitan areas, the separation index is holding steady and therefore patterns of dispersed unevenness are also holding steady. Finally, in metropolitan areas, the separation index is rising. This is indicative of patterns of unevenness that are polarizing, leading to higher levels of residential separation between White and Latino households. In contrast to the simplicity of White-Black and White-Asian segregation trends, White-Latino segregation trends demonstrate how using both indices can also provide more nuanced insights into complex patterns of unevenness.

3.9 Summary

This chapter provides a broad overview of racial and ethnic residential segregation trends across the United States from 1990 to 2010. The analysis we conducted is one of the most comprehensive performed to date based on: (a) covering a wide range of group comparisons, (b) covering metropolitan areas, micropolitan areas, and noncore counties, and (c) including many more communities. Additionally, this is the first major analysis of trends and patterns of residential segregation in the U.S. to use segregation indices that are free of the problem of index bias that has troubled researchers in the past and has forced undesirable restrictions on the segregation comparisons included for analysis. Some of the findings presented in this chapter may not be surprising, nor should they have been, but others are new and important. One less surprising finding is that, when we look at segregation involving comparisons and contexts common to previous studies, such as White-Black segregation in metropolitan areas, we are analyzing cases where index bias is less likely to distort segregation scores and therefore, we replicate previous findings. The reason this finding is not surprising is that, in cases where bias truly is negligible, scores for the unbiased versions of segregation indices we use in our study will closely replicate the scores of standard versions of segregation indices used in previous studies. The problem, of course, is that index bias is far from negligible for most cases in our analysis. Thus, our study reports the new and important finding that results for the unbiased versions of segregation indices are very different from results from previously reported standard versions of segregation indices because the availability of valid and reliable unbiased versions of measures of uneven distribution allows our study to perform analyses using a more comprehensive and more representative analysis sample.

The reason for the differences in results is simple. For most of the cases in our analysis, the impact of index bias on standard scores is not negligible; to the contrary, it is typical for bias to inflate standard index scores by large amounts. This is true when we assess segregation using data for persons, as is typical in most prior research. And the impact of bias takes on even greater importance when we assess segregation using data for households to eliminate bias that results from persons locating with and having contact with same-race members of their households. Accordingly, eliminating the impact of bias on index scores and measuring segregation of households rather than persons leads our results to differ from findings reported in any earlier studies that adopted case selection criteria that allowed analysis datasets to be larger and more comprehensive. One major difference, of course is that we find significantly lower levels of segregation. Partly this is because we focus attention on scores for the separation index (which we discuss next,) but our results for D also are much lower than scores reported in previous studies, especially for comparisons where groups are imbalanced in size. The main reason for this is that the cases we are able to include using new methods tend to have high standard scores but low unbiased scores because they are especially affected by bias. Previous studies have no effective method for working with these cases.

While previous studies underestimate the magnitude of the problem of index bias, they acknowledge it is a serious problem they must deal with. The main method they use is to minimize the impact of worrisome cases by discounting them (through differential weighting) or excluding them outright. These methods not only do not solve the problem (scores for these cases remain distorted and have undesirable effects on results), they also make the analysis less representative. Our methods allow us to include these numerous cases and obtain a more comprehensive and representative analysis dataset. Having these cases in the analysis is crucial because they are highly relevant for understanding the level and form segregation takes when groups are small in size and how the level of segregation may (or may not) change as groups grow in absolute and relative size. The method of differential weighting simply discounts the distorted scores to minimize their impact. Thus, to the extent the cases are actually allowed to influence results, their inclusion drives average scores up when using standard index scores.

In addition to using unbiased indices, our results also differ from past research because we give more attention to the separation index rather than the dissimilarity index. The reason, as we explained throughout, is that *S* provides a more accurate measure of the aspect of uneven distribution that motivates most segregation research – namely, identifying communities where groups occupy different neighborhoods and are at risk of inequality on location-based outcomes, which we refer to as *polarized unevenness.* We note that *D* cannot identify these communities, as high values of *D* will often identify communities where this pattern is absent and instead there is a pattern of *dispersed unevenness*. We also note it may be interesting to more closely compare *D* and *S* to gain a more nuanced understanding of certain kinds of patterns of uneven distribution. But that is not our main focus in this chapter. Our findings for *S* are important for showing that group separation is lower than previous research would suggest, especially for White-Latino segregation and White-Asian segregation.

Our study raises a question about how we should characterize variations in segregation across communities documented in our study in comparison with findings reported in previous research. The central issue is the analysis dataset we use in our study is larger and more representative than the analysis datasets used in previous studies and this has a nontrivial impact on findings about variations in segregation across communities. All else equal, the additional communities we are able to bring into the analysis tend to have lower levels of segregation, so their inclusion shifts the distribution of index scores to lower values for measures of central tendency and also lower values for percentile locations such as quartiles and deciles. The resulting changes in descriptive statistics represent technical improvements on previous research. But some may find the changes jarring because they depart from previous findings that are more familiar.

What consequences flow from documenting segregation in a broader, more representative set of communities? One key outcome is that the distribution of index scores shifts toward lower values. And the next question we must ask is how we should think about findings from previous studies. First, using standard scores in nonmetropolitan settings is no longer defensible. Index scores computed using smaller spatial units appropriate for measuring segregation in nonmetropolitan settings are always significantly inflated by index bias and the problem is severe for areas where group size is imbalanced and/or one group is small in absolute size. The patterns are stark, and they cannot be overcome. Excluding cases offers poor protection from the distortions of index bias. Many of the cases that are excluded are absolutely of legitimate sociological and demographic interest. Therefore, the loss in coverage and representativeness skews results and distorts findings. Furthermore, the non-excluded cases are not free from bias. When we apply conventional sample restriction constraints in a sequence of increasingly conservative steps, the problem of scores being significantly distorted by index bias never disappears even as the analysis sample becomes increasingly non-representative.

The index scores obtained using unbiased versions of index calculation formulas provide the clearly superior solution. Bootstrap simulation analysis establishes that the unbiased scores perform exactly as desired. In particular, they take average values of zero across every subset or grouping of cases in the study and thus, in dramatic and superior contrast to standard index scores, unbiased index scores have no intrinsic associations with any characteristics of communities. And, while new and not yet familiar to many researchers, the unbiased index scores have simple, intuitive interpretations as group differences in average contact with White households among neighbors that can be easily explained to broad audiences as well as to seasoned researchers. Furthermore, focusing on the separation index rather than the dissimilarity index ensures that researchers can accurately identify cases where polarized unevenness is occurring, the pattern of uneven distribution most consequential for creating the conditions of unequal outcomes.

Our intention for this chapter is that it will provide an exemplar for what is possible with new methods and establish benchmarks for evaluating segregation patterns in the future. Following this chapter, in which we also empirically explored some of the measurement issues that can be overcome using our measurement approaches, we begin to focus in on specific contexts of segregation, including nonmetropolitan communities and Latino and Asian new destinations, that have been understudied due to the limitations of conventional segregation measurement. In addition to considering nonmetropolitan contexts that are often left out of the literature, understanding the complexities of racial segregation will require considering the role of micro-level, individual-based characteristics such as immigration and acculturation as well as socioeconomic diversity, which we do in Chap. 6. With these new methods of measurement and analysis at our disposal, we can proceed to advance our understanding of the dynamics and patterns of racial and ethnic residential segregation across the United States.

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Chapter 4
Racial and Ethnic Residential Segregation in Nonmetropolitan Communities

4.1 Overview

For at least half a century, much of the literature on residential segregation has primarily focused on large metropolitan areas, where most of the population resides in one or more high-density urban cores and medium-density, outlying suburban environments.[1] Indeed, many influential landmark segregation studies such as Duncan and Duncan (1955) and Massey and Denton (1988) focused on small samples featuring primarily the largest 50–60 metropolitan areas in the country. More recent benchmark analyses of broad trends in segregation patterns across the United States have used expanded analysis datasets that include a broader set of metropolitan areas (Frey, 2018; Iceland, 2014; Logan & Stults, 2011), but studies often report summary statistics for segregation indices with cases weighted using criteria that give disproportionate influence to the very largest metropolitan areas. Analysis datasets often exclude smaller metropolitan areas and rarely include nonmetropolitan communities of any kind. The heavy focus on segregation in metropolitan settings is in part a matter of tradition, with studies of urban residential patterns dating back to the earliest days of American sociology through the work of scholars like W.E.B. Du Bois (1899) along with researchers at the Chicago School who developed their urban ecological theories by observing group settlement patterns across neighborhoods in Chicago (e.g., Park & Burgess, 1925). The tradition, therefore, is that segregation research and theorizing is centered on the urban contexts of the nation's largest metropolitan areas. But even as the literature expanded in the late twentieth century,

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[1] Metropolitan areas are delimited using counties which can and often do include low-density exurban and rural territory. But in recent decades these portions of metropolitan areas contain only a small share of the total population of the metropolitan area.

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with revived sociological and demographic interest in residential segregation exemplified by Massey and Denton's *American Apartheid* (1993) and calls by leading scholars to recognize the sociological importance of segregation in nonmetropolitan communities (Lichter & Brown, 2011), there has continued to be a hesitation to systematically analyze segregation in nonmetropolitan contexts.

The focus on racial and ethnic segregation in metropolitan areas has been and continues to be well justified. Large metropolitan centers are highly important, especially as the U.S. population has over time become increasingly concentrated in metropolitan communities. The metropolitan context is also changing through rising levels of spatial complexity due to suburban and exurban sprawl and steady trends of growing racial-ethnic diversification outpacing those seen in nonmetropolitan communities (Sharp & Lee, 2017). However, segregation in smaller metropolitan areas and nonmetropolitan communities is also highly relevant and important in its own right, despite historically receiving less attention and, in the case of nonmetropolitan communities, despite demographically losing population due to natural decrease and net population outmigration (at least, up until recently (Cromartie & Vilorio, 2019)). It is understandable that the striking and compelling patterns of segregation observed in large exemplar metropolitan areas would receive outsized attention. But it is important to not lose sight of the fact that segregation is observed across a wide range of communities and fundamental questions regarding how levels, patterns, and trends in segregation vary across communities cannot be answered by analyses with a limited focus on large metropolitan areas which, while undeniably important, are not at all representative of the breadth of variation in communities across the United States.

It is valuable therefore to examine segregation in nonmetropolitan settings to consider implications for theories of segregation and avoid the risk that prevailing theories may be overly tailored to metropolitan environments. As only one example, consider the highly plausible and widely accepted "White flight" hypothesis that high levels of racial segregation exist in metropolitan areas because higher-status White households gravitate to suburban settings that are predominantly White and higher-status rather than effort to remain in neighborhoods that are racially transitioning (Frey, 1979; Massey & Denton, 1993). Because these suburban neighborhoods they choose to occupy instead are spatially and administratively separated from the more diverse neighborhoods of the central city and surrounding suburbs that have racially transitioned (Kye, 2018), suburban White households simultaneously pay lower tax rates and enjoy attractive location-based amenities including, most notably, higher quality schools for their children. It is undeniable that White households residing in many suburban settings benefit from these consequences of segregation. But, if the hypothesis has identified a broad and powerful driver of segregation, it could be seen as implying a prediction that segregation would lower in nonmetropolitan settings because residential separation does not lead to racial segregation in public schools as, at least since the 1970s, public schools are desegregated and it is common for nonmetropolitan communities to have a single campus for high school and also at lower levels. Thus, residential segregation may not confer educational advantages to middle-class White households in nonmetropolitan settings. And, relatedly, White households whose children attend non-public schools, a strongly emergent pattern for White families after 1970 (Cready & Fossett, 1998), do not need to be residentially separated to achieve exclusivity and advantage in schooling. If, in fact, racial segregation is observed to be significantly lower in nonmetropolitan settings, it constitutes evidence consistent with the "White flight" hypothesis. But, if segregation is equally high or even higher in nonmetropolitan settings, it raises questions regarding what the fundamental drivers of segregation are. One possibility would be that different, but equally powerful, dynamics of segregation exist in both metropolitan and nonmetropolitan settings. Another possibility is that similar dynamics drive segregation in both settings and researchers need to refine theories to acknowledge the commonality.

Racial and ethnic segregation in nonmetropolitan communities particularly warrants greater attention in recent years due to the striking demographic shifts occurring in nonmetropolitan communities. Lichter and Brown (2011) argue that rural areas are often overlooked and misunderstood as socially isolated from the dynamics of urban contexts, when in fact they should be seen as increasingly interdependent with metropolitan areas, particularly due to migration patterns that have diversified the nonmetropolitan United States (Winkler & Johnson, 2016). While these areas have been characterized over the last few decades by stagnant White population growth or even decline, an opposing force has offset this trend: the migration of minoritized racial and ethnic groups to nonmetropolitan communities (Johnson, 2006; Lichter, 2012; Lichter et al., 2018; Sharp & Lee, 2017; Winkler & Johnson, 2016). Latino migrants are primarily driving this trend, but Asian presence is also substantial in some nonmetropolitan communities and can be anticipated to grow (Sharp & Lee, 2017). Additionally, many rural communities in the South have long been home to a significant number of Black residents whose history is tied to the South's agricultural economy which relied first on enslaved Black people and later on Black sharecroppers to perform most of the cultivation and production labor. Adding to this is a reversal of the Great Migration to Northern urban areas that characterized the mid-twentieth century, with Southern areas seeing a new surge of Black migrants (Hunt et al., 2008, 2013) with evidence of long-term settlement (DeWaard et al., 2016). Growing minoritized racial populations in nonmetropolitan communities combined with White population decline can lead to what appears to be growing nonmetropolitan diversity, although Lichter et al. (2018) argue that these forces do not necessarily create conditions of integration or harmonizing race relations if White residents exit these communities in a traditional "White flight" dynamic. The need to focus on residential segregation in nonmetropolitan settings is apparent, and we shift our attention to nonmetropolitan communities in this chapter through an application of the methodological innovations in segregation measurement that motivate this book.

4.2 Challenges for Nonmetropolitan Residential Segregation Research

Segregation in nonmetropolitan settings has received less attention in empirical studies of the past not due to lack of interest on the part of researchers but primarily because measuring segregation in nonmetropolitan settings involves significant challenges. One major problem has been limitations of data availability for spatial units appropriate for measuring segregation in nonmetropolitan communities. These problems have been overcome in recent decades as the U.S. Census Bureau achieved full block-level coverage of the United States, including all nonmetropolitan counties, in 1990, and from that time has distributed summary file tabulations of racial-ethnic distributions at the block-level along with related tabulations by age, sex, and other key demographic variables. Consequently, the literature has witnessed an increase in studies on segregation in nonmetropolitan communities starting in the early 2000s, with particularly important contributions by Daniel Lichter and colleagues who called for segregation researchers to devote more attention to segregation in small-towns and rural communities and provided exemplars of how such research can be undertaken (Lichter et al., 2007a). We endorse Lichter's observation that "Rural minority populations are spatially segregated and invisible in ways not usually found in America's metropolitan areas with large and densely settled inner-city minority populations" (2012: 4) and we also endorse his arguments that these patterns are compelling and justify the view that more scholarly attention be given to the often overlooked minoritized racial populations of the nonmetropolitan United States.

Studies by Lichter and colleagues and by others have indeed brought needed attention to the residential patterns of rural areas. This is especially welcome because increased attention is occurring at a critical point when the demographic composition of many nonmetropolitan communities has become more diverse, often changing in dramatic ways in comparison with earlier times when their racial-ethnic composition was more homogenous (Sharp & Lee, 2017). But, despite these welcome developments, our knowledge of nonmetropolitan residential segregation, including how it compares to metropolitan segregation and why it matters, remains incomplete. To emphasize why we may be missing something important about understanding the origins and dynamics of residential segregation, Lichter and Brown (2011), in their review article of the rural United States in relation to our national focus on urban contexts, concluded that there is a "blurring" of rural-urban spatial boundaries which "ironically…has been accompanied by the hardening of aspatial boundaries (e.g., race and class)" (Lichter & Brown, 2011: 584). If indeed the boundaries of race and class are solidifying in nonmetropolitan contexts, then we must investigate the spatial boundaries within nonmetropolitan communities for evidence of patterns of segregation that often accompany intensifying racial divisions. However, many of the studies that have attempted to expand our knowledge of nonmetropolitan segregation come with limitations and withholdings, bringing us to the primary reason why the literature remains so sparse.

While availability of relevant data has improved significantly, research on nonmetropolitan residential segregation has faced a second major challenge in measuring segregation. This is that standard approaches to measuring segregation can and often do lead to misleadingly high scores under conditions that are common in rural communities and nonmetropolitan communities with small populations. Namely, measuring segregation in nonmetropolitan communities includes having to measure segregation using data for small spatial units when groups vary widely in relative size across communities. Either condition presents a major practical problem and together the problems are compounded. Studies of segregation in nonmetropolitan settings have until recently had to take one of two paths for dealing with these practical problems. One path is to carry over practices used in studies of segregation in metropolitan areas with minimal changes, with the consequence that analysis samples are small and nonrepresentative. The other is to modify practices used in earlier studies of metropolitan areas to achieve larger, more representative analysis samples, but with the consequence that index scores are more susceptible to being distorted by index bias.

Some studies of segregation in nonmetropolitan communities have, with only minor adjustments, adopted the methodological practices used in studies of segregation in metropolitan areas. In these cases, communities are screened for inclusion in the analysis based on highly restrictive minimum population thresholds and sometimes at a level needed to sustain segregation measurement using census tracts as neighborhoods – often out of not unfounded wariness of problems associated with measuring segregation using block-level data with standard segregation indices (Fossett, 2017). For example, Byerly's (2019) study of American Indian and Alaska Native (AIAN) segregation used an area-level sample restricted to metropolitan and micropolitan areas where there were at least 1000 single-race AIAN individuals and 1000 multiracial AIAN individuals with segregation measured at the census tract level. At this end of the spectrum of methodological choices, the sample restrictions adopted have undesirable consequences of distorting our understanding of nonmetropolitan segregation due to limiting attention to a small and decidedly nonrepresentative set of communities that are larger in size and to group comparisons where both groups are larger in both absolute and relative size. In particular, case restrictions that apply high minimum population thresholds for the groups in the comparison exclude a large swath of nonmetropolitan communities where minoritized racial populations are newly emerging and potentially impacting residential distributions, thus precluding the opportunity to directly observe how segregation patterns initially form in small communities and change as new groups grow in absolute and relative size.

This is both concerning and ironic because we find that the restrictions do not necessarily lead to more effective measurements of segregation. Measuring segregation at the census tract level in nonmetropolitan communities may screen cases in a way that reduces the impact of index bias, but it carries an unwelcome consequence of systematically underestimating the level of segregation in nonmetropolitan settings because census tracts are too large to capture patterns of segregation as they occur in smaller communities; specifically, they obscure clear patterns of segregation that occur across smaller spatial units such as census blocks by combining blocks that differ on racial composition into much larger census tracts that then misleadingly appear to be substantially integrated. This is not necessarily a problem in large metropolitan areas where individual tracts contain a small share of the population in the community and, due to clustering dynamics, segregation typically is manifest in patterns that can be captured by tracts. But these conditions do not necessarily hold in smaller metropolitan areas and they certainly do not hold in nonmetropolitan settings.

To avoid the problem of having small non-representative samples where segregation is systematically underestimated in smaller communities, researchers must consider the alternative path of modifying practices used in studies of segregation in large metropolitan areas. Relaxing sample restrictions to use lower screening thresholds on absolute and relative group size will yield larger, more representative samples. Measuring segregation using block-level data will capture segregation in smaller communities as well as in larger communities. But adopting these changes leads to increased risk that scores obtained using standard formulas for calculating values of segregation indices will be inflated by index bias that varies in magnitude across communities and is especially high in communities where new groups are small in absolute and relative size. Lichter et al. (2007a) elected to measure segregation using block-level data because they would otherwise not be able to adequately detect the sort of small-scale segregation that occurs in small towns and rural communities. But it required accepting the risk that segregation index scores were potentially distorted by index bias.

We recognize previous researchers have faced difficult choices and sympathize with their dilemmas. One of our major goals for this book is to identify and use strategies for measuring segregation more accurately and appropriately, especially in noncore and micropolitan communities and in new destination communities (see Chap. 5) where groups may be small in absolute and/or relative size. On this point we bring welcome news. Specifically, new developments in methods for measuring segregation have introduced solutions that overcome these longstanding problems in measuring segregation in nonmetropolitan communities. Adopting these new methods enables us, and other researchers, to conduct the most inclusive and precise analysis of nonmetropolitan residential segregation to date and set accurate benchmarks and methodological guidelines for future analyses.

4.3 Segregation in Nonmetropolitan Communities: What We Know, and What We Question

The research over the past few decades on segregation in nonmetropolitan communities has been valuable, but also limited and somewhat inconsistent. Hwang and Murdock (1983) produced some of the earliest research in this area, examining segregation in nonmetropolitan communities and metropolitan areas of Texas and finding that segregation was highest in nonmetropolitan communities that were not adjacent to metropolitan areas. In a subsequent study, Murdock et al. (1994) noted that there had been very few attempts to study and understand segregation in nonmetropolitan communities, making it difficult to answer even the most basic questions about the nature of segregation in nonmetropolitan contexts or draw out comparisons with metropolitan areas where patterns of segregation were better understood. They tried to address this gap in the literature by examining block-level segregation in Texas cities but were not able to cover all nonmetropolitan communities due to the limited coverage of block-level census tabulations at the time. Nearly 30 years later, their initial observation on the state of the literature still holds mostly true with the notable exception of significant contributions by a few research teams. Despite much better census data coverage and public-use data availability, research on segregation in nonmetropolitan communities remains limited. The literature, while growing over the last decade, is still far from comprehensive or definitive.

Studies that have sought to describe patterns and trends of segregation in nonmetropolitan communities have at times offered inconsistent findings on whether racial segregation is higher or lower in nonmetropolitan communities compared to metropolitan areas. For example, while the majority of studies have argued that White-Latino segregation is higher in nonmetropolitan communities (Hwang & Murdock, 1983; Lichter et al., 2007a, 2010; Murdock et al., 1994), some studies have found White-Latino segregation in nonmetropolitan communities to be lower, including one notable study by Wahl et al. (2007) where White-Latino segregation in micropolitan areas was considerably lower than in metropolitan areas, on average. The literature is also conflicted on how segregation is changing in these areas over time and why Murdock et al.'s 1994 study found substantial White-Black segregation declines from 1980 to 1990 in both metropolitan areas and nonmetropolitan communities in Texas, with larger declines occurring in areas with population growth. Lichter and colleagues' 2007 research reported similar findings in a national-level study. Both studies also reported findings that White-Latino segregation was declining as well (Lichter et al., 2007a; Murdock et al., 1994). Other studies, sometimes using non-standard approaches to segregation measurement (e.g. Logan & Parman, 2017), have found more varying trends over time.

Lichter et al. (2007a) have to date made the most comprehensive effort to measure segregation in smaller and rural communities with their analysis of place-based segregation, and thus we treat their research somewhat as the benchmark for this chapter. Their article importantly recognizes that segregation observed in nonmetropolitan communities is substantively meaningful and consequential. They also echo the observations of Murdock and colleagues 13 years prior – that there continues to be little social scientific interest in the residential patterns of nonmetropolitan communities. These researchers describe the social and demographic conditions that have existed in the nonmetropolitan United States which set the stage for segregation to rise in response to the demographic trend of steady nonwhite population growth in nonmetropolitan communities over the past three decades. These conditions include the persistence of residential patterns established during the Jim Crow era for Black households in the nonmetropolitan South and of the concentration of Native American households on tribal reservation lands (Lichter et al., 2007a), the history of informal and formal tactics of discrimination and violence that created and maintained all-White "sundown towns" above as well as below the Mason-Dixon line (Loewen, 2006), the lower socioeconomic standing of nonwhite groups moving to nonmetropolitan areas, the foreign born status and limited English-language ability of Latino immigrants, and pre-existing and persistent White racial intolerance (Lichter et al., 2007a).

Measuring segregation using the dissimilarity index (*D*), Lichter et al. (2007a) find that White-Black segregation overall is extremely high with levels in nonmetropolitan communities slightly higher than in metropolitan areas.[2] Allen and Turner (2012) similarly found that White-Black segregation was very high in nonmetropolitan communities. Lichter and colleagues additionally reported that White-Black segregation is declining, in a manner similar to that reported in studies documenting trends in metropolitan areas. High and declining levels of White-Black segregation may not be surprising, but what may come as a surprise is that the researchers also document moderate to high levels of White-Latino segregation in both metropolitan and nonmetropolitan communities. Indeed, when we use the standard dissimilarity index, we also find a sizable percentage of nonmetropolitan communities with medium to high scores for both White-Black and White-Latino segregation (Table 4.1). But, while it is useful and perhaps reassuring to replicate past findings, we caution against placing undue confidence in these particular results

Table 4.1 Distribution of nonmetropolitan communities across low, moderate, and high levels of segregation, standard and unbiased dissimilarity index

	White-Black			White-Latino		
	Low	Moderate	High	Low	Moderate	High
1990						
Conventional D	0.1%	1.6%	98.3%	0.6%	19.3%	80.1%
Unbiased D	7.3%	23.3%	69.4%	76.5%	22.5%	1.0%
2000						
Conventional D	0%	2.6%	97.5%	0.2%	16.1%	83.7%
Unbiased D	13.5%	33.8%	52.7%	75.2%	23.8%	1.0%

[2] Lichter and colleagues weighted cases by the size of the Black population following a practice that is common in empirical studies where it is portrayed as a useful strategy for "dealing with" the problem of index bias. We replicated this reported finding and can additionally report that if cases are weighted equally White-Black segregation as measured by the standard version of *D* is even higher in nonmetropolitan areas compared to metropolitan areas. We note that differential case weighting does not remove or otherwise control for bias in index scores. The best a researcher can accomplish with the strategy is to minimize the impact of cases suspected of having inflated scores. In analyses not reported here we find values of the unbiased version of *D* have a positive (not negative) relationship with the size of the Black population. The same is true for both the standard and unbiased versions of the separation index.

because the standard version of the dissimilarity index is far more likely to be affected by index bias in exactly these scenarios.

When we compare scores for the standard and unbiased versions of the dissimilarity index, we find important differences for White-Black segregation. Not surprisingly, average index scores are lower, and more communities register low-to-moderate scores on the unbiased dissimilarity index. The reductions are especially large in nonmetropolitan communities with Black populations that are small in absolute and relative size.

We find the impact of bias is even larger and more concerning in the case of White-Latino segregation, where the contrast between the values of the standard and unbiased versions of the dissimilarity index is nothing short of dramatic. We find that 19 percent of nonmetropolitan communities in 1990 had moderate scores on the standard dissimilarity index and 80 percent had high scores when measuring White-Latino segregation. This distribution between moderate and high values of *D* is more pronounced than that reported by Lichter et al. (2007a), who found that 56 percent of areas had moderate scores and only 30 percent had high scores for White-Latino segregation. One reason for this is that our case selection criteria can be more inclusive and less restrictive as a direct benefit of using unbiased index scores. Thus, our analysis dataset includes more communities and the extra cases are ones that would have been excluded in early studies based on concerns that standard index scores were likely to be distorted by upward index bias.

One might understandably hope to find that the ad hoc strategies for dealing with the problem of index bias used in previous studies of segregation would be adequate in some sense when analyzing White-Latino segregation in nonmetropolitan communities. Unfortunately, this is not so. When we review scores obtained using the unbiased version of the dissimilarity index, we find a remarkably different distribution of communities along a low-to-high continuum of levels of segregation. Based on the unbiased dissimilarity index, 76 percent of nonmetropolitan areas have *low* scores, 22 percent have moderate scores, and only 1 percent have high scores. This distribution is completely opposite to what we observed using the standard version of the dissimilarity index and is very different from the patterns reported by Lichter et al. (2007a). The contrasts are clear and stark – scores for the standard version of *D* are inflated by index bias. The magnitude of bias varies in complex ways across cases, but it is never negligible. Instead, it ranges from moderate to severe and on average is high and thus shifts the distribution of scores to a fundamentally different range and pattern. These differences indicate that researchers have been right to worry about the impact of index bias on findings. New methods now make it possible to eliminate the impact of bias directly at the point of measurement so index scores can be examined and analyzed as is, removing concerns that individual scores and scores for particular kinds of communities cannot be trusted.

Our discussions of methods in Chap. 2 make the case in more detail. Here we briefly assert that the methods we use to deal with index bias are superior to any used in previous research with the most fundamental advantage being that all individual scores are accurate, valid, and free of bias as calculated and thus can be interpreted individually and compared across cases without concern for how findings might be distorted by bias. All previous strategies for dealing with index bias have necessarily worked with inherently flawed scores, with researchers attempting to minimize the impact of bias by excluding the most severely flawed cases and discounting less severely flawed cases based on screening and weighting variables that are presumed to be correlated with bias. By drawing on new methods (Fossett, 2017), we dispense with the need to use proxy correlates of bias to identify cases where standard scores are inflated by bias. We have direct estimates of bias based on the difference between the values of standard and unbiased scores for the same cases.

More importantly, having accurate unbiased scores wholly negates the need to unnecessarily exclude valid cases from the analysis and/or discount valid cases based on concerns about bias. Thus, as evidenced in Table 4.1, this also allows us to expand the study design to include a larger number of communities. When measuring segregation using block-level data, as is crucial in studies of nonmetropolitan communities, the problem of bias cannot be dealt with effectively by imposing selective restrictions on analysis samples. It can only be addressed by directly adjusting the index formula itself to eliminate bias at the point of measurement. Doing so produces substantially different results. Therefore, our knowledge about nonmetropolitan segregation, echoed in a more recent study by Lichter et al. (2016) where they again found that Latino segregation in nonmetropolitan communities is "exceptionally high" (Lichter et al., 2016: 512) with the dissimilarity index reaching scores as high as 60 – scores that we would also categorize as "very high" – must be reexamined and reconsidered in light of the different findings that emerge when measures are adjusted to eliminate the impact of index bias.

4.4 The Choice of Segregation Index for Nonmetropolitan Segregation Research

A major strength of our study is that we adopt a careful and nuanced approach to measuring segregation that is especially important for obtaining a more complete understanding of the nature of levels and trends in segregation in nonmetropolitan settings. In particular, we identify multiple methodological factors, including some that are not recognized in previous research, and we address them by using measurement strategies that are superior to those used in previous research on segregation in nonmetropolitan communities. The single most troublesome problem is the upward bias inherent in scores obtained using standard segregation index formulas. It is no exaggeration to characterize the problem as critical in studies of emerging segregation for new groups in nonmetropolitan communities. We argue, and present evidence to support our view, that findings based on measuring segregation in nonmetropolitan communities with scores obtained using the standard formula for the dissimilarity index should not be accepted at face value.

One might acknowledge the problem of index bias and yet have hope that certain findings regarding trends in segregation, variation in segregation across communities, and differences in levels of segregation across different group comparisons will nevertheless be unaffected. This welcome result would be possible in principle if bias inflated index scores in a uniform way across all circumstances. If so, one might acknowledge that scores are inflated by bias but could still be confident in findings that, for example, White-Black segregation is higher than White-Latino segregation in nonmetropolitan communities or that levels of segregation are declining over time. Unfortunately, we document that, in fact, this situation does not hold. The reason is both simple and devastating. The impact of bias on index scores in nonmetropolitan settings is far from uniform. It is sometimes small and sometimes very large, and the variation affects assessments of trends over time, variation across communities, and levels for different group comparisons. All of these problems are particularly pronounced for communities that are seeing sustained influxes of new groups, especially the many Latino new destination communities.

Index bias is not the only problem that causes us to reconsider and re-evaluate patterns of segregation documented in previous studies using only the dissimilarity index. Whether adjusted for index bias or not, the scores of the dissimilarity index are not able to distinguish between two very different patterns – namely, polarized unevenness associated with *prototypical* segregation and dispersed unevenness associated with a more benign pattern that is rarely discussed in the literature despite being surprisingly common (Fossett, 2017). Both patterns are common in nonmetropolitan contexts so the distinction between the forms of segregation associated with these patterns is highly relevant in the present study. As we explained in more detail in Chap. 2, the inability of the dissimilarity index to distinguish between polarized unevenness and dispersed unevenness takes on much greater practical significance in contexts where one group is disproportionately larger than the other (i.e., with a larger to smaller group ratio reaching 6:1 or higher). For example, consider a nonmetropolitan community where 98 percent of the pairwise population is White. If the typical minoritized group household lives on a block where the composition of the block is 96 percent White, they will technically live in a neighborhood that departs from parity on percent White. While the departure from parity on percent White is quantitatively small (i.e., 2 points), the prevalence of this pattern can easily produce very high scores on D because D is extremely sensitive to this aspect of uneven distribution, which we term dispersed unevenness. In simplest terms, at a given value of D, uneven distribution is maximally dispersed when as large a share of the minoritized group population as needed to produce the value of D in question resides in below parity areas that are as close to parity as possible.

Technically, the value of D in this situation will be correct as calculated and the usual interpretations will apply; for example, a value of 70 would indeed indicate that the majority-minoritized group difference in percentage residing in areas at or above parity is 70 with the consequence that at least 70 percent of the households in one group would have to change neighborhoods to bring about exact even distribution. The problem is that practices in the literature have fostered assumptions about the implications of the value of D that not only are not always correct but often are incorrect and highly misleading. Specifically, a high score on D is likely to be misinterpreted as signaling that a prototypical pattern of segregation associated with polarized unevenness is present when the reality of the situation is that this may be far from the case. The basis for this mistaken assumption is that didactic illustrations of segregation involving high scores of *D* (e.g., Iceland et al., 2002; Jaret, 1995; Taeuber & Taeuber, 1965) invariably show a pattern of polarized unevenness where neighborhoods that depart from even distribution are polarized on group composition into, for example, all-White (or nearly so) and all-Black (or nearly so) neighborhoods. What is never shown (at least to the best of our knowledge) outside of Fossett (2017) and this book, is that high values of *D* can arise in the more benign situation where the minoritized group generally or even exclusively lives alongside the majority group in areas that are close to parity on percent majority group in a pattern of dispersed unevenness that is rarely acknowledged and for which it is much harder to make the case that segregation in this form carries actual or potentially meaningful consequences for life chances.

We find that not only is it logically possible for *D* to register high scores when the two groups in question are unevenly distributed *without* a pattern of prototypical segregation, it is empirically common. This generally unrecognized possibility for the dissimilarity index to take high scores based on a pattern of dispersed unevenness is particularly relevant for measuring White-Latino and White-Asian segregation in nonmetropolitan communities, and, to a lesser degree, also for White-Black segregation. That is, White-Black segregation is more often characterized by a prototypical pattern of segregation wherein White and Black households are truly living in different neighborhoods in nonmetropolitan communities as well as in large metropolitan areas. In contrast, White-Latino segregation in nonmetropolitan communities is more varied and frequently takes the pattern of dispersed unevenness wherein the dissimilarity index takes high scores, but Latino households co-reside extensively with White households and rarely reside in predominantly Latino neighborhoods, if ever. Accordingly, analysis of White-Latino segregation must be measured in a more careful and nuanced way that can distinguish between the distinctly different possibilities for patterns of Latino settlement and residential distribution. The limitations of *D* are even more salient when evaluating patterns of White-Asian segregation as high values for *D* are almost never linked to patterns of prototypical segregation as typically seen for White-Black segregation. To be clear, this is not a technical issue in measuring White-Asian segregation. White-Asian segregation logically could take the form of prototypical segregation and sometimes does. But these cases are the exception and the overwhelming pattern is that White-Asian segregation takes the largely unrecognized pattern of dispersed unevenness.

To amplify the point, White-Black segregation takes the prototypical form of group separation into homogeneous enclaves on a more frequent basis. But this result is not dictated by any technical considerations such as the group being small or large in absolute or relative size. White-Black segregation logically can take the form of dispersed unevenness, and it occasionally does. But this pattern is the exception. The variation in these distinctly different patterns across group comparisons, across communities, and over time is sociologically important. It cannot be identified in studies using only the dissimilarity index. Over the past four decades, nonmetropolitan communities have been reshaped in relatively dramatic ways by migration with many areas experiencing non-trivial Latino settlement for the first time and racially diversifying in other ways. But in general, most of these areas remain predominately White with the median pairwise percent White ranging between 93 percent and 99 percent from 1990 to 2010. These disproportionate racial and ethnic compositions create scenarios where high values of the dissimilarity index often are the result of uneven distribution in the form of dispersed unevenness. For example, most Latino residents live on blocks that are slightly less White than the area overall but are nonetheless predominantly, and often overwhelmingly, White.

White-Latino segregation in nonmetropolitan communities can, and we find sometimes does, take on a more prototypical form in nonmetropolitan communities, particularly those communities where Latino populations are more settled and racial dynamics that might lead to enclave formation or racial conflict and group stratification have had time to take effect. But we cannot rely on the dissimilarity index to distinguish between the communities where this happens and the communities where it does not. This limitation of D – namely, the potential for a high score to reflect either polarized unevenness or dispersed unevenness, is fundamental. The only way to distinguish between the pattern of polarized unevenness and the pattern of dispersed unevenness – the former of which there is a strong consensus that the pattern is substantively meaningful and potentially highly consequential for life chances and the latter of which is rarely discussed and has never been identified as substantively important – is to examine alternative measures that are sensitive to this aspect of uneven distribution.

As we undertake our study, we acknowledge and appreciate the work done by those few groups of researchers over the past four decades who have advocated for giving greater attention to nonmetropolitan communities and segregation patterns and who have made important contributions to filling gaps in our knowledge in this area. But we also note that research in this area has had to deal with significant methodological challenges beyond what those researchers would encounter when investigating segregation in the largest metropolitan areas, including some challenges that have only recently become clear. Our goal in this chapter is to build on and extend their pioneering efforts and contribute to this body of research by using new methods to address and overcome these measurement challenges and thereby gain a clearer understanding of the state of segregation in nonmetropolitan communities and how these patterns are shifting over time. But before we do that, we must address a fundamental question: What does residential segregation mean in nonmetropolitan communities?

4.5 Debates Over Meaningfulness of Residential Segregation in Nonmetropolitan Communities

It is possible for a nonmetropolitan community to sustain a racially diverse population with high levels of integration and little to no systemic racial conflict, but this outcome is not a given. Studies focusing on large metropolitan areas have established that residential segregation serves as an effective mechanism, often being explicit in intent and design, for excluding minoritized racial and ethnic groups from access to resources that can be hoarded to the benefit and enhancement of White neighborhoods (Massey & Denton, 1993; Trounstine, 2018). Traditional place stratification perspectives emphasize this key motivation behind segregation, which whether by active intent and/or by inertia, serves as a tool for maintaining White privilege and advantaged status position (Logan, 1978). A key example of this would be the nature of school districts, with school funding tied to local tax bases and private donations. Racial inequities in K-12 education can be dramatic in segregated metropolitan areas and primarily harm communities of color, with no negative educational attainment effects on White children (Kozol, 2005; Quillian, 2014).

Segregation also has consequences for urban development, with neighborhoods where minoritized racial groups predominate being more likely to be disrupted by highway expansions or industrial zoning. Finally, Massey and Denton (1993) made the compelling argument that the residential concentration of minoritized racial groups in homogeneous ghetto or enclave neighborhoods can intersect with concentrated poverty and enable profound economic disadvantage, with these neighborhoods bearing the brunt of economic downturns and being more likely to experience high levels of poverty. While some of the specific aspects of segregation in metropolitan environments may not directly translate to nonmetropolitan settings (e.g., racial segregation in public high schools), we may still ask: Do similar consequences of segregation occur in nonmetropolitan communities? If so, what form do they take? As the presence of minoritized racial and ethnic groups in nonmetropolitan communities grows, we must consider the hypothesis that social conditions of competition for resources may crystalize along racial lines. This competition can lead to racial intolerance, racial conflict, persistent racist ideology, and structured racial inequality across many domains (Fossett & Kiecolt, 1989).

Cities and towns in micropolitan areas and noncore counties are by definition less populated and also often less densely settled, and therefore do not replicate some kinds of enduring, large-scale patterns of segregation observed in large metropolitan areas like Chicago, Detroit, Los Angeles, or New York City where large portions of groups reside in deep racial isolation, resulting from expansive regions of adjacent neighborhoods that are highly polarized on group composition. This condition sharply inhibits intergroup interactions and shared experiences and creates structural conditions that make group inequality on location-based outcomes logically possible. But patterns of segregation in nonmetropolitan settings can and often are enduring and consequential in their own right. Intriguingly, much of nonmetropolitan America has seen growth in minoritized racial populations in the post-Civil Rights era, raising questions regarding how settlement patterns form given the existence of fair housing laws and the end of most *de jure* segregation practices. Furthermore, neighborhoods in nonmetropolitan communities are smaller in scale compared to the ethnic ghettos, barrios, and enclaves seen in some metropolitan areas. Thus, in small towns and rural communities, there are more opportunities for intergroup interactions within a municipality where it is feasible, at least in principle, for most residents to access the same shops, services, and communal spaces while children attend the same schools.

However, anyone with even passing familiarity with nonmetropolitan communities will understand that differential spatial distributions can still be consequential in these settings and can create the logical potential for group inequality on location-based outcomes when racially polarized neighborhoods form at a smaller spatial scale. For example, residential segregation and associated spatial distributions can signal the state of race relations in the community, sometimes in very dramatic and explicit ways that carry practical as well as symbolic import. As Lichter (2012) cautions, the closer proximity and higher levels of interaction between White and minoritized racial groups in nonmetropolitan communities can potentially foster "mutual understanding" but it can also provide more opportunities for group conflict and the emergence of relations of racial hierarchy and dominance (2012: 26) as suggested by group competition theory (Blalock, 1967; Olzak & Nagel, 1986), which have been supported by findings from previous research on racial inequality in nonmetropolitan communities (Fossett & Therese Seibert, 1997). As an example of how this conflict can manifest, Lichter et al. (2018) discussed how heightened political divisiveness and anti-immigrant sentiment could be affecting reactions to growing Latino populations in nonmetropolitan communities, which has largely been driven by foreign-born migrants (Lichter et al., 2018).

Powerful historical evidence of the possibility of conflict and segregation in nonmetropolitan communities is exemplified by the "sundown towns" that emerged across the United States beginning in the early twentieth century, which were indicative of the resurfacing of overt racism and racial discrimination in the post-Reconstruction era throughout the nation in tandem with Jim Crow segregation taking root in the South (Loewen, 2006). Communities of all sizes and predominately outside of the South drove out Black households through intimidation, violence, and local law, creating intentionally all-White communities with Black households being excluded and relegated to rural settings, often outside of administrative boundaries for city services and political representation. James Loewen's deep archival research and analysis of census data identified thousands of definite and probable sundown towns in the United States, some of which maintain this status to the present (Loewen, 2006). These extreme patterns of segregation in nonmetropolitan settings and their implications differ in key ways from urban neighborhood segregation, as they often resulted in entirely White municipalities with Black households fleeing to larger urban areas or to rural all-Black towns and enclaves shut out from economic and political advancement (Loewen, 2006).

As for other consequences of segregation that are more apparent in metropolitan areas such as economic inequality, school inequality, housing disparities, and health disparities, we may see different expressions of inequality in nonmetropolitan communities. For example, in smaller towns and communities, all the children likely attend the same schools given that many rural communities only have a single elementary school, junior high, and high school. Consequently, Logan and Burdwick-Will (2017) find that racial and ethnic school segregation is significantly lower in rural areas compared to urban areas, although rural schools tend to underperform as a result of higher levels of poverty. Even so, we still might find that integration in public schools in nonmetropolitan settings often turns out to be a phantom achievement. In the Jim Crow South, White and Black children attended schools that were separate and massively unequal, and the Civil Rights Era brought an end to this formal system. But Cready and Fossett (1998) documented a historical transition over the period 1969–1990 where the end of *de jure* school segregation and racial inequality in quality and quantity of education in the nonmetropolitan South was followed by large-scale movement of White families into White-dominated non-public schools and increasing neglect and even abandonment of public schools in counties where the Black population reached thresholds at or exceeding 10–15 percent of the population. Public schools then received lower funding as White families paying enrollment fees for non-public schools had reduced incentives to maintain the quality of public schools. In this broader perspective, separate and unequal did not really disappear. Consistent with this pattern, segregation may occur at the meso-level in noncore counties with multiple schooling options.[3]

What can also clearly vary in disparate ways is socioeconomic status, access to resources and services, and exposure to poverty. For example, Albrecht et al. (2005) studied nonmetropolitan minoritized group concentration and reported two key findings: minoritized racial groups experienced greater economic disadvantage when living in counties with higher minoritized group concentration, and White residents experienced greater advantage in counties with larger minoritized racial populations. While they did not measure segregation within counties, their findings suggest that racial inequalities can exist in nonmetropolitan communities which are tied to spatially bounded demographics. In micropolitan areas and noncore communities, unique problems not generally seen in large metropolitan areas can emerge for those who live near incorporated areas. Municipal and other administrative boundaries can be highly consequential in these contexts, especially for households without the socioeconomic resources needed to offset certain challenges that result when residing on the wrong side of the boundary. Excluded residents may be disadvantaged on many important dimensions including access to municipal services relating to healthcare, emergency services, road maintenance, treated water, sewage and sanitation services, existence and maintenance of drainage and flood control systems, internet service, and transportation (Johnson et al., 2004). Lichter and Parisi (2008) found that rural poverty disproportionately impacts Latino and Black households, leading to social and economic isolation. As they argue, the interplay of race and class dynamics that are known to correlate with segregation are also evident in rural contexts but with greater constraints as it is more difficult for those who are most disadvantaged to seek out new environments and opportunities (Lichter & Parisi, 2008).

[3] This pattern is familiar to many residents of rural communities, but to our knowledge has not yet been studied in a comprehensive manner, in part because relevant data are not easy to obtain.

We name here a few other examples of how segregation in nonmetropolitan communities may be consequential for disparities in access to resources. First, Julia Caldwell et al. (2017) found that Black and Latino residents in segregated rural communities reported having worse access to a usual source of healthcare, although they were also more likely to report that their healthcare needs were being met, which the authors attribute to a possible "ethnic density" effect, particularly in areas where Latino population growth via migration has been high. Second, Erin York Cornwell and Matthew Hall (2017) reported that the risk of exposure to neighborhood problems has increased in rural areas for Black and Latino residents, and that racial disparities in perceived neighborhood problems are on the rise in these same communities.

There is also mixed evidence in the literature that White-dominated communities may be selective in annexing new neighborhoods depending on the racial composition of the neighborhood, echoing the "sundown town" dynamic. Lichter et al. (2007b) studied municipal under-bounding in rural southern communities, where municipalities will choose not to annex areas if doing so would change the demographics of the community and extend public service access to marginalized populations. They found mixed results, but one telling finding is that predominately White communities were less likely to annex neighborhoods with predominately Black populations. In contrast, Wilson and Edwards (2014) found no conclusive evidence of ethnicity-based municipal under-bounding in Midwestern communities when looking at percent Latino in fringe areas. To the extent that it may occur, municipal under-bounding holds implications for the health and well-being of excluded populations, in addition to the costs that these residents face by having to rely on privatized services which would otherwise be publicly funded such as sanitation, water, road maintenance, and emergency services. These political decisions bear consequences for segregation and equal access to resources and opportunities. Therefore, segregation can still be meaningful if, for instance, a minoritized racial group is predominately residing outside of a town's boundaries in rural enclaves, mobile home parks, and the like without services and amenities that are available in towns and nonmetropolitan cities.

In cases where the minoritized racial groups present in a nonmetropolitan community are a relatively new but growing population, a trend that emerged in the 1980s and 1990s, racial segregation can also serve as an indicator of the sort of reception these groups are given by the predominately White population established in these areas. Questions that may be asked in these situations include: What do initial settlement patterns look like?, How do these patterns shift over time? and, What role do changing demographics play in shaping the nature of social interactions as new migrants become permanently settled, start or are rejoined by their families, and interact more with the institutions of their new communities? The possibilities remain open for enclaves to form, for the newcomers to become fully integrated, or for racial conflict to emerge or intensify and lead to place stratification dynamics. This specific category of communities, referred to as new destinations, has been of particular interest in the nonmetropolitan segregation literature and is one that we focus on in the next chapter.

In sum, the literature on how and why nonmetropolitan segregation matters is mixed and far from conclusive, but there is enough to suggest that spatial residential distributions in nonmetropolitan communities can be and often are consequential for group inequality on location-based outcomes. To what extent and under what conditions remains to be understood and likely has much to do with local context and demographic changes. While we will not go as far as analyzing the consequences of segregation in nonmetropolitan communities, we undertake the important first step of producing valid measures of segregation in these areas that are free of the inherent biases which have vexed previous attempts to study nonmetropolitan segregation. The measurement choices that we make allow us to avoid the problems of upward bias and the risk of overstating the extent to which groups are residentially separated from one another without having to impose any major restrictions on the areas selected for analysis.

Perhaps with these refined baselines established, the literature can advance towards a better understanding of what nonmetropolitan segregation looks like and what it means for the people who experience it. We will summarize trends and patterns of racial segregation in nonmetropolitan communities. But we will also explore these patterns more deeply by conducting more aggregate-level analyses, mapping case studies, and comparing areas where prototypical segregation is occurring to areas where dispersed unevenness is evident and group separation is absent. In doing so we will further emphasize a central methodological point, which is that the choice of segregation measurement can be highly consequential for how we understand segregation, especially in nonmetropolitan communities.

4.6 Data

For the analyses in this chapter we continue to use data from decennial census summary files for 1990, 2000, and 2010, drawing specifically on census block tabulations of householder race and ethnicity data to calculate values of index scores for White-Black, White-Latino, and White-Asian household segregation in micropolitan areas and noncore counties. Micropolitan areas are similar to metropolitan areas in being Core Based Statistical Areas (CBSAs) constructed from one or more counties associated with a well-defined urban core. The main distinction is size and scale. Micropolitan areas have urban cores with populations between 10,000 and 50,000 and are thus smaller in size and scale in comparison with metropolitan areas, which have urban cores with populations from 50,000 up into the millions. Micropolitan areas are by definition not entirely rural but in many cases do have larger percentages of population residing in rural communities because they have smaller urban cores. Noncore counties, by contrast, are counties that do not contain an urban core of 10,000 and are not closely linked to a nearby urban core (e.g., through discernable commuting patterns).

We again impose minimal restrictions on our case selection, excluding areas where either group in the analysis has less than 50 households present in the area and areas where either group in the analysis comprises less than 0.5% of the pairwise population. This is to ensure that we are only measuring segregation in areas where block-level segregation could meaningfully occur. When one group in the analysis falls below these thresholds, it is highly unlikely that segregation could be sustained in any consequential way. Applying our selection criteria creates an analysis dataset that includes 46 percent of all U.S. nonmetropolitan communities for our White-Black analysis, 71 percent for our White-Latino analysis, and 18 percent for our White-Asian analysis by 2010.

4.7 Measurement and Approach

The majority of this chapter consists of descriptive analyses of White-Black, White-Latino, and White-Asian segregation in nonmetropolitan communities using direct quantitative measures of segregation as well as GIS mapping. As we did in Chap. 3, we adopt three innovative approaches to segregation measurement, which we hold are especially critical for gaining more accurate and informative assessments of the nature of segregation patterns in nonmetropolitan areas. First, we rely on the separation index (*S*) to measure important aspects of *evenness* that cannot be identified using the dissimilarity index (*D*). The separation index, like all measures of uneven distribution, registers positive values when the racial composition of one or more neighborhoods deviates from the overall composition of the community. The key for our needs is how different measures register the deviations. The separation index (*S*) takes high values only when deviations from even distribution are quantitatively large for at least one group (and maybe both groups). The popular alternative is the dissimilarity index (*D*), another measure of evenness that has historically dominated the segregation literature. Methodological studies note it is insensitive to the quantitative magnitude of departures from even distribution. But readers and even many researchers do not always appreciate how this can lead high scores on *D* to be misleading.

For the sake of self-containing this chapter, we offer here again a brief explanation of how the dissimilarity index and separation index are commonly calculated and interpreted, and how both are altered using the new methods developed by Fossett (2017) and employed in this book. Both *D* and *S* have fairly straightforward, easy-to-explain interpretations, especially when conceptualized in the difference-of-means formulation introduced by Fossett (2017). In this framework, all widely used measures of uneven distribution are reconceptualized as a simple arithmetic difference in group means on a neighborhood outcome (y) scored on the basis of area racial composition. The attractive quality of this framework is that it reveals very clearly how indices differ in registering large and small departures from even distribution. In the case of segregation from White residents, the commonly used dissimilarity index can be interpreted as the simple difference between the proportion of each group (e.g. White households and Black households) that lives in a neighborhood where the neighborhood proportion White is equal to or greater than the proportion of the population that is White for the community overall. The separation index has an equally easy interpretation; it is the simple difference in the average neighborhood-level proportion White between the two groups in the analysis. A thorough discussion of the implications of these differences in measurement for segregation research is presented in Chap. 2.

Significantly, the inherent level of upward index bias in *S* is always lower than the inherent bias in *D*. The difference in impact of bias on the respective scores of *S* and *D* can be large when measuring segregation using block data and it can be extremely large when measuring segregation for new, emerging groups. Fossett (2017) provides procedures for calculating versions of *D* and *S* that are free of index bias. This approach to computing unbiased index scores draws on the difference-of-means framework mentioned earlier. In this framework the source of bias can be described in fairly simple terms (see Chap. 2 for a more thorough technical discussion). Index scores for White-Latino segregation, for example, are computed as the White-Latino difference of group means on residential outcomes (y) for households scored on residential contact with White households as indicated by proportion White in their neighborhood of residence. The standard calculation of contact includes both contact with others and contact with self. Under random assignment, contact with others will have the same expected value for both groups and therefore does not contribute to index bias. In contrast, contact with self is fixed and cannot be randomly assigned. It is automatically higher for White households and lower for the minoritized group households. This is the sole source of bias in indices of uneven distribution (Fossett, 2017). This insight leads to a simple adjustment that eliminates index bias. It is to calculate contact for a household after removing the household from the terms of the calculation. Or in other words, contact should be computed for neighbors rather than for the entire neighborhood population. The logic is simple: Do not treat a household as its own "neighbor" and the source of index bias will be eliminated. We apply this correction in our formula of the separation index by first casting the separation index as a difference of means, as shown below:

$$S = \overline{Y}_1 - \overline{Y}_2 \tag{4.1}$$

Where Y_1 is the average contact score for the first group in the analysis and Y_2 is the average contact score for the second group in the analysis. For the separation index, the contact scores are calculated as shown below:

$$p_i' = (n_{1i} - 1)/(n_{1i} + n_{2i} - 1) \text{ for households in the reference group, and} \tag{4.2}$$

$$p_i' = (n_{1i} - 0)/(n_{1i} + n_{2i} - 1) \text{ for households in the comparison group.} \tag{4.3}$$

Where n_{1i} is the count of households belonging to the reference group in the analysis in the reference household's spatial unit, or neighborhood, *i*, and n_{2i} is the count of households belonging to the comparison group in the analysis in the reference household's spatial unit. The bias correction can be found in these equations, where the reference household is subtracted. In the case of households that belong to the reference group, they are subtracted from both the numerator and denominator. For households that belong to the comparison group, they are only subtracted from the denominator because their counts are not included in the numerator (for example, in a calculation of pairwise proportion White, only households with White householders would be removed from both the numerator and the denominator).

Finally, the third measurement innovation is that we chose to measure segregation of households as opposed to the convention of measuring segregation of persons. Most empirical studies of segregation calculate segregation index scores using tabulations for persons. There are several understandable reasons for this. Person data tabulations are more widely available and person data tabulations are the first to be released after any decennial census. And, it is substantively reasonable to wish to consider the full populations of the groups involved when assessing segregation. Unfortunately, segregation index scores based on person data are susceptible to a source of index bias than is not generally recognized. As a result, the problem of index bias is more severe than is widely appreciated and sound, effective options for dealing with index bias when using person data are not available.[4]

The last statement may seem odd since the sections above outlined multiple ways to obtain unbiased scores for segregation indices. Note, however, that the methods for obtaining unbiased index scores reviewed above are appropriate for application to data for households but they are not appropriate for application to measuring residential segregation using data for persons. This distinction between households and persons is important but not widely appreciated. To explain the issues involved, we now consider the nature of the results obtained when the procedure for obtaining unbiased index scores given in the last section is applied with person data instead of household data. The key to the procedure is to adopt a refined formula for calculating contact with the reference group that excludes contributions of self-contact – the source of bias in standard (biased) computing formulas. When the procedure for working with data for households is applied to data for persons, the exercise will reduce the level of bias in the obtained index scores in comparison to scores obtained using standard (fully biased) formulas. But, importantly, the reduction in bias will only be partial rather than complete. Data we review in Chap. 2 suggests that on average, eliminating self-contact for persons eliminates only about a third of index bias that originates in fixed same-race contact within households. So, the scores obtained are closer to standard (biased) scores than to fully unbiased scores obtained using data for households.

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[4]The one exception is when person data are tabulated by size of household as well as by race-ethnicity. Complex calculations can then remove bias associated with same-race contact within households. But such data are not widely available and methodological studies show that the results obtained using these data correlate very closely (e.g., $r > 98$) with results obtained using data for households.

This disappointing result traces to a simple but highly consequential fact. It is that most individuals do not locate independently; instead, most individuals locate in coordination with a cluster of individuals that together form a household and in an overwhelming majority of cases the households are racially homogeneous. This fact makes all of the procedures for obtaining unbiased index scores outlined above inappropriate for use with person data. To help draw out the basis for this conclusion, consider the following. Under random assignment of persons as members of racially homogeneous households, they are assigned in n-person clusters of same-race where n is the number of persons in the household. This will produce index scores that are much higher than when persons are distributed independently of the other members of their household, and the difference can be large. To bring these higher index scores down, one would have to break up many households and redistribute the individuals in them to other neighborhoods, and that is obviously a non-sensical proposition.

4.7.1 Summary of Methodological Approach

Our segregation measurement choices make it possible to draw out conclusions that reflect the reality of segregation in nonmetropolitan communities over time more accurately and fully. Measuring segregation of households using an index that is free of bias and that is up to the task of indicating when two groups are truly living in different neighborhoods, regardless of the size of either population or the spatial unit, makes it possible to study more nonmetropolitan communities across the U.S. than has been done before. Although our substantive interpretations are restricted to results from the unbiased separation index, we still take the opportunity in this chapter to compare outcomes measured with both the unbiased separation index and the unbiased dissimilarity index because nonmetropolitan communities are prime candidates for the sort of discordance that can occur between the two indices. We limit our analysis and discussion of this issue to summary scores and a selection of case studies that represent circumstances when the indices are in alignment and when they are not. This exploration of measurement issues is bolstered by GIS mapping, which allows us to visualize the extent to which groups are actually experiencing prototypical residential segregation in a nonmetropolitan community. This gives us a deeper, more nuanced analysis of segregation in nonmetropolitan contexts, and also permits us to showcase some of our methodological points, with the primary point being that segregation indices can react in considerably different ways to uneven distribution that occurs without high levels of residential separation. Shapefiles for GIS mapping are obtained from the National Historic Geographic Information System (NHGIS) through IPUMS at the University of Minnesota (Manson et al. 2022).

4.8 Changing Demographics of Nonmetropolitan Communities

The changing sizes of our analysis samples over time using our household population-based selection criteria hint at the changes taking place in nonmetropolitan communities with regards to racial and ethnic diversity (Table 4.2). The criteria that neither group in the pairwise analysis have a household population of less than 50 in the area means that the number of cases included for analysis varies from one decade to the next. Typically, this results when the minoritized racial group in the analysis is small in 1990 but grew in size in the following two decades – a pattern that is especially common for the Latino population. In 1990, these selection criteria give us 808 communities for analyzing White-Black segregation, 694 communities for analyzing White-Latino segregation, and 123 communities for analyzing White-Asian segregation. The majority of the communities included in our White-Latino and White-Asian analyses in 1990 are micropolitan areas, which by definition tend to be larger in overall population size than noncore counties. What is notable is that by 2010, the number of communities included for analysis increased by 72 for White-Black comparisons, 671 for White-Latino comparisons, and 227 for White-Asian comparisons. For our analyses of White-Latino and White-Asian segregation, these are sizable increases that were primarily driven by growing racial diversity, especially in noncore counties. While not all micropolitan areas are uniformly diversifying or experiencing nonwhite population growth, these overall trends demonstrate that the nonmetropolitan U.S. is increasingly heterogeneous on race-ethnicity of persons and households. In Table 4.3 we also present the pairwise percentage of each nonwhite group across time and communities. What is notable here is the pairwise percentages of Latino and Asian populations in micropolitan and noncore counties are quite low, which creates the conditions under which standard segregation indices may generate misleading results impacted by index bias.

Nonmetropolitan communities in general have seen increases in nonwhite populations from 1990 to 2010 (Table 4.4), with the largest increases occurring for

Table 4.2 Nonmetropolitan communities included in analysis by year, community type, and pairing

Group comparison and area type	1990	2000	2010
White-Black			
Noncore	442	439	452
Micropolitan	366	383	428
White-Latino			
Noncore	337	594	800
Micropolitan	357	511	565
White-Asian			
Noncore	13	28	66
Micropolitan	110	199	284

Table 4.3 Racial composition (pairwise) by year and community type

Group comparison and area type	1990	2000	2010
% Black (White-Black)			
Noncore	17.34	17.38	16.77
Micropolitan	11.57	11.50	10.71
% Latino (White-Latino)			
Noncore	10.11	7.75	7.66
Micropolitan	5.59	5.61	6.82
% Asian (White-Asian)			
Noncore	2.96	2.57	2.00
Micropolitan	2.50	1.95	1.81

Table 4.4 Median percent changes in minoritized group by community type, 1990–2010

Population change	Nonmetropolitan areas (included in analysis)	Nonmetropolitan areas (all)	Metropolitan areas
Median percent changes in black population	17.9%	32.0%	51.1%
Median percent changes in Latino population	220.0%	200.0%	198.8%
Median percent changes in Asian population	160.7%	128.1%	169.5%

the Latino population. Based on household data, which exclude group quarters and institutionalized populations, Latino percentage growth rates in all nonmetropolitan communities are keeping pace with metropolitan areas at a median of 200 percent over the two decades, and the median growth rate is higher when we look only at the subset of nonmetropolitan communities included in our analysis (i.e., leaving out areas where population sizes are especially small and either group's share of the population is below 0.5 percent). Median Asian population growth rates in nonmetropolitan communities are lower than in metropolitan areas, but nearly on par when we only look at the subset of nonmetropolitan communities included in our analysis.

Finally, median Black population growth rates are always lower in nonmetropolitan communities than in metropolitan areas, but especially when we only look at the nonmetropolitan communities included in our analysis. Black population growth rates are also lower in comparison to Latino and Asian growth rates, in part because growth of the latter groups is bolstered by immigration in addition to natural increase. These numbers lend support to the call for more research on segregation and racial diversification in the nonmetropolitan communities of the United States. With this sense of growing diversity in nonmetropolitan communities, the central questions we ask next are: What does residential segregation look like in nonmetropolitan communities, and how has it changed?

4.9 Overall Trends in Nonmetropolitan Residential Segregation

In Table 4.5 we summarize segregation according to the separation index for White-Black, White-Latino, and White-Asian comparisons in 2010 by community type. Generally, we find that segregation is higher in noncore counties for White-Latino and White-Black segregation, communities that are by definition smaller in population size and more remote from urban centers than micropolitan areas. For White-Asian segregation, we find no important differences between noncore counties and micropolitan areas, likely because the nonmetropolitan Asian population comprises a much smaller share of overall community populations, making it unlikely to find anything other than low levels of segregation regardless of type of community. Unsurprisingly, given documented national trends, segregation is highest between White and Black households, but not as high as what we have observed in large metropolitan areas where patterns of White-Black spatial distributions often coalesce into pronounced levels of hypersegregation – that is, high levels of segregation on several additional dimensions of segregation beyond uneven distribution (Massey, 2020; Massey & Denton, 1989; Massey & Tannen, 2015; Wilkes & Iceland, 2004; also see Chap. 3).

White-Black segregation was high in noncore counties and micropolitan areas and declined to moderate levels in micropolitan areas, while White-Latino segregation and White-Asian segregation have been low in both types of areas. Notably, White-Black segregation is declining across nonmetropolitan communities, tracking national trends towards lower, albeit still relatively high, levels. What differs drastically from previous research on nonmetropolitan segregation is that we find no evidence that White-Latino segregation is *typically* high in nonmetropolitan communities. Indeed, White-Latino segregation scores barely reach medium levels, and that is only observed in 1990 in micropolitan areas. Since 1990, nonmetropolitan White-Latino segregation has declined to low levels in micropolitan areas and has held steady at low levels in noncore counties. While less is said about nonmetropolitan White-Asian segregation in the literature, our findings clarify it would be wrong to adopt a default assumption that White-Asian segregation is high

Table 4.5 Separation index (unbiased) by year, community type, and pairing

Group comparison and area type	1990	2000	2010
White-Black			
Noncore	49.18	42.09	37.15
Micropolitan	38.95	31.09	24.60
White-Latino			
Noncore	14.86	12.50	11.55
Micropolitan	10.43	10.64	11.18
White-Asian			
Noncore	6.42	7.92	6.55
Micropolitan	8.91	6.99	6.62

or even medium in nonmetropolitan communities. Instead, we find White-Asian segregation has been steadily at low levels over the decades of our analysis in both micropolitan areas and noncore counties.

Our finding that segregation scores in nonmetropolitan communities are lower than have been previously reported applies across all major White-nonwhite group comparisons. Consequently, much of what we know about the relative differences between White-Black, White-Latino, and White-Asian segregation based on earlier research focused on metropolitan areas also applies in nonmetropolitan communities. Most importantly, Black households are usually the most segregated while Asian households are the least segregated. However, because this knowledge is mostly derived from studies of metropolitan contexts, we must consider the different demographic circumstances and dynamics of changing racial composition occurring in these nonmetropolitan communities where populations generally are more homogenous and disproportionately White than in metropolitan communities and where minoritized racial groups initially comprise smaller shares of the population, but in many cases are growing rapidly. Thus, we next turn to a bivariate analysis of the relationship between minoritized group population growth and levels of nonmetropolitan segregation in 2010.

In Table 4.6 we correlate the percent change in the (pairwise) minoritized racial population with point changes in the separation index from 1990 to 2010. For White-Black and White-Latino segregation we find moderate correlations and for White-Asian segregation, where patterns are more static over time, we find a weak correlation. In general, minoritized racial population increases are correlated with rises in segregation for the minoritized racial group in the comparison, holding implications for the many nonmetropolitan communities across the United States that have been racially diversifying over the last few decades. Previous research on this issue has already speculated on what it means for race relations, with recent work by Lichter et al. (2018) finding that White flight from nonmetropolitan communities could be undermining the potential for integration and intergroup exposure.

Our overview of segregation trends in nonmetropolitan communities relied on the separation index. As explained previously, this is because the more widely used dissimilarity index is not a good choice for describing levels of segregation in nonmetropolitan contexts because of its inability to distinguish between the different patterns of dispersed and polarized unevenness, both of which are common in nonmetropolitan communities. The technical basis for this decision is established

Table 4.6 Correlations between minoritized population change and changes in the separation index

Pairing	Correlation (r) between minoritized percent change and point changes in S, 1990–2010
White-Black	0.45
White-Asian	0.57
White-Latino	0.27

in Chap. 2. However, we provide a less-technical review of examples to highlight how very different patterns of uneven distribution can produce equally high scores on the dissimilarity index and to help explain why the literature has so far reported high levels of segregation in nonmetropolitan communities, when that is mostly not what we have found here. Thus, in the next section we elaborate on some of our methodological points about segregation measurement which become especially relevant for studying nonmetropolitan communities. We also ask a related substantive question: How have patterns, rather than levels, of uneven distribution been changing over time in these communities?

4.10 Diverging Measures of Segregation and Patterns of Uneven Distribution

We previously described why and how the dissimilarity index can report high levels of segregation when close review of the residential distributions for the two groups in the comparison reveal that they in fact are living together, occupying the same neighborhoods, experiencing similar levels of contact, and, by logical implication, experiencing similar averages on location-based outcomes. We have also highlighted how considering both indices together can reveal more about the patterns of unevenness that are occurring in communities. Here we again review the qualities of the dissimilarity index and the separation index in more detail to document and clarify the residential patterns that prevail when the two indices diverge, which occurs frequently in nonmetropolitan contexts. Thus, we are capitalizing on the inherent limitations of the dissimilarity index and the superior qualities of the separation index to describe patterns of uneven distribution, a term that we tend to use interchangeably with *segregation,* in nonmetropolitan communities. We draw on Fossett's (2017) terminology that distinguishes between prototypical segregation associated with polarized unevenness and the more benign pattern of dispersed unevenness. Both residential patterns involve particular aspects of uneven distribution, but each with different implications for intergroup residential contact.

To review, Fossett defines patterns of prototypical segregation as “displacement from even distribution [that] concentrates the populations of the two groups into homogenous areas that differ by quantitatively large amounts on area racial composition” (2017: 78). In contrast, dispersed unevenness is defined as the opposite, where uneven distribution is occurring but “group residential separation and area racial polarization are far below the maximum levels possible for a given level of displacement” (2017:78). The research on nonmetropolitan communities has by and large reported that segregation is high in nonmetropolitan communities based on the dissimilarity index, to the point that it is treated as conventional knowledge. We argue that in many cases, the high scores on the dissimilarity index are produced by a pattern of dispersed unevenness rather than a pattern of prototypical segregation. We can support this argument by contrasting scores for the dissimilarity index with scores for the separation index, which only gives high scores under conditions of prototypical segregation. To put it another way, the separation index will never give a high score when the pattern of dispersed unevenness is present and a high score on *S* always indicates the presence of the pattern of polarized unevenness.

Therefore, in Table 4.7 we present summarized scores of the dissimilarity index in micropolitan areas and noncore counties alongside the previously reported separation index. Focusing first on White-Black segregation we observe that over time, there has been little overall discordance between the dissimilarity index and the separation index. As we expected, even in nonmetropolitan communities patterns of White-Black uneven distribution are more likely to manifest as prototypical segregation where White and Black households live apart from each other and occupy different neighborhoods, thus resulting in limited residential contact with one another and creating the possibility of the groups experiencing systematically different exposure to location-based outcomes. There is also only moderate discordance between the dissimilarity index and the separation index when measuring White-Latino segregation in nonmetropolitan communities, with quantitative differences between the two indices shrinking over time as the Latino nonmetropolitan population grows rapidly.

However, there are substantive differences between the index scores when measuring White-Latino segregation that are worth noting because they hold implications for previous findings on this topic. Previous research had reported that nonmetropolitan White-Latino segregation reaches medium to high levels. We find significantly lower levels of segregation then previously reported when scores are calculated using the unbiased version of the dissimilarity index; indeed, scores shift down markedly to the lower end of medium levels. But as it turns out, even this change in results for *D* does not provide the full story of White-Latino segregation in nonmetropolitan communities because values of *D* do not typically indicate the same pattern of prototypical segregation that is present in White-Black segregation. In 1990 and 2000, we find that while the dissimilarity index signals medium levels of

Table 4.7 Separation index and dissimilarity index side-by-side

	Noncore counties		Micropolitan areas	
Pairing and year	D	S	D	S
White-Black				
1990	66.50	49.18	59.84	38.95
2000	60.70	42.09	54.03	31.09
2010	55.15	37.15	47.91	24.60
White-Latino				
1990	29.77	14.86	30.53	10.43
2000	28.45	12.50	29.79	10.64
2010	25.72	11.55	27.99	11.18
White-Asian				
1990	28.18	6.42	36.77	8.91
2000	31.51	7.92	36.44	6.99
2010	30.30	6.55	33.66	6.62

White-Latino segregation in micropolitan areas, the separation index indicates that White-Latino segregation is low. The dissimilarity index does not indicate low levels of White-Latino segregation in micropolitan areas until 2010. Here we draw out the substantive conclusions about shifting patterns of White-Latino uneven distribution based on comparing scores for *D* and *S*.

The discordance between *D* and *S* for micropolitan communities in 1990 and 2000 indicates the presence of the pattern of dispersed unevenness. The high value of *D* indicates that White and Latino households were unevenly distributed in the specific fact that, in comparison with White households, a greater proportion of Latino households were living in neighborhoods that were below parity on neighborhood proportion White. The substantially lower value of *S* indicates that in general White and Latino households were not living apart from each other and thus were not occupying fundamentally different neighborhoods as occurs under prototypical segregation. Latino households on average lived in neighborhoods that, while below parity on proportion White, were quantitatively close to parity. Thus, Latino households had average levels of residential contact with White households that were close to parity and we can conclude that Latino households necessarily experienced averages on location-based outcomes that were similar to those experienced by White households. However, by 2010, the separation index increases, indicating that Latino households are increasingly living in different neighborhoods apart from White households. This brings scores for *D* and *S* into closer alignment as scores for the dissimilarity index are more stable by comparison because scores for *D* are already high based on its strong response to dispersed unevenness and because *D* is much less sensitive than *S* when unevenness transitions from the more benign condition of being dispersed to the more potentially consequential condition of being polarized.

In the case of White-Asian segregation we find the most distinct discordance between the two indices out of all the comparisons. The dissimilarity index consistently shows medium levels of White-Asian segregation over time in both noncore counties and micropolitan areas while the separation index consistently shows very low levels of segregation. Unlike in the case of White-Latino segregation, this discordance does not subside over time because the pattern of dispersed unevenness for White-Asian segregation does not transition toward prototypical segregation. Thus, we have a clear example here of a situation where the dissimilarity index is reacting to uneven distribution without polarization (i.e. the two groups living apart from each other in neighborhoods that are polarized on group composition), while the separation index tells in a more straightforward way that White and Asian households in nonmetropolitan communities have quantitatively similar levels of residential contact with White households. In sum, there is no indication of prototypical segregation as the typical outcome for White-Asian segregation in nonmetropolitan communities. What appears to more often be the case is that Asian households in nonmetropolitan communities are more likely to live in neighborhoods that are slightly below parity on neighborhood proportion White – creating a pattern of dispersed unevenness which *D*, but not *S*, responds to strongly – but overall are still living in neighborhoods that are near-parity on contact with White households.

4.11 Case Studies: Areas with Dispersed Unevenness Versus Prototypical Segregation

To illustrate the differences between *dispersed unevenness* and *prototypical segregation (polarized unevenness)*, we present a selection of case studies where the separation index and dissimilarity index are discordant, and when they are not. Using GIS mapping, we are able to demonstrate what residential patterns look like when both the dissimilarity index and the separation index are concordantly high and contrast those patterns to situations where the dissimilarity index is high, but the separation index is low. These comparisons will reveal quite strikingly what is meant by prototypical segregation versus dispersed unevenness and will illuminate the shortcomings of the dissimilarity index to distinguish between the two patterns of uneven distribution. We will present a pair of case studies for each group comparison, examining patterns of White-Black, White-Latino, and White-Asian uneven distribution.

For comparing patterns of White-Black uneven distribution, we selected two nonmetropolitan communities in Missouri and Kentucky. To serve as an example of prototypical segregation with a pattern of polarized unevenness, we focus on the case of the Sedalia, MO Micropolitan Statistical Area in 1990, which is composed of Pettis County, MO. In 1990 the area had 14,056 households. Of those households, 3.4 percent had a Black householder. White-Black segregation is measured with a score of 66.6 on the dissimilarity index and a score of 60.9 on the separation index. Values of both indices thus would be categorized as "high" segregation under the classification scheme we are using in this study (given in Table 3.2), suggesting prototypical segregation. Indeed, while Fig. 4.1 depicts a micropolitan area where most blocks in the less populated parts of the county are predominately White, a pattern of prototypical segregation is apparent in Sedalia, the central town and county seat of Pettis County. In this town, a cluster of neighborhoods north of a railroad track are 80–100% Black, while all other neighborhoods outside of this area are 80–100% White. It then follows that households from the two groups have little residential contact with each other because they live apart from each other in neighborhoods that are polarized on group composition. With the exception of the "clustering" aspect of segregation revealed in the figure, we can reach the main conclusions about the nature of segregation based solely on the value of the separation index, as the score is the difference in mean neighborhood percent White between White and Black households – a difference of over 60 percent. It is clear that within some of the central urban core of this county there is a pattern of prototypical segregation with White and Black residents living on opposite sides of the town. These patterns reflect an "other side of the tracks" form of segregation where there is often a physical boundary such as a road or railroad track that divides White and Black neighborhoods. Thus, while high levels of prototypical segregation are not as common in nonmetropolitan communities as in large metropolitan areas of the Midwest and Northeast, they are certainly possible, as we observe in this micropolitan area.

Fig. 4.1 Sedalia, MO MSA, 1990

We next examine the case in 2010 of Garrard County, KY, a noncore county, in Fig. 4.2. We first note that the racial composition of Garrard County is similar to that of Sedalia, with percent Black at 2.2 percent. However, as a noncore county, the area has a smaller household population of 6,668 households. Despite that, this county has a dissimilarity index score of 57.8, which, while a bit lower than in Sedalia, is still easily categorized as high. The major difference between the two counties is that the separation index in Garrard County is only 8.9, a value falling in the category of low (or even very low) segregation and over 50 points lower than the value for the separation index score of 60.9 for Sedalia. This documents that communities that have similar scores on the dissimilarity index can have fundamentally different patterns of group separation and levels of minoritized group contact with White households. It also documents that the potential for a high degree of discordance between values of *D* and *S* is not an artifact of group size. The two cases considered have a low level of Black population presence (3 percent for Sedalia and 2 percent for Garrard County) and yet differ dramatically on *S*. This is because the Black population in Sedalia is concentrated in racially polarized neighborhoods while in Garrard County Black households generally live alongside White households in neighborhoods where proportion White is near parity (which in this case is 97 percent White).

The discordance between the two indices in Garrard County is an indicator of dispersed unevenness, meaning that while uneven distribution is technically occurring, both groups live in neighborhoods that are near parity, which in this case is predominantly White, and the group differences on neighborhood racial composition are not remarkable. Indeed, when we map pairwise White-Black plurality in Garrard County, we find only one neighborhood where Black households constitute a numerical majority, and it is less than 80%. This is corroborated by a tabulation of blocks in Garrard County by levels of plurality. Thus, while it is more often the case that White-Black uneven distribution in nonmetropolitan communities takes the spatial form of prototypical segregation, as indicated by the on-average medium scores on the separation index, we cannot trust the dissimilarity index to tell us that, especially when we are trying to identify specific areas where prototypical segregation is occurring. For instance, without a better understanding of the nature of the dissimilarity index, we might incorrectly assume that a prototypical pattern of White-Black segregation prevails in both the Sedalia micropolitan area and Garrard County. GIS mapping reveals that this is clearly not the case in Garrard County.

In Figs. 4.3, 4.4, 4.5, and 4.6 we present comparable case studies for White-Asian segregation and White-Latino segregation. The two communities that demonstrate these divergent patterns for White-Asian segregation are the Morgan City, LA Micropolitan Statistical Area and the Midland, MI Micropolitan Statistical Area in 2010. These nonmetropolitan communities have similar scores on *D* of 60.2 and 57.0 but markedly different scores on *S* of 31.4 and 5.9, respectively. As in the previous example, both communities are similar on relative group size; the Asian population makes up between 1 and 2 percent of the pairwise and total populations in both communities and also is similar in absolute size. The difference in the values of *S* arises because White-Asian uneven distribution in Morgan City is polarized while

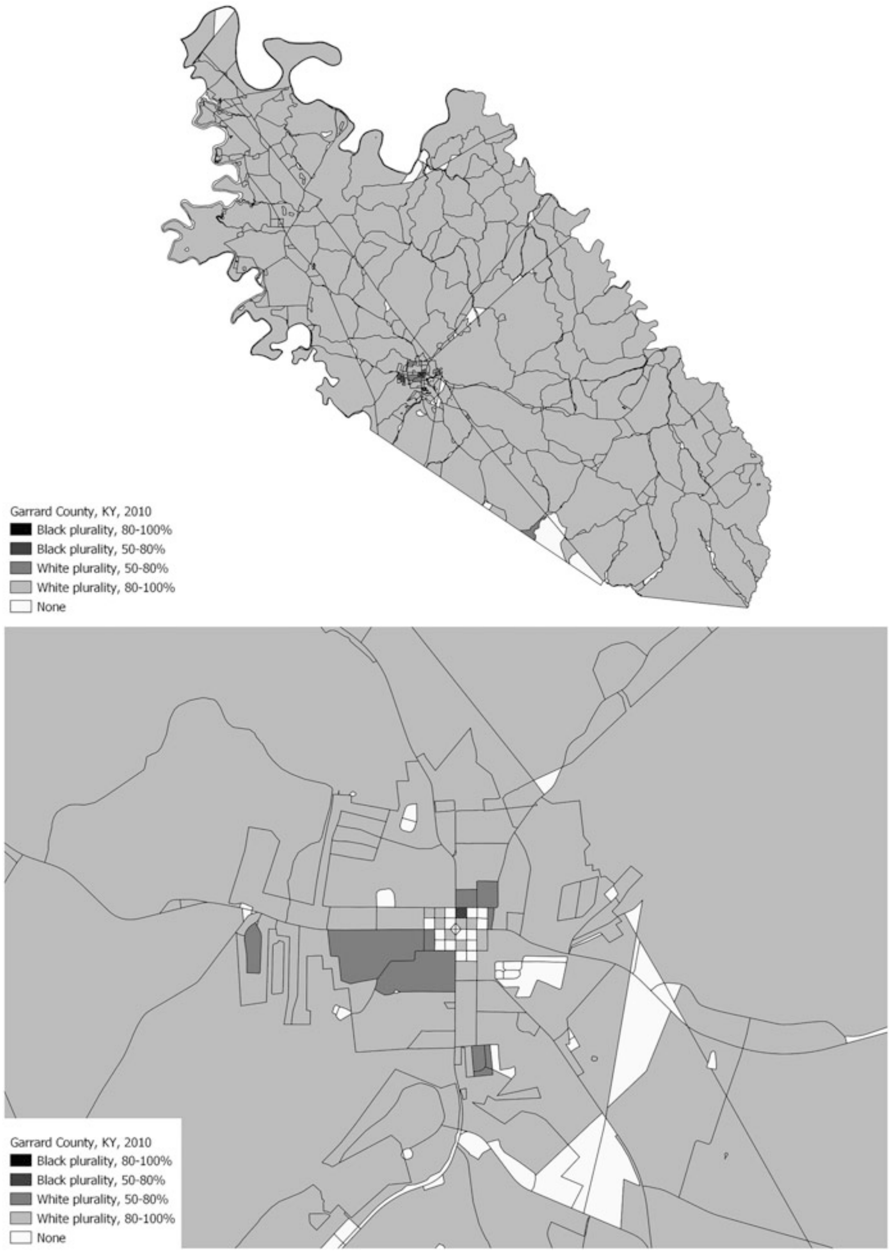

Fig. 4.2 Garrard County, KY, 2010

the uneven distribution in Midland is dispersed. Choropleth maps (and associated block-level tabulations) document that the Morgan City micropolitan area contains a distinct and predominately Asian neighborhood along the Gulf Coast in a small

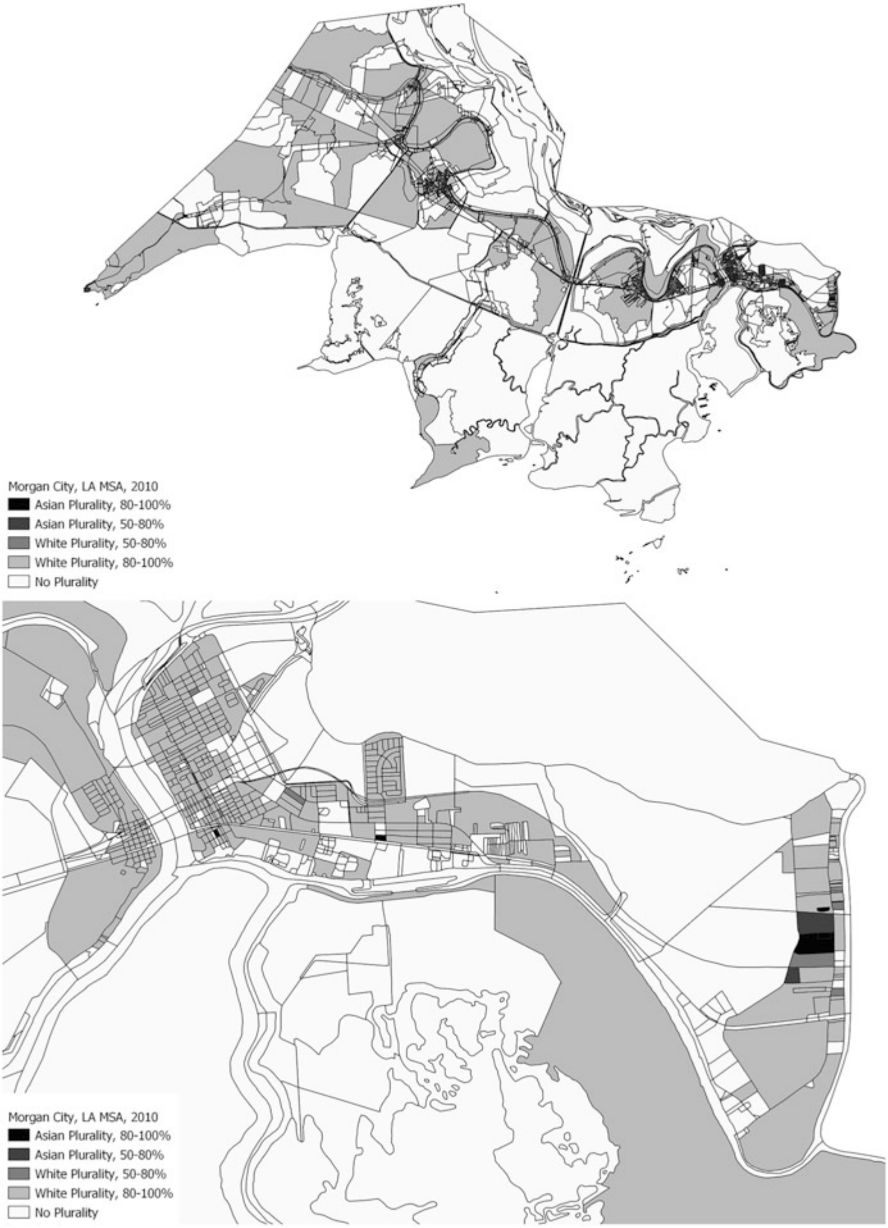

Fig. 4.3 Morgan City, LA MSA, 2010

community called Amelia. An examination of satellite images reveals that this predominately Asian neighborhood in Amelia consists of a sizeable mobile home park near a harbor out of which many Vietnamese-owned fishing and shrimping

Fig. 4.4 Midland, MI MSA, 2010

boats operate. Meanwhile, the choropleth maps (and associated block-level tabulations) for Midland reveal no predominately Asian neighborhoods. Habits of interpretation that are established in the literature could easily lead a researcher to

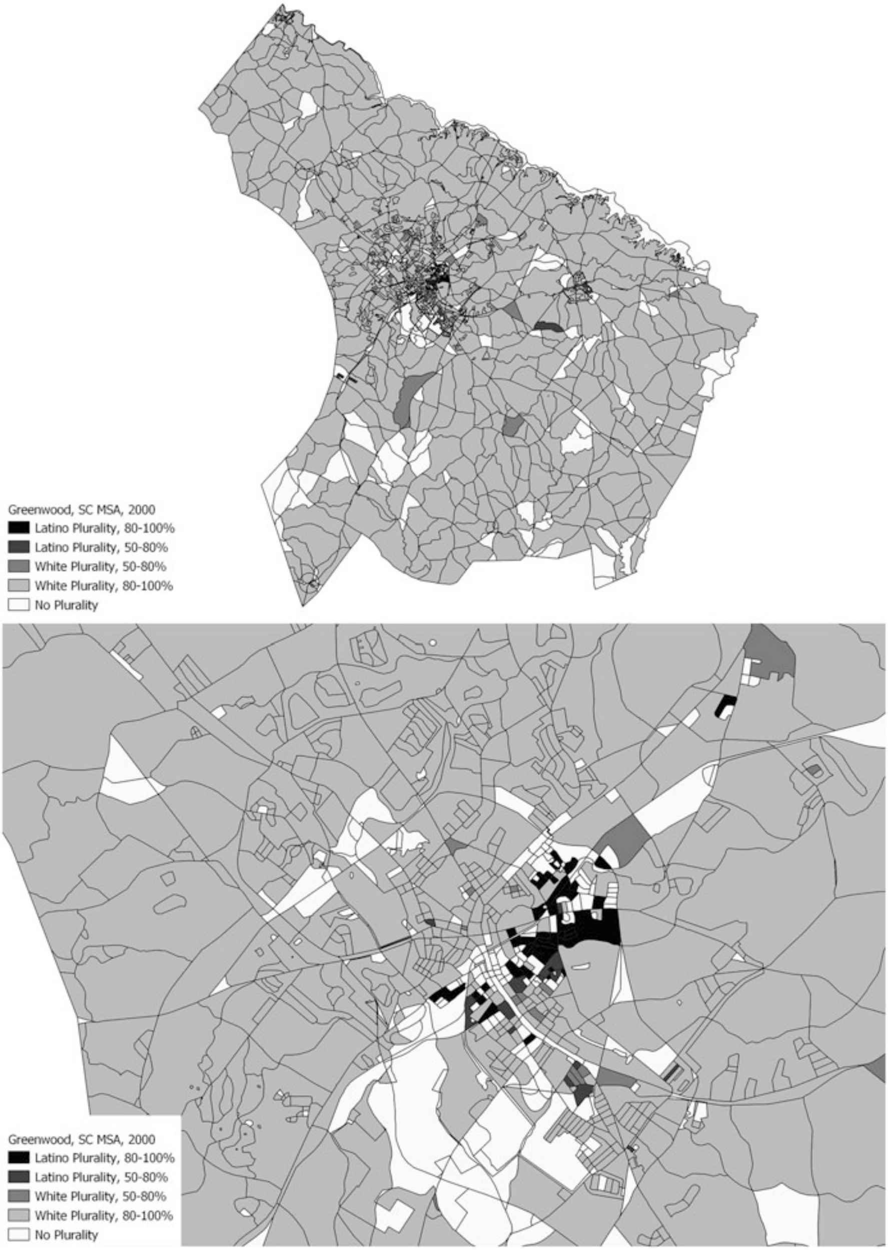

Fig. 4.5 Greenwood, SC MSA, 2000

mistakenly assume the comparable high scores on the dissimilarity index for both areas indicate that the level and pattern of White-Asian segregation is similar with Asian households living apart from White households in both communities. But the

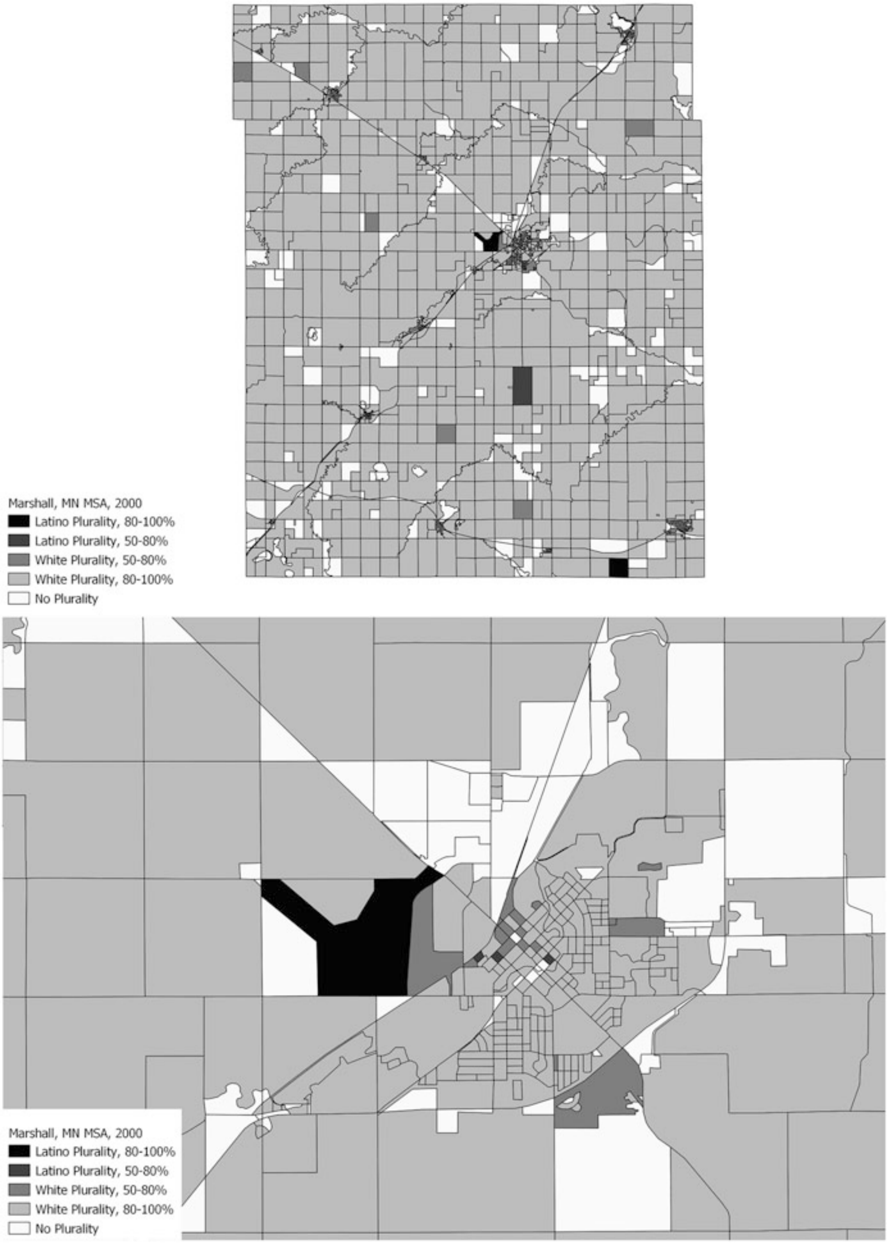

Fig. 4.6 Marshall, MN MSA, 2000

values of the separation index signal and clarify what the choropleth maps (and underlying block-level tabulations) reveal in more detail, which is that the comparatively high score for *S* for Morgan City indicates that White-Asian segregation takes the form of prototypical segregation associated with polarized unevenness while Midland, with a very low score on *S* and a high score on *D,* takes the much different form of dispersed unevenness.

Finally, we show comparisons of two areas with divergent patterns of uneven distribution for White-Latino segregation. The first is the Greenwood, SC Micropolitan Statistical Area in 2000, where the pairwise percent Latino is 2.6, the dissimilarity index is 59.0, and the separation index is 44.5. The second is the Marshall, MN Micropolitan Statistical Area in 2000 where the pairwise percent Latino is 2.5, the dissimilarity index is 48.0, and the separation index is 8.6. The choropleth maps for each community again document the dramatically different patterns of racial composition of neighborhoods that can occur in communities that have similarly high scores on the dissimilarity index but very different scores on the separation index. The figure for Marshall shows scant evidence of Latino concentration in Latino neighborhoods as only a few very lightly populated blocks have a Latino plurality, with the highest Latino plurality neighborhood containing only five individuals. Instead, unevenness for Latino households involves dispersal across neighborhoods that are below parity but only by small quantitative amounts and therefore are predominantly White. In contrast, the city of Greenwood, the namesake and county seat of Greenwood County, has a clear pattern of polarized unevenness. The Latino population in the city of Greenwood lives apart from White households and is concentrated in neighborhoods on the southern side of the city that are predominately Latino in pairwise group composition. Note that since the overall racial composition of Greenwood is 45 percent Black, one would have to consider other measures such as overall Latino isolation (as measured by the P* contact index) and/or the value of *S* for the Black-Latino comparison to determine whether Latino households are separated from all other groups, or just White households.

What is very apparent from these cases is that when the dissimilarity index and the separation index are discordant, one will find no visual (or quantitative) evidence that the minoritized racial group is segregated into different neighborhoods from White households. A systematic GIS analysis would show that in every nonmetropolitan community where the dissimilarity index is high and the separation index is low, the neighborhoods in the community will not be polarized on racial composition but instead the (pairwise) racial composition of neighborhoods will vary in a narrow range relatively close to parity. While both indices are recognized measures of uneven distribution, *D* is less capable of distinguishing between the important difference between polarized unevenness associated with prototypical segregation and dispersed unevenness, which is more benign in terms of logical implications for the potential for groups to experience inequality on location-based outcomes.

Unfortunately, it is currently the case that the dissimilarity index is widely used in the segregation literature but with little awareness that a high score on the dissimilarity index may not correctly signal the presence of a prototypical pattern of polarized unevenness that most researchers will reflexively assume is present. Instead, it is often the case that high scores on *D* in nonmetropolitan communities are associated with the decidedly different pattern of dispersed unevenness. Thus, we return to the earlier methodological point, which is that it is appropriate to assign priority to reviewing scores for the separation index because, in addition to being far less susceptible to bias than the dissimilarity index when measuring segregation using block-level data, it will correctly signal whether uneven distribution takes the form of prototypical segregation associated with polarized unevenness and will do so reliably even when groups are small in absolute and relative size. As the GIS maps demonstrate, residential segregation in nonmetropolitan communities can take the highly polarized patterns we are accustomed to seeing in metropolitan areas, and we can rely on the separation index to indicate when this is so. The maps additionally demonstrate that segregation can also take the much different form of dispersed unevenness wherein *S* will take a low value and high values on *D* will be misleading if they are mistakenly interpreted as indicating that groups live apart from each other.

4.12 Summary

We undertook several major tasks in this chapter. First, we discussed how the literature has struggled to overcome the limitations of standard segregation measurement when analyzing segregation in nonmetropolitan communities. Then we illustrated how adopting new methods and refined formulations of familiar indices in combination with data for households rather than data for persons can overcome the problem of index bias and thereby open up a new era of research where studies of segregation in nonmetropolitan communities can include a larger and more representative set of communities and group comparisons. Next, we illustrated how considering the values of the separation index can, more so than any other measure of uneven distribution, reliably identify segregation comparisons that involve the prototypical segregation pattern associated with polarized unevenness, a necessary precursor for group inequality on location-based outcomes. Finally, we illustrated how one can identify the more benign segregation pattern associated with dispersed unevenness based on the discordant combination of a high value of *D* and a low value of *S*.

Our review of segregation measured using the separation index and block-level data for households identified new and important understandings of how patterns of White-Black, White-Latino, and White-Asian segregation vary across nonmetropolitan communities. Specifically, we found that the pattern of segregation we refer to as prototypical segregation *does* indeed occur in nonmetropolitan communities but not nearly as commonly or to the degree that previous research would lead one to believe. We find prototypical segregation involving polarized unevenness is more often the case for White-Black segregation, which tends to be relatively high even outside of large metropolitan areas. We also find that White-Latino and White-Asian segregation also sometimes takes the form of prototypical segregation in nonmetropolitan communities, but we find this occurs much less frequently than is seen in patterns of White-Black segregation. This leads to the major finding that, contrary what previous research would suggest, White-Latino segregation in nonmetropolitan communities is low rather than high and is stable or increasing rather than declining. The key takeaway here is that conclusions about White-Latino segregation in nonmetropolitan settings based on previous studies that relied primarily on scores for the dissimilarity index must be reconsidered for two reasons. First, index bias has substantial and complicated impacts on the levels and variation in values of *D* across communities and over time. Second, with much greater frequency than is generally appreciated, high values of *D* do not provide a reliable signal of the presence of prototypical segregation and register a more benign form of segregation we term dispersed unevenness. This same finding applies with equal force to conclusions about White-Asian segregation in nonmetropolitan communities where our analyses document that segregation is very low and has remained low since at least 1990.

Our primary substantive conclusion from both Chap. 3 and this chapter is that segregation in nonmetropolitan communities is often not as high as what is observed in metropolitan areas, especially for Asian and Latino households. However, segregation can be and sometimes is high in nonmetropolitan communities, even when the minoritized group proportion is small in absolute and relative size, a point that we highlighted through GIS mapping of case study areas. This finding should negate any skepticism that segregation in nonmetropolitan communities can approach levels seen in metropolitan areas. It can, and does, in particular communities and group comparisons. But the finding that segregation in nonmetropolitan settings is lower is not an artifact of methods of measurement; it is a sociological fact. One of the questions for future research is what consequences can flow from nonmetropolitan segregation. At the level of index scores there is overlap in distributions of scores, but it is not appropriate to project conclusions about the consequences of segregation gleaned from studies focusing on metropolitan areas to nonmetropolitan communities. The consequences and relevance of segregation in nonmetropolitan and rural settings are important, but they are not necessarily the same as in metropolitan settings.

We argue our conclusions regarding methods for studying segregation in nonmetropolitan settings should have a more immediate impact on segregation research. Our review of the existing literature on residential segregation in nonmetropolitan communities left us with one overarching assessment: past research encountered serious methodological challenges that prompted, or forced, researchers to both restrict analysis samples, invariably leading to smaller, nonrepresentative samples, and also to adopt a variety of questionable ad hoc practices in analysis. These decisions are all motivated by well-founded concerns about the potential for index bias to distort findings when segregation is measured at small spatial scales, especially when groups are small in absolute and/or relative size. We demonstrated how new methods of segregation measurement in combination with using data for households rather than persons provide highly effective solutions to the central problem of obtaining unbiased index scores, thereby freeing researchers from any need to adopt onerous sample restrictions and questionable strategies of analysis. Findings based on these new methods show that previous research reporting high levels of segregation in nonmetropolitan communities using the dissimilarity index must be called into question on two counts. First, because unbiased scores are much lower and vary in different ways across communities and over time. Second, because the dissimilarity index cannot distinguish between dispersed and polarized patterns of unevenness, the latter of which we term prototypical segregation. Prototypical segregation is the form of segregation that motivates research on segregation and researchers and lay audiences alike frequently and mistakenly assume this pattern is present when the dissimilarity index takes a high value. We document this is not the case both as a logical possibility and as a frequent empirical result in analyses that involve broader, more representative samples and a wider range of community settings. Accordingly, we caution researchers to avoid making the mistake of assuming high scores on the dissimilarity index are sufficient to support the conclusion that two racial groups are living apart in different neighborhoods that are polarized on racial composition and thus can experience inequality on location-based outcomes.

Other indices, in particular the separation index, are superior options that can be relied upon to provide a definitive signal that a pattern of prototypical segregation is present when the index value is high. This is important for studying segregation in nonmetropolitan communities, which often present circumstances of measurement under which the dissimilarity index is most likely to be problematic. Thus, we make two recommendations for measuring segregation in nonmetropolitan communities. First, always use the unbiased formulations of segregation indices as developed by Fossett (2017). Simply put, one is never worse off when using the unbiased scores, as they only deviate from standard scores in circumstances where the standard scores are flawed. Second, review scores of the separation index either alone or in combination with the dissimilarity index to get a complete picture of the nature of uneven distribution. The separation index is better suited than any other widely used index to indicate when the spatial distribution of groups across neighborhoods in a community takes the form of polarized unevenness associated with prototypical residential segregation that is invariably depicted in didactive presentations of high levels of residential segregation (e.g., White-Black segregation in Chicago).

Again, one is never worse off for examining values of the separation index. If values of D and S are concordant, the values of S provide confirmation that, by empirical coincidence, not logical necessity, high values of D are associated with prototypical segregation. If values of D and S are discordant, the low value of S provides the definitive basis for concluding the pattern of prototypical segregation is not present and instead the underlying pattern is one of dispersed unevenness. Adopting both options for segregation measurement will free segregation researchers to study residential segregation in nonmetropolitan communities across larger, more representative samples without being hampered by the long-standing and frustrating methodological challenges relating to index bias. These new approaches to measuring segregation yield superior measurements that can help researchers answer the call in the literature over many decades to better document and understand residential segregation in nonmetropolitan communities.

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Chapter 5
Latino and Asian Segregation in New Destinations

5.1 Overview

Beginning in the 1980s and 1990s, hundreds of large and small communities across the United States underwent significant demographic changes as immigrant households began moving away from initial destinations in traditional "gateway" cities and regions and migrating to areas of the United States where the population had been predominately native-born and often predominately White (Lichter & Johnson, 2006; Hall, 2013; Massey & Capoferro, 2008). As their numbers grew, they were in many cases also joined by immigrants who migrated directly to these "new destination" communities. This new migration pattern captured researchers' attention for a multitude of reasons. First, it has largely been driven by Latino migrants (Kandel & Cromartie, 2004), and to a lesser extent by Asian migrants, who have historically been concentrated along the U.S. borders and in select large metropolitan areas that have been and remain popular gateway destinations for immigrants like Los Angeles, Chicago, and New York City. Consequentially, the areas that are now receiving new but steady streams of migrants and immigrants are now commonly referred to as new destinations because they are communities where a co-ethnic population was not already in place. This fact alone has sparked significant scholarly interest, with researchers seeking to understand how new destinations are receiving and reacting to new migrants and how these communities are transformed socially, demographically, and economically as a result of growing racial and ethnic diversity (Lichter & Johnson, 2020; Ludwig-Dehm & Iceland, 2017; Waters & Jiménez, 2005).

A second reason for interest in these communities is more specific to residential segregation research. It is that new destinations can serve as empirical testing grounds for longstanding theories about how segregation patterns for new groups emerge and change over time. The segregation literature is dominated by studies of large metropolitan areas where segregation patterns in many cases were established

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many decades ago before comprehensive data for neighborhoods was available and have been durable over time. The new destinations of the contemporary era can sustain studies of segregation more readily because neighborhood-level data is more detailed and comprehensive and, by their very nature, they offer a more dynamic setting for observing spatial population distributions and potentially identifying the causal factors that underlie contemporary residential segregation patterns. As a result, over the past decade we have seen a growing number of studies of segregation in new destination settings, particularly studies comparing patterns of White-Latino, White-Asian, and immigrant segregation across new destinations and established areas of settlement (e.g. Hall, 2013; Lichter et al., 2010; Park & Iceland, 2011). Some of these studies have also examined how segregation patterns in new destinations have changed over time as newly arrived populations become more settled and more visible in the area (e.g. in the labor force, in schools, and in community settings) and how nonmetropolitan communities in particular are affected.

In this chapter we contribute to this developing body of research by providing a comprehensive analysis of White-Latino and White-Asian residential segregation in new destinations that takes advantage of superior methods for measuring residential segregation (as described previously in Chap. 2). In doing so we are able to address and overcome some of the significant obstacles that have limited this empirical literature, including the fact that index bias often renders conventional measures of segregation problematic for communities where segregation involves groups that are small in absolute and/or relative size and where segregation must be assessed using data for small spatial units. The problems are similar to those affecting studies of segregation in nonmetropolitan communities more generally (as discussed in Chap. 4) – namely, researchers rightly worry that segregation scores are distorted by bias and that ad hoc strategies for dealing with the problem result in smaller and less representative samples of communities. On top of that, research on segregation in new destinations includes the added complication that new destination communities are undergoing rapid demographic changes in racial-ethnic composition, often starting from minimal or no minoritized group presence and transitioning to significant and rapidly growing minoritized group presence. As discussed in more detail earlier, the challenges of measuring segregation under these circumstances pose major problems for drawing general conclusions about trends in segregation in new destination communities and comparisons with segregation in communities with established minoritized group presence based on minoritized group settlement in earlier decades. New methods for measuring segregation without bias makes it possible to address these problems more completely and effectively than has been possible in previous research.

By also focusing on Asian new destinations, we contribute to the literature by expanding our knowledge of White-Asian residential segregation in emerging Asian settlement areas. This topic has been neglected and understudied and, thus, is not well-understood in the residential segregation literature (Flippen & Farrell-Bryan, 2021). Finally, we conduct a more exploratory parallel analysis of White-Black segregation in areas that might be designated as Black new destinations, where increasing presence of Black households is less related to immigration and more related to regional and spatial diffusion of this primarily native-born population. As we did in our previous chapter on nonmetropolitan residential segregation, we use our new methods of measurement and analysis to broaden the possibilities for understanding the nature of residential segregation in communities beyond the highly populated, diverse metropolitan areas that dominate the literature.

5.2 New Destinations: An Overview of Changes and Potential Trajectories

New migration across the United States to the Midwest and South, primarily driven by Latino immigrants, has transformed areas that had previously and over generations been predominately native-born White. This has produced the demographic trend of emerging ethnic diversity in new destination communities in locations far removed from the traditional gateway communities where Latino and Asian immigrants have historically settled upon arrival. When immigration to the United States from countries in Asia and Latin America surged following immigration reforms in the 1960s, immigrants initially tended to settle primarily in major cities along the East and West coasts such as Los Angeles, New York City, and San Francisco, and also in a few other large metropolitan areas including Chicago and Houston. In general, the largest Latino and Asian populations are found in major metropolitan areas on the West coast, along the U.S.-Mexico border, in some areas of the Upper Midwest, and in the Northeast. The attractiveness of these cities is easy to understand. Migrants seeking economic opportunity and the "American dream" found the best opportunities in the welcoming labor markets of rapidly growing metropolitan areas in the 1960s and early 1970s. Immigrants who came later would be drawn by inertia of pre-existing migration patterns reinforced by expanding migration networks to many of the same communities and often to ethnic neighborhoods that were established by their predecessors in response to a combination of constraints on residential options, co-ethnic settlement based on personal ties involved in chain migration of kin, friends, and co-ethnic networks, and the attractiveness of enclave areas to many first-generation immigrants.

Given this history, it is not surprising that much of segregation research focusing specifically on Latino or Asian segregation has mostly given attention to the major metropolitan areas where many Latino and Asian communities are located in racially and ethnically segregated neighborhoods. This has shaped how scholars theorize about segregation formation. Traditional theories of assimilation, ethnic disadvantage, and racial conflict that emerged from studies focusing on the experiences of White immigrant groups in the early twentieth century and White-Black segregation since the twentieth century are being continually revisited and used to build a lens for understanding Asian and Latino segregation in large and mostly urban metropolitan settings. For the most part, the research focusing on new destination communities that has emerged in recent decades has drawn from this foundation to build theoretical frameworks for understanding patterns of segregation in new destination communities.

The features of Latino immigration and migration that have led to the trend of emerging new destination communities have already been well-documented by demographers and examined by social scientists in the sociological, economic, geographic, and demographic literature. We note in particular an article by Daniel Lichter in 2012 that provides a thorough review of Latino settlement in new destinations and several important reports and books that have examined both quantitative and qualitative aspects of the shifting social landscape of new destinations, including William Kandel and John Cromartie's 2004 report *New Patterns of Hispanic Settlement in Rural America,* Douglas Massey's edited volume *New Faces in New Places: The Changing Geography of American Immigration* (2008) and Victor Zúñiga and Rubén Hernández-León's edited volume *New Destinations: Mexican Immigration in the United States* (2005). What is less well-documented but is also contributing to the changing racial demography of these previously homogenous communities is the migration of Asian households to new destinations. The factors that draw Asian immigrants and migrants away from traditional, urban areas and into smaller, sometimes rural, communities in the interior are not as well established. New destination emergence for Asian migrants is in some ways a different dynamic as immigration from Asian nations over the past several decades has been driven not only by economic "pull" factors but also by "push" factors due to conflict in home countries, especially in Southeast Asia. Some of this migration is driven by refugee resettlement, as in the case of communities in the upper Midwest known for welcoming the largest numbers of Hmong refugees (Singer & Wilson, 2006). Other push and pull factors that are bringing Asian migrants to new destinations are likely playing a role, including economic drivers.

One reason why Asian new destinations are less well understood, as Chenoa Flippen and Eunbi Kim (2015) argue, is that the distinction between new and established destinations is less clear for the Asian population because such a large portion of the Asian population in the U.S. is foreign-born, which means that many destinations are, in a sense, "new" destinations. Indeed, many communities with established Asian presence, in comparison to communities with established Latino or Black presence, tend to be at lower levels on absolute and relative size of the Asian population and often are experiencing increases in Asian presence that are comparable to those seen in new destinations. A secondary and more practical reason why Asian new destinations receive less attention, particularly in studies of residential segregation, is due to the technical challenges researchers encounter when measuring segregation in new destinations. The concerns we previously noted as relevant in studies of nonmetropolitan communities are equally if not more relevant here; namely, conventional approaches to measuring segregation yield flawed index scores when groups are small in absolute and/or relative size and when the scope of analysis extends beyond the largest metropolitan areas. Despite all of this, Flippen and Kim (2015) insist that it is important to expand our understanding of new destination migration as a phenomenon to include Asian migration as well, especially as immigration overall to the United States is now dominated by migrants arriving from Asian countries and there is enough preliminary evidence to justify studying Asian residential segregation in new destinations (Hall, 2013; Park & Iceland, 2011).

The changing demography of new destination communities is of interest here for substantive as well as methodological reasons. By definition, new destinations are communities where a specific population initially had a small or perhaps no presence but then grew rapidly over a short period of time due primarily to migration. Theory provides two contrasting scenarios for how inter-group relations may play out in these scenarios. The competitive group relations perspective includes a scenario of initially low segregation that will later transition into high segregation. In the earliest stages of this sequence, hierarchical relations among the groups may not yet exist, partly because the minimal presence of the minoritized group carries no practical consequences for the established majority group. In this situation, the minoritized group population in question may settle based primarily on housing availability and affordability and is not necessarily likely to be segregated except under certain special conditions, such as when dedicated housing for migrant workers concentrates the group into a single neighborhood. Later, as the minoritized group population grows rapidly in absolute and relative size, they can become more visible as a distinctive group in the community, potentially triggering a negative reaction on the part of the majority group. Blalock's racial threat theory (1967) and theories of competitive ethnic relations (Olzak & Nagel, 1986; Fossett & Cready, 1998) emphasize ethnic composition of the population as a factor shaping the extent to which members of the majority group will come to recognize the presence of the new group, increasingly view competition for scarce resources in group terms, and, ultimately, become less tolerant of the minoritized group's presence and engage in discrimination against the minoritized group out of motivation to preserve the majority group's advantaged position in the community.

An alternative perspective outlines a possible assimilation scenario involving a sequence of initially high segregation at time of settlement later transitioning to lower segregation over time as the new group is incorporated more broadly into the life of the community. In this scenario, initial segregation is high because members of the new group tend to congregate in one or a few neighborhoods based on strong ties of kinship and mutual support and the attractions of ethnic community institutions that serve the specialized linguistic and cultural needs of the minoritized group population (e.g., particular religious services, establishments conducting business and providing services in the group's language, stores and restaurants providing familiar products and cuisine, etc.). In the next stages of group relations, the new minoritized group population undergoes relatively rapid cultural and linguistic assimilation over time within generations and also across generations. They additionally are expected to experience increasing assimilation in social and economic spheres (e.g., education, employment, etc.). Segregation then falls over time as cultural assimilation reduces the attraction of the enclave and socioeconomic assimilation brings increasing wherewithal to move to better housing in neighborhoods outside the enclave. Under this scenario, the level of segregation will be a balance of two processes. Continuing arrival of new immigrants can serve to maintain segregation by replenishing and sustaining ethnic enclave neighborhoods even as settlement patterns of later generations of the group lead segregation to decline.

It is important to note that these two scenarios are not mutually exclusive. In a given community both hypothesized dynamics can play out along the lines just described, or in a wide variety of hybrid combinations. White communities in areas that have received a large and rapid influx of Latino and Asian migrants may develop a sense of threat and competition and begin engaging in behaviors that hoard resources and opportunities along racial and ethnic lines. One of the most effective ways to restrict group access to resources is to create conditions of residential segregation through economic and social exclusion, which can cut off a minoritized group not only from housing but also to a variety of other resources and amenities tied to neighborhoods. At the same time, however, new migrants could also assimilate rapidly on language and other aspects of culture, as well as on socioeconomic outcomes, and this may reduce their level of social distance from White households. This would manifest spatially as greater integration with White residents over time.

These two dynamics together represent the dominant hypotheses of segregation research: place stratification and spatial assimilation. Therefore, an important question to ask about these communities is: do these communities respond to rapidly changing population composition by segregating? If so, to what extent is segregation offset by reductions in social distance? As Flippen and Farrell-Bryan (2021) point out in their recent review article, new destinations have provided the opportunity to refine and revise theories of incorporation that lay at the heart of migration research. However, these authors also note that even after three decades of research the literature has hardly reached a consensus regarding the degree to which these different hypothesized dynamics shape group relations in new destination communities. This conclusion is equally true for studies focusing on trends in residential segregation in new destinations.

5.3 Residential Segregation Studies of New Destinations: Findings and Limitations

The state of the research literature focusing specifically on residential segregation in new destinations is similar to that of the broader research literature focusing on segregation in nonmetropolitan communities (which we reviewed previously in Chap. 4) in the fact that findings vary across studies and a consensus has yet to emerge regarding the exact nature of patterns and levels of segregation across communities and the trajectory of segregation over time. Flippen and Farrell-Bryan (2021) rightly point out that this is partly because findings from studies of segregation in new destinations are sensitive to multiple methodological choices including which groups are considered, which communities are included in the analyses, how communities are categorized (i.e., as "new," "established," and "other"), and which spatial units are used to capture group distributions across neighborhoods. In this section we review these and related issues, noting relevant limitations affecting past research and how we address them in this study.

The literature on segregation patterns and trends in new destinations has overwhelmingly focused on Latino and immigrant segregation. This is unsurprising in light of the fact that the largest proportion of new destination situations involves Latino migrants and immigrants settling in previously racially homogeneous communities in the Midwest and South and particularly, but not exclusively, in nonmetropolitan communities. But we argue Asian new destinations should receive greater attention than in the past both because these communities represent an increasingly important demographic phenomenon and also because Asian new destinations add value for understanding segregation since they involve a minoritized racial population that is similar to the Latino population in some respects and also different in other respects. For example, until recently, the Asian population nationally was concentrated in a small number of coastal metropolitan areas and a small number of nonmetropolitan communities in the western United States, particularly on the West Coast. Consequently, in most of the country, Asian populations are not only new in Asian new destinations, they also are new to the broader region, especially in nonmetropolitan settings. Thus, since there is no prior sizable Asian presence, there are no co-ethnic communities or histories of group relations to give shape to Asian residential settlement patterns. In communities newly receiving Asian migrants, the driving questions are the same: Where do they live?, Who do they live among?, and How do these outcomes change over time? Answers to these questions give us important knowledge for understanding the reception of new racial and ethnic groups in a community in a contemporary context, allowing us to reevaluate predominant theories of segregation and incorporation. With recent attention now given to anti-Asian racism in the wake of the COVID19 pandemic, the segregation literature must also be called upon to give greater priority to documenting and better understanding the experiences of Asian populations in the United States.

As we mentioned earlier, the literature is not guided by a consensus view on patterns and trends of residential segregation in new destinations and what implications they hold, due partly because findings vary with variations in methodology and also likely due to the limitations of available neighborhood-level data for Asian and Latino groups (Flippen & Farrell-Bryan, 2021; Hall, 2013). Some studies suggest a developing process of minoritized group exclusion and racialization in new destinations leading to higher levels of segregation than in established areas (e.g. Lichter et al., 2010) and which may be pronounced when undocumented immigration is driving the formation of a new destination (Hall & Stringfield, 2014). Other studies report that segregation is lower in new destinations than in established areas (Park & Iceland, 2011) and yet others report that levels of segregation are at similar levels in both area types (Hall, 2013).

Two basic choices concern how new destinations are defined and what communities are included in the analysis. For example, Lichter et al. (2010) examined census-designated places, drawing distinctions between urban, suburban, and rural communities. Others have focused exclusively on metropolitan or micropolitan areas (e.g., Fischer & Tienda, 2006; Park & Iceland, 2011). In addition, studies adopt different practices for identifying new destinations based on factors such as minimum population thresholds, population changes over time, and how population changes compare to larger trends. The challenge here is to identify areas where a certain group's presence in the community has risen from demographically small to sizable, where the group is growing rapidly in absolute and relative size and is most likely, but not exclusively, driven by migration, and where these demographic trends are fundamentally changing the racial or ethnic composition of the receiving community.

Some of the more well-known work over the past decade, particularly studies by Daniel Lichter and colleagues (e.g. 2010) and Matthew Hall (2013), have presented evidence that segregation is an emerging outcome in new destinations. All studies that examine segregation in new destinations encounter challenges in measuring segregation for small groups. Studies focusing on nonmetropolitan settings necessarily must be less restrictive because it is necessary to use data for small spatial units to measure segregation in nonmetropolitan communities. Non-trivial index bias is certain to be present in these situations. Thus, studies adopt multiple strategies starting with using sample restrictions to try to exclude the most egregiously concerning situations and using various ad hoc practices such as differential case weighting to mitigate the unwanted impact of index bias on cases in the analysis sample. Research focusing on metropolitan areas can adopt study designs aimed at providing greater protection from bias, but at the expense of limiting analysis to a smaller, less representative set of communities. For example, Matthew Hall's (2013) study provides one of the more detailed analyses on Asian segregation in new destinations by examining immigrant segregation in new destinations by specific ethnic groups, including Asian ethnic subgroups. Like many studies, this analysis was restricted to cases where scores for conventional segregation measures could be deemed more trustworthy, and on this basis limited the study to large metropolitan areas.

Given the salience of these measurement concerns and the impact of methodological choices on study findings, we contribute to the literature by using new methods that allow for superior measurement of segregation and larger, more representative samples of communities. New destinations, by their definition, are initially overwhelmingly White with an emerging minoritized group population which, while growing rapidly, still comprises a small fraction (e.g., less than 10 percent) of the population in most cases. Additionally, many new destinations have emerged in nonmetropolitan settings which present challenges for measuring segregation due to the need to use data for small spatial units (e.g., census blocks). These are the very conditions that make conventional segregation measurement untrustworthy first because index scores are certain to be inflated by index bias and second because the magnitude of the impact of bias varies from one community to the next. The problems are so concerning and so variable across measurement situations, one cannot safely perform close analysis of segregation scores and cannot even assess changes in scores over time in the same community.

We overcome these problems and limitations on analysis by using new methods to obtain scores for segregation indices that are unbiased across all group comparisons, even when segregation is measured using small spatial units (as is necessary when investigating segregation in nonmetropolitan settings) and when the groups are imbalanced in size and/or one or both groups are small in absolute size. Accordingly, the scores we use can sustain close case analysis including, for example, directly comparing White-Latino segregation in a given community with segregation in another community, or in the same community over time. And, because the scores are unbiased even under extreme conditions where standard index scores cannot be trusted, we can examine segregation in large, representative samples of communities. Thus, the analyses we present in this chapter make a valuable contribution to the literature on segregation in new destinations by examining Latino, Asian, and Black segregation in new destinations in a larger, more representative analysis sample than has been possible in past research, and we are able to trust the segregation scores in our analysis as giving an accurate representation of how residential patterns have emerged and changed in new destination communities over the past few decades.

Our first task in this chapter will be to summarize levels and trends in segregation scores for metropolitan, micropolitan, and noncore communities from 1990 to 2010. When doing so, we will compare scores across new destination communities and communities with established minoritized group presence as defined based on the absolute and relative size of group populations in 1990 and the rate of growth of the minoritized racial group over time. Our second task in this chapter will be to analyze how levels and patterns of segregation in new destinations vary with the relative presence and rate of growth of the minoritized racial population, region, community type, industrial composition of the labor force, and other community-level covariates. Our third task is to review aspects of segregation measurement that have been neglected in past research including what insights are gained by contrasting results obtained using the dissimilarity index and the separation index. The former can and does take high scores when uneven distribution is dispersed, while the latter takes high scores only when uneven distribution is polarized, and one can safely conclude groups are separated across different spatial units and can potentially experience inequality on location-based outcomes.

5.4 Data and Measurement

As we did in the previous chapters of this book, we use block-level tabulations of householder by race-ethnicity from the 1990, 2000, and 2010 decennial censuses to measure residential segregation between groups. This is a carefully considered departure from previous segregation research on new destinations which uses data for persons instead of data for households. Having reviewed the basis for this decision in detail earlier in Chap. 2, we limit comment here to noting that the choice makes it possible for us to obtain unbiased scores for segregation indices based on eliminating the impact of fixed levels of same-group contact that are incorporated into standard index calculations which implicitly and incorrectly treat all individuals as locating independently, when in fact most individuals locate as part of a household composed of multiple, often same-race individuals. Acknowledging this social fact brings two problems with standard index scores into clear focus.

The first problem is that the standard of exact even distribution cannot be achieved when the integrity of households and individuals is respected. That is, standard versions of indices of uneven distribution will take non-zero values when households and individuals are assigned to neighborhoods "intact", not in fractional parts. As a matter of measurement theory, this problem originates with the decision to define integration as exact even distribution instead of as statistical independence of race and neighborhood. The consequence is that, even under "optimal" or "strategic" assignment, standard versions of indices will take positive scores (not zero) if households and individuals are assigned to neighborhoods intact. The issue generally escapes notice in the broader segregation literature because the practical consequences for index scores typically is negligible when segregation is measured for large groups using large spatial units such as census tracts. Unfortunately, the issue becomes consequential and cannot be ignored when segregation is measured using small spatial units such as census blocks. As our discussion in Chap. 2 explains in more detail, if households are distributed intact across blocks, standard versions of indices of uneven distribution will have two non-negligible sources of bias: a random component that can be eliminated in principle by assigning households to neighborhoods in arrangements that are "optimal" for reducing index scores and a "floor" component that can only be eliminated by assigning first households and then individuals to neighborhoods in fractional parts.

The crucial point is that the impact of bias on index scores calculated using block-level data is much larger and consequential than is generally appreciated. The problem is even more concerning when measuring White-Latino segregation in micropolitan and noncore new destination communities because the average number of households per block is smaller in micropolitan areas compared to metropolitan areas and smaller still in noncore counties and, additionally, because the average size of households is larger for Latino households than for White, Black, or Asian households. Both factors lead to higher levels of index bias for White-Latino segregation in micropolitan areas and noncore counties compared to, for example, White-Black or White-Asian segregation in metropolitan areas. Finally, these problems exacerbate the initial problem that segregation index values are inflated by bias to a greater degree in new destination communities because, by the nature of these communities, the groups are more imbalanced in size than is the case in communities with established minoritized group presence. This set of problems poses major challenges for studying segregation in new destinations using standard versions of index scores computed using data for persons. We address and overcome these problems by measuring segregation using unbiased versions of indices and data for households. The resulting index scores we obtain are superior to those reported in previous research. Put simply, we can describe every index score we obtain as being valid and free of distortion from bias and this description cannot be applied to index scores reported in previous studies of segregation in nonmetropolitan new destination communities.

Methodological studies establish that unbiased versions of index scores perform as desired and are trustworthy across a much wider range of circumstances than is the case for standard versions of index scores (Fossett, 2017). Consequently, we can include many more cases in our analysis than is typical in previous studies. Specifically, we include cases where both groups in the comparison have at least 50 households and the pairwise percentage of either group in the comparison is at least 0.5 percent.[1] As we described in previous chapters, these criteria are to ensure that we are only measuring segregation in areas where the notion of segregation between groups is meaningful and unbiased index scores are reliable.[2]

We use the race and ethnicity tabulations from the 1990 to 2010 censuses to calculate racial composition measures and measures of group-specific population change over time from 1990 to 2010. We then use the results of these calculations to categorize metropolitan areas, micropolitan areas, and noncore counties as either new destinations, communities with established group presence, or some other type of community based on a protocol similar to that used by Lichter et al. (2010). Specifically, we define new destinations as those communities where the referenced minoritized racial population was less than 10 percent of the total population in 1990 and experienced a rate of growth above group-specific thresholds based on absolute percentage growth and relative percentage growth (noted below). Communities with established group presence are defined as those where the minoritized racial population was at least 10 percent of the area population in 1990. We also identify a subset of cases as communities of "highly established" presence when the minoritized racial population was at least 30 percent of the community population in 1990.

In addition to these two primary community types, we identify communities of low minoritized group presence where the minoritized racial population was less than 10 percent of the population in the community and did not grow at a high enough rate over time. The rate-of-growth thresholds were adjusted by group to take into account that expected growth rates cannot be applied uniformly across groups. Thus, the minimum growth rate for the Latino population is higher than it is for the Asian population based on their higher rate of growth overall in areas outside of established gateways. For an area to be designated as a Latino new destination, the absolute Latino growth rate had to be at least 3 percentage points, or the relative

[1] In most, but not all, cases, the smaller group is also the minoritized racial group. However, the White population is the smaller group in many White-Latino comparisons in communities near the U.S.-Mexico border.

[2] The worst-case scenario under these case selection criteria is that the value of the unbiased score for *D* will have a standard error of 10 points (under the null hypothesis of random distribution in a community with only 50 households for each group). The observed standard errors are much smaller, because counts for one or both groups are well above 50 and group ratios are imbalanced (standard errors are larger when groups are equal in size). Thus, the values of the 50th, 90th, and 99th percentile scores in the distribution of observed standard errors for unbiased scores of *D* are only 0.8, 1.6, and 3.1, respectively, and the maximum value over all cases is 6.6. Based on this, we do not bother reporting standard errors for individual scores except in methodological discussions such as this note.

growth rate had to be at least a 50 percent increase. For Asian new destinations, the absolute Asian growth rate had to be at least 2.5 percentage points, or the relative growth rate had to be at least a 50 percent increase. For exploring the possibility of Black new destinations (discussed more below), we applied the same criteria as we used for Asian new destinations.

We measure segregation for group comparisons by applying the formulas for obtaining both unbiased and standard versions of the dissimilarity index (*D*) and the separation index (*S*) as reviewed in Chap. 2 (and Fossett, 2017). We calculated standard scores primarily to document problems of index bias. Our discussion of findings focuses exclusively on unbiased scores and, in general, assign priority to scores for the separation index (*S*). Our justification for these choices follows the reasoning we outlined in our analysis of segregation in nonmetropolitan communities (see Chap. 4). The justification is even stronger when focusing on segregation in new destination communities because they are prime candidates for index scores, particularly scores for the dissimilarity index (*D*), to be distorted due to the problems that arise when segregation indices are not corrected to eliminate the impact of inherent upward bias. Our measurement methods provide the most accurate and trustworthy measurements of segregation of any similar study to date and thus make it possible to provide better descriptions and reach better conclusions regarding the reality of segregation in new destination communities over time and how it compares with segregation in established areas of group presence.

We conclude our discussion of case selection, methodology, and measurement by noting that this chapter focuses primarily on Latino and Asian new destinations because the growth and spatial diffusion of these two populations are the primary drivers of the emergence of new destination communities across the United States. However, we recognize that Black migration and spatial diffusion trends deserve attention as well, particularly Black migration to the South. Most of the receiving areas would likely not fall under the conceptual definition of "new destination" based on population history, although there is evidence that more of Black migration to the South is driven by "primary" migration (as opposed to "return" migration), which refers to Black migrants to the South who were not born in the South (Hunt et al., 2008). However, for the sake of exploration we chose to also consider areas where Black population growth is substantial using our schema for defining new destinations and established areas of group presence. In Table 5.1, we document the number of new destinations and established areas of group presence by group in 2010 based on our criteria. A distinct finding is that the new destination phenomenon is more common for Latino populations than for other groups with 368 metropolitan areas, micropolitan areas, and noncore counties identified as Latino new

Table 5.1 Frequency of communities by destination type by group, 2010

Area type	Latino	Asian	Black
Established	167	13	296
Highly established	116	6	262
New destination	368	37	21
Low settlement	1098	658	671

destinations. In contrast, we found only 37 Asian new destinations and 21 Black new destinations, despite using more liberal growth rate criteria for these two groups. Many areas, consisting mostly of noncore counties and micropolitan areas, remain classified as areas of low settlement for each of these groups.

5.5 Residential Segregation in Latino New Destinations and Established Areas of Settlement

We begin by summarizing how levels of White-Latino segregation vary across communities categorized on Latino presence over the period 1990 to 2010 in Table 5.2. In 1990, at the onset of significant Latino population growth for most new destination communities that emerged over the following decades, White-Latino segregation in new destination communities was very low, particularly in comparison to communities with established Latino presence where the average level of segregation was in the medium range and even more so in comparison to communities where Latino presence is very high. At the same time, the average level for White-Latino segregation in new destination communities is only slightly higher than the average level seen in communities with low levels of Latino presence. The major contrast, however, is that while average levels of segregation were steady or declining over time in all other categories of Latino presence, the average level of segregation in new destinations communities was rising and even doubling from 1990 to 2010, at which point it was close to the average level of segregation seen in areas of established Latino presence.

There are two ways in which these findings in whole or partially depart from what has been posited in the Latino new destination literature. First, average levels of White-Latino segregation are in the low-to-medium range from 1990 to 2010 across all categories of Latino presence. Second, although White-Latino segregation was rising in new destination communities, the average levels remained lower than the average levels observed for communities of established Latino presence.

The divergent patterns across categories of Latino presence help us understand general patterns and trends for White-Latino segregation across the United States. Communities that have seen sudden and significant Latino population growth are experiencing rising segregation, but communities with established Latino presence have had stable levels of segregation and communities with highly established Latino presence have experienced declines in average levels of segregation. Breaking trends down this way yields a more nuanced and dynamic picture of White-

Table 5.2 Mean separation index scores by Latino community types, 1990–2010

Year	Established	Highly established	New destination	Low settlement
1990	20.96	32.85	9.49	5.91
2000	21.71	30.86	16.50	6.17
2010	21.73	28.28	19.25	6.95

Latino segregation in the United States. Segregation is generally higher in communities with established Latino presence but has been stable or declining over recent decades. In contrast, average levels of segregation in new destination communities are initially much lower, but as Latino presence increases, average levels of segregation rise in the direction of converging on levels observed in communities with established Latino presence. Interestingly, the rising average level of segregation in Latino new destination communities results in the average level of segregation for these communities in 2010 matching the average level of segregation observed for areas of established Latino presence in 1990.

5.6 Residential Segregation in Asian New Destinations and Established Areas of Settlement

Less is known about Asian new destinations because it is less widespread and has not been the object of many studies. Consequently, we cannot draw on perspectives from prior research focusing on the origins and trajectories of new areas of Asian settlement as we were able to do for Latino new destinations. However, since the Asian population is growing rapidly and is diffusing out from historical areas of settlement, it is appropriate to apply a similar schema for identifying new destinations and communities of established group presence based on initial levels of Asian population presence and rates of increase over time and compare levels of segregation in categories of Asian presence over time. As we showed earlier in Table 5.1, our schema does not identify as many Asian new destination communities as Latino new destination communities. But we identify more than enough to sustain a preliminary review of patterns and trends based on the average scores for White-Asian segregation for communities classified by category of Asian presence presented in Table 5.3.

We find that in 1990 Asian new destination communities have lower levels of segregation than communities where Asian presence is established and much lower than in communities where Asian presence is highly established. Indeed, the average level for White-Asian segregation in new destination communities is not much higher than the average level seen in communities with low levels of Asian presence. This changes in later decades as the average level of segregation in Asian new destination communities increases in each decade and more than doubles by 2010 while the average level of segregation in communities with low Asian presence is stable. Echoing the patterns for White-Latino segregation in Latino new destinations,

Table 5.3 Mean separation index scores by Asian community types, 1990–2010

Year	Established	Highly established	New destination	Low settlement
1990	17.70	26.20	8.87	7.37
2000	22.13	30.41	11.74	6.68
2010	24.54	30.71	17.51	6.51

the rising average level of segregation in Asian new destination communities leads the average level for these communities to match the average level of segregation observed for communities with established Asian presence in 1990. A major difference here, however, is that, where average levels of White-Latino segregation were stable or declining over time in communities with established Latino presence, average levels of segregation are rising over time in communities with established Asian presence as well.

Before turning next to consider patterns for Black new destination communities, we first note that the patterns of segregation across categories of Latino and Asian presence in communities are surprisingly similar. Average levels of segregation are very low in the low group presence category, initially very low but rising over time in the new destinations category, at the low end of the medium range in areas of established group presence, and solidly in the medium range in areas where group presence is well established. The main difference across the patterns for Latino and Asian segregation is that average levels of segregation are rising over time in communities with established Asian presence but stable or slightly declining in communities with established Latino presence. While we do note differences between patterns and trends for White-Latino and White-Asian segregation, they are much more similar to each other than they are to the patterns and trends seen for White-Black segregation, especially with regard to average levels of segregation in communities with established Black presence.

5.7 Residential Segregation in Black New Destinations and Established Areas of Settlement

As is the case for Asian new destinations, communities that have only recently experienced initial Black settlement and population growth have not received as much attention as Latino new destinations in prior research and thus these communities are not as well documented or as well understood. Indeed, because sustained post-1965 immigration is often a major factor in emerging Latino and Asian new destinations, it is not surprising that less thought and attention has been given to assessing the existence or prevalence of Black new destination communities and the levels and trends in segregation that may be present in them. Certainly, it is true that immigration is a lesser, albeit not negligible factor, for the growth of the Black population. Nevertheless, it is still possible for Black new destinations to emerge when migration and spatial diffusion of the Black population leads Black households to settle in communities where previously Black presence has been minimal. We address this gap in the literature by applying the same schema and measurement approach we used for Asian new destinations to first identify Black new destination communities based on Black population presence and growth over time and then to compare segregation patterns and trends in White-Black segregation across the resulting categories of Black population presence. Not surprisingly, we identified far fewer Black new destination communities that experienced Black settlement around 1990 and subsequent population growth from 1990 to 2010 at a level that would elevate the community from low Black presence to Black new destination. In contrast, we identified hundreds of communities that had established Black populations, far outnumbering communities with established Latino or Asian populations.

This reflects fundamental differences in the demographic history of each of these populations, with the Latino and Asian populations seeing rapid growth and spatial diffusion in recent decades whereas the Black population has seen slower growth and only modest spatial diffusion during this same period. The large number of communities with established Black presence reflects the demographic legacy of the historical forced migration of enslaved people primarily to Southern states, and then the Great Migration of Black households in the early part of the twentieth century fleeing racial oppression and limited economic opportunities in the post-Reconstruction, Jim Crow era in the South and gravitating toward relatively better economic opportunities in the growing metropolitan centers in the North and Midwest. The Black population remains disproportionately concentrated in these regions and communities where high levels of Black presence were established many decades ago. This leaves open the possibility that migration and spatial diffusion of the Black population could create Black new destination communities. But the actual occurrence of this demographic sequence is limited to a small number of communities. Of course, this does not mean that the spatial distribution of the Black population has been stagnant. But it does mean that it has been more evident within metropolitan and nonmetropolitan communities (e.g., movement toward suburban settings in metropolitan areas) than across communities on the scale seen for the Latino and Asian populations.

Despite the fact that the number of Black new destination communities is not large, we still see value in comparing levels and trends in White-Black segregation across communities classified on the basis of Black population and also with levels and trends in White-Latino and White-Asian segregation across communities classified on the basis of Latino and Asian presence, respectively. One reason for this is that, while we know a great deal about how *de jure* Black segregation developed and intensified in northern U.S. metropolitan areas to the highest levels in the nation in response to the Black Great Migration, we know less about what happens to spatial patterns in communities where Black populations are emergent in the post-Fair Housing era. A second reason is that Black segregation in the United States is one of the more entrenched spatial patterns that characterizes urban areas, and it is implicit that we often understand Latino and Asian segregation patterns and trends by how they compare to Black segregation patterns and trends. The broad consensus in the literature is that White-Latino segregation and White-Asian segregation by comparison are more moderate and more fluid than White-Black segregation in part because factors relevant in spatial assimilation theory such as acculturation and socioeconomic assimilation within and across generations appear to play a greater role in Latino and Asian residential segregation – a pattern we document in detail in Chap. 6. However, evidence for these group differences, including the evidence we review later in this monograph, is primarily based on studies of large metropolitan

Table 5.4 Mean separation index scores by Black community types, 1990–2010

Year	Established	Highly established	New destination	Low settlement
1990	56.03	60.99	26.72	28.74
2000	48.95	55.85	19.81	21.13
2010	43.58	52.55	22.49	16.12

areas which could not be considered new destinations for any group (e.g. Los Angeles, Houston, Chicago, etc.). So, we take the present opportunity to address the narrower question of how segregation patterns for these minoritized groups compare across communities that vary on group presence.

To serve this goal, we document how average levels of White-Black segregation as measured by the separation index (S) vary across communities classified on level of Black presence in Table 5.4. Based on reviewing the results presented in this table we can draw some tentative conclusions about the nature of segregation in Black new destinations and how these outcomes compare with patterns observed for other minoritized racial groups. First, we must note that the most important overall finding is that White-Black segregation is higher than White-Latino and White-Asian segregation across all four categories of group presence, ranging from low settlement to highly established settlement. Even though segregation is declining over time within all categories, it is always the highest level in every category in every time period. The highest average levels of White-Black segregation are seen in highly established areas of Black settlement where the Black population is at or above 30 percent. The average score for the separation index is at the high level of 61 in 1990 and, despite declining to 53 by 2010 it remains more than 20 points higher than White-Latino and White-Asian segregation in the same category of group presence. A similar pattern is seen for communities of established Black settlement where the Black population comprises 10 to 30 percent of the total population. These communities have a slightly lower average score for S in 1990 of 56, and despite having a larger absolute and relative decline to an average score of 44 in 2010, it also remains about 20–22 points higher than average scores for White-Latino and White-Asian segregation. As we just described, the main pattern in communities with established group presence is that White-Black segregation is much higher than White-Latino and White-Asian segregation. But we also should note a secondary pattern of convergence because White-Black segregation is declining from 1990 through 2010 while White-Latino segregation is mostly stable over this time and White-Asian segregation is increasing.

White-Black segregation is also clearly higher than White-Latino and White-Asian segregation in communities of low group presence. Average levels of White-Latino and White-Asian segregation in these communities are around 6–7 points, which is very low, across all decades. In contrast, the average for White-Black segregation in 1990 is over 20 points higher at 29 points which is well into the medium range and is at or above the average levels of segregation observed for White-Latino and White-Asian segregation in communities where the minoritized racial group in the comparison has an established presence. We do observe that

White-Black segregation in communities with low Black presence declines significantly over time in both absolute (down 12.5 points) and relative (down 44 percent) terms. But even so, it remains 10 points higher than White-Latino and White-Asian segregation in 2010.

Findings for White-Black segregation in new destinations are both similar to and different from White-Latino and White-Asian segregation in new destinations. The main points of similarity are that, across all three groups, the average levels of segregation in new destination communities in 1990 are much lower than the average levels of segregation seen in communities of established group presence and are not very different from the average levels in communities of low group presence. The most important difference is that the average level of White-Black segregation in new destinations in 1990 is much higher than the average levels for White-Latino and White-Asian segregation, with White-Black segregation in new destinations in 1990 exceeding the average levels of White-Latino and White Asian segregation in communities of established Latino and Asian presence. However, a second point of difference is that White-Black segregation in new destinations is declining over time while White-Latino and White-Asian segregation in new destinations is increasing over time. By 2010, the average levels of segregation substantially converged across the three groups. The level of White-Black segregation remains higher by 3–5 points in 2010 but at a much smaller margin than the 16–17-point gap in 1990.

We conclude by commenting that it is intriguing to observe that the average level of White-Black segregation in new destination communities is much lower than the levels of segregation observed in communities with established Black presence, and this lower average level of segregation is declining over time. The very high levels of White-Black segregation in areas of established Black presence first emerged in Black new destinations of the North and Midwest nearly a century ago when segregation increased rapidly as the Black population changed from being a low presence to an established presence in a short period of time. Those high levels of segregation persisted for decades and have only begun to decline in recent years. This trend, plus the downward trend we see in average levels of White-Black segregation in new destination communities provides a possible basis for anticipating that segregation in Black new destinations of the present era will not follow the trajectory seen a century ago. However, we must temper this hope based on the fact that the number of Black new destination communities is small, and also that the averages for White-Latino and White-Asian segregation in new destinations are increasing over time and are based on a larger number of cases.

5.8 Understanding Segregation Patterns Across New Destinations and Established Areas of Settlement

In this section of the chapter we move beyond the review of broad summary statistics in the previous section to try to gain a better understanding of how segregation varies across communities that differ on categories of group presence. We do this by also taking account of other characteristics of communities that may be relevant. To serve this goal, we report results for a set of fractional regression models by group comparison where the outcome is the separation index and the covariates are temporal and cross-sectional characteristics of the group comparison and community. In addition to including variables for established areas of settlement and new destinations, we also draw on data from the 2010 census and 2012 American Community Survey 5-year estimates to develop several predictor variables suggested in previous research including: overall population growth, type of community (metropolitan area, micropolitan area, or noncore county), and region. We include measures of industry employment profiles and percent enrolled in college to take account of situations where minoritized group population growth is potentially correlated with broader patterns in the growth and composition of the labor force and higher education opportunities. We present descriptive statistics for the relevant variables in the analysis in Table 5.5, and in Table 5.6 we present the regression coefficients and standard errors for White-Latino, White-Asian, and White-Black segregation.

First, we find that White-Latino segregation is significantly higher in communities with high established Latino presence compared to new destinations as well as areas with established but lower Latino presence and areas with stable and minimal Latino presence. This pattern is consistent with the broad patterns we reported earlier in this chapter and also with the general hypothesis that segregation varies as a positive function of relative group size. Relatedly, we also find that absolute Latino population growth from 1990 to 2010 has a large and significant positive impact on White-Latino segregation.

Regarding the effects of other community characteristics, we find segregation is higher in larger communities (based on natural log of total population) and that White-Latino segregation is significantly higher in communities located in the South and Northeast than in the West. We also find that communities with larger percentages of workers employed in the manufacturing sector have higher levels of White-Latino segregation while communities with higher percentages of workers in the retail sector have lower levels of White-Latino segregation. Finally, we find no significant effect of the percent enrolled in college on levels of White-Latino segregation. Overall, we find that the largest effects on White-Latino segregation are the rate of Latino population growth and categories of group presence, with the contrasts between new destinations and communities of established Latino presence being of special interest here. While segregation is on average lower in new destinations compared to established areas of settlement, the large positive effect of Latino population growth signals that new destinations may be likely to experience increasing segregation over time and, potentially, eventually converge on levels of segregation seen in communities with established Latino presence.

The results for White-Asian segregation closely follow the patterns we just described for White-Latino segregation. White-Asian segregation in communities with a highly established Asian presence is significantly higher than in Asian new destination communities and in communities with low Asian presence. The magnitude of the differences is even larger than those seen for White-Latino segregation. In

Table 5.5 Descriptive statistics for communities in 2010

	White-Latino		White-Asian		White-Black	
Variable	Percentage		Percentage		Percentage	
Area type						
Highly established	6.6%		0.8%		21.0%	
Established	9.6%		1.8%		23.7%	
New destination	21.0%		5.2%		1.7%	
Low settlement	62.8%		92.2%		53.7%	
Region						
West	17.6%		24.7%		10.2%	
Northeast	7.3%		10.8%		7.4%	
Midwest	28.5%		23.0%		20.5%	
South	46.7%		41.6%		61.9%	
Demographics	Mean	SD	Mean	SD	Mean	SD
Minority Growth Rate, 1990–2010	0.05	0.05	0.01	0.02	0.001	0.03
Population size	173,408	609,907	385,121	913,840	231,073	713,051
Industry						
% in government	5.7%	3.3	5.7%	3.5	5.9%	3.3
% in manufacturing	12.6%	7.3	11.5%	6.7	13.2%	6.8
% in retail	11.7%	2.2	12.0%	1.7	11.9%	2.0
% in service	18.6%	3.4	18.8%	3.0	18.7%	3.3
% enrolled in college	5.9%	4.3	8.0%	5.3	6.4%	4.7

addition, community population size has a positive relationship with White-Asian segregation, but here the magnitude of the effect is smaller. Where variables relating to region and industry composition of labor force had modest, but statistically significant, associations with White-Latino segregation, we found that only the percentage of the labor force specializing in retail had a significant, and negative, association with White-Asian segregation. However, the percentage of the population enrolled in college is positively associated with White-Asian segregation. As with White-Latino segregation, the most important finding relative to our interests is that Asian new destinations have lower average levels of White-Asian segregation than communities with established Asian presence.

We find that the effects of greatest relevance to this chapter are not only evident in the case of White-Black segregation, but, if anything, are stronger. Specifically, we find that for White-Black segregation, communities with established Black presence have much higher levels of White-Black segregation than Black new destinations and communities with low Black presence. We also find that Black population growth has a strong positive effect on White-Black segregation. The patterns here are thus consistent with the idea that Black households in new destination communities experience lower levels of segregation in comparison to Black households in communities of established Black presence but, due to the positive effect of growing

Table 5.6 Fractional regression analysis of White-Latino, White-Asian, and White-Black segregation, 2010

	White-Latino		White-Asian		White-Black	
Variable	b	S.E.	b	S.E.	b	S.E.
Area type						
Highly established (ref)						
Established	−0.449***	0.066	−0.668*	0.303	−0.329***	0.039
New destination	−0.637***	0.066	−1.112***	0.313	−1.148***	0.171
Low settlement	−1.517***	0.084	−1.987***	0.281	−1.489***	0.047
Demographics						
Minority Growth Rate, 1990–2010	3.554***	0.431	0.551	1.206	2.050***	0.479
Population size (ln)	0.093***	0.012	0.076*	0.032	0.056***	0.014
Region						
West (ref)						
Northeast	0.238*	0.098	0.002	0.109	0.701***	0.117
Midwest	−0.051	0.059	0.045	0.106	0.899***	0.103
South	0.310***	0.046	0.181	0.097	1.202***	0.093
Industry						
Percent in government	0.013	0.007	−0.005	0.012	−0.025***	0.007
Percent in manufacturing	0.015***	0.003	0.014	0.007	−0.015***	0.003
Percent in retail	−0.029**	0.009	−0.080**	0.029	−0.040***	0.008
Percent in service	−0.011	0.006	0.002	0.016	0.004	0.006
Percent enrolled in college	0.002	0.004	0.036***	0.006	−0.044***	0.004
Constant	−2.048***	0.225	−1.177	0.743	−0.657*	0.280

Note: *p < .05; **p < .01; ***p < .001

Black presence, sustained Black growth in new destinations would likely lead segregation to converge on the higher levels seen in communities with an established Black presence. Regarding the secondary independent variables, we find a pattern of results that is distinct from the findings for White-Latino and White-Asian segregation. We find larger regional differences where, in comparison with average levels of White-Black segregation in communities in the West, communities in the Northeast and Midwest have higher levels of White-Black segregation. As seen for White-Latino and White-Asian segregation, community specialization in retail has a negative association with White-Black segregation. But unique to White-Black segregation, specialization in the government and manufacturing sectors also has a negative association with segregation. Finally, and uniquely across the three group-specific analyses, the percent of the population enrolled in college has a significant negative effect on White-Black segregation.

The primary focus of the analyses we reviewed in this section is to gain better insight into how White-nonwhite segregation in new destination communities compares with segregation in other communities. The first takeaway point is that the basic findings from the initial review of variation in mean levels of segregation across communities categorized by level of minoritized group presence persist net of controls for a variety of community characteristics that are also associated with White-nonwhite segregation. The findings here are consistent with the general view that minoritized groups experience lower levels of segregation in new destination communities in comparison with communities with established minoritized group presence. The contrast is with another possibility, for which there is scant evidence, that when first arriving in sizable numbers in a community that previously had low group presence, minoritized racial groups would experience a high level of initial segregation out of a combination of one or more dynamics that foster this outcome. One is encountering discrimination and constrained opportunities in the local housing market when the local population does not accept the new group due to social distance tracing to prejudice and/or group differences in culture and socioeconomic characteristics. Another is the rapid formation of ethnic enclave neighborhoods as households in the group co-locate with kin and other co-ethnics connected via social networks of migration. Subsequently, these high levels of segregation may potentially decline as the new group assimilates on culture and/or socioeconomic characteristics and intolerance declines and acceptance grows in the broader community.

The findings here suggest a different trajectory may be more common. White-nonwhite segregation is lowest of all in communities where the minoritized group has a non-negligible, but low and stable, presence. Possibly this is because the group's presence in the community does not register with the much larger White majority population, thus leaving ethnic relations inchoate and allowing minoritized group households to locate opportunistically where housing is available. Because the size of the minoritized group population is small, enclave formation is not strong because the group cannot support minority-serving institutions (Breton, 1964) that could make enclave neighborhoods attractive. Segregation is then higher, but still generally lower, in new destination communities as the minoritized group's presence begins to rise rapidly (by definition). This can result from one or more factors such as the co-location of members of the same ethnic group arriving in larger numbers during the surge of immigration/migration, the first beginnings of enclave formation, and the onset of awareness by the White majority that a new ethnic presence is emerging in the community. Subsequently, as minoritized group population growth continues and the minoritized group population becomes established in the community, White-nonwhite segregation also steadily grows as the White population's initially, possibly benign, low-level awareness of minoritized group presence turns into concern that White dominant position in the community may be threatened by the minoritized group population's growing presence, thus leading to greater racial intolerance and discrimination on the part of White individuals and institutions

(Blalock, 1967; Olzak & Nagel, 1986; Fossett & Kiecolt, 1989; Fossett & Cready, 1998). Under this scenario, ethnic enclave neighborhoods can emerge and persist for multiple reasons including as a response to discrimination and blocked housing opportunities in the broader community as well as having well-developed institutions that independently can attract and retain many minoritized group households.

5.9 Differences in Segregation Measurement When Studying New Destinations

In Chap. 2 we reviewed an important distinction between types of uneven distribution: polarized and dispersed displacement from even distribution. White-Black segregation is especially likely to involve polarized unevenness, where White and Black households live apart from each other in different neighborhoods and thus have little residential contact with one another. We refer to this pattern as prototypical segregation because it is invariably the form of uneven distribution depicted in didactic discussions of segregation measurement (Fossett, 2017) and it also is the form of segregation observed in the best known examples of hypersegregated metropolitan areas such as Chicago, Cleveland, Detroit, and Milwaukee. It also is found in more moderate expressions in many other metropolitan areas across the United States. In cases such as these, where segregation involves a high degree of polarized unevenness, index choice is not very consequential as all segregation index scores will be high regardless of whether one chooses to use the popular dissimilarity index or our preferred, albeit less widely used, separation index.

The situation is very different when segregation involves dispersed unevenness. Index choice matters and researchers who rely solely on the dissimilarity index run the risk of misinterpreting a high score on D as indicating groups are separated across residential space when the separation index would correctly take a low score and indicate that this aspect of segregation is in fact low. Situations involving D-S discordance associated with dispersed unevenness are likely to occur in new destination communities due to the fact that, by definition, the segregation comparison involves an emerging group that is much smaller in size than the other group in the analysis. In general, our primary focus is on the separation index because it signals the presence of polarized unevenness, the pattern that characterizes prototypical segregation and creates the necessary preconditions for group inequality on location-based outcomes. Here we also take special interest in identifying situations involving dispersed unevenness because they are common in new destination communities and this fact is not widely appreciated.

5.9.1 Myth or Fact: Low Minoritized Group Size Necessarily Leads to Low Values for the Separation Index

We take a moment here to forcefully debunk a mistaken belief regarding the separation index. The belief in question is that *S* somehow necessarily takes low values when groups are imbalanced in size, as will always be the case for emerging minoritized group populations in new destination communities. Simply put, this view is unfounded and should be discarded. Detailed review of the issue in Fossett (2017) points out several relevant findings including: there is no formal basis for this view, it is easy to construct simple examples that refute the view, and one can also find empirical examples that refute the view. Thus, we offer the following statement:

> The separation index is more reliable than any other index in being able to indicate when uneven distribution is polarized, such that both groups in the segregation comparison disproportionately reside in mostly homogeneous (same-group) neighborhoods.

Segregation involving polarized unevenness may or may not occur when groups are imbalanced in size. Whether it does occur is a matter of social process; not an artifact of index choice. When uneven distribution is polarized, groups live apart from each other and occupy different neighborhoods. The separation index will always correctly take a high value in this situation and, equally importantly, the separation index will always correctly take a low value when polarized unevenness is absent. In this regard, the separation index differs from other indices – particularly the dissimilarity index and the Gini index – that give ambiguous signals about segregation because they will take high values when the separation index does but also will take high values when uneven distribution is dispersed and does not involve group separation.

The primary methodological concern when groups are imbalanced in size is a concern that applies with equal force to all indices of uneven distribution, not specifically the separation index. It is the concern of whether the spatial units used in the analysis are adequate for the task of measuring segregation. The issue is especially important in nonmetropolitan communities where larger spatial units such as census tracts cannot reliably register the full extent of any aspect of segregation and are especially incapable of revealing when a small group is concentrated in homogeneous neighborhoods. We address this concern in our study by using data for census blocks. The separation index will reliably detect and signal the presence of polarized unevenness involving small groups when using block data. Equally important, a low value on the separation index obtained using block data will reliably indicate that polarized unevenness and group separation is not present.

As a final technical side point, we note that the dissimilarity index will be more likely than the separation index to take intermediate and even high values when larger spatial units such as census tracts are used to measure segregation in nonmetropolitan communities. But this should not be construed as suggesting *D* is valid and reliable for measuring group separation. To state it bluntly, *D* is never reliable for measuring group separation. When polarized unevenness is manifest at the block level but not at the tract level, the separation index will correctly yield a high score using block-level data and a low score using tract-level data. In this circumstance, *D* will yield a high score using block-level data, a necessary result when the value of *S* is high, and *D* may also yield an intermediate or high score using tract-level data, even when the value of *S* is low, when polarized blocks associated with predominately minoritized group neighborhoods are found only in one or two tracts – as would be likely in a nonmetropolitan community. This is because the polarized unevenness at the block level will be manifest as dispersed unevenness at the tract level and *D,* but not *S*, will respond strongly to this pattern of unevenness. The problem of course is that the value of *D* cannot sustain an unambiguous conclusion regarding the nature of segregation.

As just described, an intermediate score could occur because group separation across small spatial units is registered as dispersed unevenness across larger units. Or, it could occur simply because segregation involves only dispersed unevenness across both smaller and larger spatial units. What then can safely be inferred about the pattern of segregation? As always, discordant values of *D* and *S* obtained using larger spatial units definitively signal dispersed unevenness at that level of spatial resolution. After that, nothing more can be inferred with confidence. The fact that this result is compatible with multiple, distinctly different patterns of segregation across smaller spatial units may be intriguing. But ultimately, nothing specific can be safely inferred. The only way to clarify the situation is to use smaller spatial units that are well-suited for the task of measuring segregation in new destinations, particularly those that are also nonmetropolitan communities.

5.10 Findings for Dispersed and Polarized Unevenness in New Destinations

In this section we distinguish between patterns of polarized and dispersed unevenness in new destinations by comparing values of the separation index and the dissimilarity index. Concordant values of *D* and *S* indicate polarized unevenness, while discordant values on *D* and *S* indicate dispersed unevenness. In Table 5.7 we report average values of both the separation index, the measure we assign priority to throughout this book, and average values of the dissimilarity index for Latino, Asian, and Black new destination communities. Comparing the values of these two indices provides insight into the nature of the pattern of segregation in new destinations. The

Table 5.7 Comparing segregation indices in Latino, Asian, and Black new destinations, 2010

	White-Latino		White-Asian		White-Black	
Year	*S* index	*D* index	*S* index	*D* index	*S* index	*D* index
1990	9.49	30.88	8.87	39.94	26.72	54.37
2000	16.50	39.90	11.74	44.77	19.81	51.57
2010	19.25	39.61	17.51	46.04	22.49	52.59

results document clear patterns of systematic discordance between the separation index and dissimilarity index in Latino new destinations with, as is necessarily the case, values of *D* being higher than values of *S*. In 1990 the average value of *D* for White-Latino segregation was 30.9 which, in comparison with the average value of *S* of 9.5, is higher by a factor of three and a margin of more than 20 points. These results suggest, and close review of individual cases confirms, that the pattern of White-Latino segregation in the typical Latino new destination community is one of dispersed unevenness. In this situation, most Latino households live in neighborhoods where the representation of White households among their neighbors, while often technically below parity on proportion White with the community overall, is consistently high and quantitatively close to parity. At the same time, most Latino households live in neighborhoods where the representation of Latino households among their neighbors is also close to parity, which in new destination communities means that the level of Latino presence among neighbors is low. Under this pattern, White and Latino households generally share similar neighborhood contexts, and this minimizes the potential for segregation to produce White-Latino inequality on location-based outcomes.

From 1990 to 2010 average values of *D* and *S* for White-Latino segregation both rise by approximately 10 points to stand at 39.6 and 19.3, respectively. *D-S* discordance remains high in absolute terms as the average value of *D* remains 20 points higher than the average value of *S*. But *D-S* discordance is falling in relative terms as the average value of *D* in 2010 is higher than *S* by a factor of two, down from a factor of three in 1990. The rising average value of *S* relative to *D* indicates a transition from highly dispersed unevenness to moderately dispersed unevenness, but not fully polarized unevenness. In terms of Latino residential experiences, this means that a larger percentage of Latino households in Latino new destination communities are residing in neighborhoods where the presence of White and Latino households is further from parity than was initially the case. These changes indicate that, on average, White and Latino households are less likely than before to share neighborhood contexts and thus the potential for segregation to produce White-Latino inequality on location-based outcomes increased over the two decades. In other words, from 1990 to 2010, White-Latino segregation moved away from dispersed unevenness and toward polarized unevenness and prototypical segregation, the pattern typically seen in communities with high levels of established Latino presence.

Importantly, while we observe that values of *S* for White-Latino segregation are rising at a faster rate than values of *D,* thus indicating a transition from dispersed unevenness toward more polarized unevenness, this was not a foregone conclusion, as other trends were possible. This is why crucial aspects of trends in White-Latino segregation in new destinations cannot be established by examining only the value of the dissimilarity index. By conventional interpretation, the average value of *D* was already at a medium level in 1990 and stayed in the medium range when rising by almost 10 points from 30.9 in 1990 to 39.6 in 2010. But the value of *D* by itself cannot reveal whether the pattern of segregation at any point in time involves the relatively benign pattern of dispersed unevenness with a high level of group co-residence and shared residential experiences or the more consequential pattern of polarized unevenness where both groups are separated in space based on being disproportionately concentrated in neighborhoods where they do not share location-based outcomes with members of the other group.

To definitively establish what is happening for this aspect of segregation, one must examine values of *S*. The reason for this is that values of *D* and *S* can not only be discordant at a point in time, they can and sometimes do vary independently over time, including potentially moving in opposite directions. Thus, when *D* is increasing by over 10 points from 1990 to 2010, the value of *S* could be falling, stable, or increasing and each result would indicate something distinct about the segregation pattern. If the value of *S* is rising at roughly the same rate as the value of *D* and is not rising rapidly, it indicates the pattern of segregation is holding steady at the initial level of dispersed unevenness. If the value of *S* is falling or stable, it indicates the pattern of segregation is moving toward even greater dispersion in uneven distribution wherein the fraction of Latino households living in below-parity neighborhoods is increasing (leading to rising *D*) but the below-parity neighborhoods are generally moving closer to parity (leading to falling *S*). Finally, if the value of *S* is rising at a faster rate than the value of *D,* it indicates the pattern of segregation is moving toward more polarized unevenness.

We find the broad pattern for White-Asian segregation in new destinations is generally similar to the pattern just described for White-Latino segregation in new destinations with White-Asian segregation in new destinations initially taking a form of dispersed unevenness in all three decades but moving toward higher levels of polarized unevenness between 1990 and 2010. We also find two notable points of difference for White-Asian segregation in new destinations. The first is that the initial pattern of dispersed unevenness in 1990 was more pronounced for White-Asian segregation and the second is that movement toward more polarized unevenness over time was weaker for White-Asian segregation. In 1990, the separation index indicated low levels of White-Asian segregation while at the same time the dissimilarity index indicated moderately high levels. This is a clear sign that while there was uneven distribution occurring in 1990 between White and Asian households, it was dispersed unevenness and Asian households were not living in fundamentally different neighborhoods. The discordance between the two scores drops only slightly in 2010 as the separation index shows increasing polarized unevenness between White and Asian households in new destinations over time. However even in 2010, the separation index shows only medium levels of segregation while the dissimilarity index indicates even higher levels of segregation, which means that White-Asian uneven distribution in new destinations is still more dispersed than polarized.

Regarding the first point, systematic discordance between the separation index and dissimilarity index for White-Asian segregation in Asian new destinations is even more pronounced in 1990 than was the case for White-Latino segregation in Latino new destinations. The average value of *D* for White-Asian segregation was 39.9, which is higher than the average value of *S* by a factor of more than four and a difference of more than 31 points. Thus, White-Asian segregation in a typical Asian new destination community is characterized by highly dispersed unevenness in which a large fraction of Asian households live in below-parity neighborhoods where White households are technically underrepresented among their neighbors but with shortfalls from parity that are quantitatively small. Accordingly, in Asian new destinations, most Asian households live in neighborhoods where the presence of White and Asian households among neighbors is close to levels expected under random distribution, which would consist of a very high presence of White households and a very low presence of Asian households. Therefore, Asian households generally reside in the same neighborhood contexts as White households and the logical potential for White-Asian inequality on location-based outcomes is very low.

From 1990 to 2010 average values of *D* and *S* for White-Asian segregation both increased, reaching the values of 17.5 and 46.0, respectively. The separation index increased more both in absolute terms (8.6 points compared to 6.1 points for *D*) and in relative terms (up over 96 percent compared to about 15 percent for *D*). However, because the initial absolute *D*-*S* discordance was more than 31 points, the *D*-*S* difference in 2010 remains extremely high at more than 28 points even though the average value of *S* increased by 2.5 points more than the average value of *D*. The change in the relative discordance of *D* and *S* was more noticeable as the average value of *D* was larger than the average value of *S* by a factor of more than four in 1990, and this dropped to less than a factor of three in 2010. The increase in the average value of *S* from 8.9 in 1990 to 17.5 in 2010 does indicate appreciable movement in the direction of greater polarization in White and Asian residential distributions. But the main finding is that the level of polarization remains low in 2010 and is lower for White-Asian segregation in new destinations than for White-Latino segregation in new destinations.

The results for Black new destinations differ from the results for Latino and Asian new destinations on multiple points. Our earlier discussion of variation in White-nonwhite segregation across communities by level of minoritized group presence established that average levels of segregation in new destinations were lower than in communities with highly established minoritized group presence. The differences were large across all group comparisons but the difference of over 33 points for White-Black segregation was easily the largest. However, at the same time the average level of the separation index of 26.7 for Black new destinations in 1990 was much higher than the averages of 9.5 and 8.9 for Latino and Asian new destinations, respectively. In this regard, White-Black segregation in new destinations follows the earlier finding that White-Black segregation is higher than White-Latino and White-Asian segregation across all categories of minoritized group presence.

Another point of difference is that the discordance between the dissimilarity index and the separation index in new destination communities is appreciably lower for White-Black segregation than for White-Latino and White-Asian segregation. The magnitude of the difference in average levels of *D* and *S* of 27.7 points is not especially small since it falls between the levels seen for White-Latino segregation (21.4) and White-Asian segregation (31.1). But the relative comparison of average values for *D* and *S* is the smallest across the three White-nonwhite comparisons with the average value of *D* for White-Black segregation being higher than the average value of *S* by a factor of just over two (2.0) compared to a factor of over three (3.3) for White-Latino segregation and a factor of over four (4.5) for White-Asian segregation. The low ratio of *D* to *S* in combination with the much higher level of *S* helps clarify that White-Black segregation in new destinations involves uneven distribution that is more polarized and less dispersed than White-Latino and White-Asian segregation and so creates more potential for White-Black inequality on location-based outcomes. We place this last point in further perspective by noting that, while White-Black segregation in new destinations is more polarized and less dispersed in comparison to White-Latino and White-Asian segregation in new destinations, White-Black uneven distribution is still much more dispersed and less polarized than in major metropolitan areas such as Los Angeles and Houston, where *S* is in the low 60s. Compared to Chicago, the definitive example of a maximally polarized city with *S* at 79 and, with *D* only 6 points higher, a *D-S* ratio of 1.1, White-Black segregation in new destinations is hardly comparable. So, in contrast to these examples, Black new destination communities have unevenness that is much more dispersed and thus a large portion of Black households that live in below-parity neighborhoods experience a presence of White households among neighbors at levels that rarely occur in prototypically segregated areas.

The final point of contrast for White-Black segregation in new destinations is that it is stable or even declining slightly from 1990 to 2010 while White-Latino and White-Asian segregation in new destinations is rising. However, because the initial level for White-Black segregation is higher, it is trending toward convergence on the patterns seen for White-Latino and White-Asian segregation, not decreasing to levels below them.

5.11 Highlighting Measurement Issues: The Case of Worthington, Minnesota

Many of the findings we report in this chapter cast a new and different perspective on segregation in new destinations in comparison to findings previously reported in the literature. There are two main reasons for this. One is that we focus attention on aspects of uneven distribution – namely, polarization and group separation – that have been neglected in previous research. The other is that our study is the first to use new methods for measuring segregation. We do so because the task of measuring segregation of small groups in new destination communities presents difficult problems that can easily distort index scores and raise concerns regarding whether findings based on them are fully trustworthy. The new methods for measuring segregation we use in this book were developed to specifically address these problems. One of their attractive characteristics is that they only yield different results in situations where conventional measurement practices yield questionable and potentially misleading results. Thus, when past measurement practices yield trustworthy results, the new methods we use will replicate these results. But, when the new methods we use yield different results, these results will be superior and should be preferred over results obtained using past measurement practices. Given the importance of this issue, we use this section of the chapter to present an in-depth technical review of the case of White-Latino segregation in Worthington, MN, a micropolitan area and Latino new destination in the Midwest with patterns of White-Latino segregation that are typical across many Latino new destination communities.

The Latino population in the Worthington, MN micropolitan area grew rapidly in both absolute and relative terms from 1990 to 2010. In 1990, the number of Latino households in the community was just 70 and comprised slightly less than 1 percent of the 7,682 total households in the community. By 2000 the community had a net gain of an additional 471 Latino households to stand at 541, a more than sevenfold increase, leading Latino households to increase to 6.5 percent of all households. By 2010 the community had a similar net gain of an additional 481 Latino households and nearly doubled to stand at 1,022 households, comprising 12.9 percent of all households. Throughout this period, the average size of Latino households was larger than the size of White households and the disparity grew in absolute and relative magnitude with each decade. By 2010 the average Latino household size was more than double that of White households. Consequently, the Latino percentage representation among persons was larger, and growing faster than the Latino percentage representation among households. The demographic trends and patterns observed for Worthington are not in any way unique. To the contrary, they are typical of Latino demographic trends in new destination communities. Moreover, these demographic circumstances – an initially small, rapidly growing population in a nonmetropolitan setting – exactly embody the sort of scenario where we should be concerned by how analyses of patterns and trends in segregation are affected by the following two issues relating to segregation measurement: the distorting impact of index bias and the related consequences of measuring segregation of persons rather than households, and neglecting to consider whether displacement from even distribution is dispersed or polarized.

In Table 5.8 we present results for scores of the separation index and the dissimilarity index obtained using data for census blocks under selected combinations of methodological choices regarding microunit (segregation of persons versus households) and whether or not the index score has been corrected for index bias. Our point of reference for discussing the impact of methodological choices on the value of each index score is the unbiased separation index score obtained using data for households, as we hold scores obtained under this particular combination of choices as the benchmarks against which other results should be evaluated. The unbiased version of the separation index calculated using data for households in Worthington starts at a low value of 3.7 in 1990, increases to 22.5 in 2000, and increases further to 27.7 in 2010. The unbiased version of the dissimilarity index calculated using data for households starts at a value of 30.2 in 1990, increases to 55.3 in 2000, and decreases slightly to 51.4 in 2010.

The first thing we note regarding how these scores compare to scores obtained using other combinations of practices is that index bias is an important issue

Table 5.8 White-Latino segregation in Worthington, MN, 1990–2010

Measurement	1990	2000	2010
Separation index			
Persons, standard	15.3	37.2	44.8
Persons, unbiased	13.3	35.7	43.3
Households, standard	9.7	28.3	34.4
Households, unbiased	3.7	22.5	27.7
Dissimilarity index			
Persons, standard	81.3	72.7	66.9
Persons, unbiased	70.8	70.7	64.5
Households, standard	85.3	70.4	65.4
Households, unbiased	30.2	55.3	51.4

regardless of what index is used and whether the micro-level units are persons or households. The impact of bias is never negligible, but it varies dramatically in magnitude. The smallest impact of bias is seen for the standard version of the separation index calculated using data for households. It runs 6–7 points higher than the unbiased version of the separation index. Shifting to using person data increases the impact of bias to much higher levels because the scores register "lumpy" spatial distributions due to the fact that persons typically locate as members of households that are homogeneous on race. Person-level adjustments for bias partially reduce bias but are insufficient because they do not take account of a person's co-location with other members of their household. Bias in the separation index is unaffected by imbalance in group size, so bias levels remain relatively stable across time even though Latino group size is changing rapidly. However, bias in the separation index is affected by changes in "effective neighborhood size," the size of the combined count of the two groups in a given spatial unit. Thus, to the extent that bias in *S* changes over time, it is either random or possibly reflects changes in the number of households per block over time and/or changes in the relative presence of other groups in the population.

The dissimilarity index is much more susceptible to index bias than is the separation index, and it is well known that bias in *D* can reach extreme levels when groups are imbalanced in size and segregation is measured using data for small spatial units (Winship, 1977; Fossett, 2017). Thus, while it is alarming, it should not be surprising to see that the impact of bias for *D* is extremely high in 1990 with values in the range of 40–55 points across the three alternative options for measurement. It is also alarming, but again should not be surprising, to see that the impact of bias on *D* differs dramatically over time. The reason for this is that bias in *D* is sensitive to imbalance in group size, and imbalance in group size declines substantially over time due to the rapid growth of the Latino population. As a result, bias falls to still high, but far less extreme, values in the range of about 13–15 points in 2010.

These findings have several implications for how our findings may differ from findings reported in previous studies focusing on new destination communities in nonmetropolitan settings. First, and most obviously, previous studies overwhelmingly use the dissimilarity index and the analysis here shows that not only are values of *D* highly distorted by index bias, but the magnitude of the impact of bias on values of *D* is changing dramatically over time. Segregation scores are at their highest for White-Latino segregation in Worthington when using the dissimilarity index to measure segregation of persons or households without correcting for bias, with scores of 81.3 and 85.3, respectively, in 1990. If accepted at face value, these scores indicate a level of segregation comparable to that observed for White-Black segregation in large hypersegregated metropolitan areas like Chicago, Detroit, or Milwaukee, all of which are consistently found at or near the top of lists of the most segregated metropolitan areas in the United States. The problem with these scores, which correspond to the raw data used in almost all analyses of segregation in new destinations, is that they absolutely cannot be accepted at face value. To the contrary, these scores are fatally compromised by index bias and taking them at face value will lead to grossly incorrect conclusions about the nature of White-Latino segregation in communities like Worthington.

Close inspection of GIS-based mapping of group distributions across census blocks in Worthington shows no evidence that White-Latino segregation in 1990 (or in 2000 or 2010) is in any way comparable to White-Black segregation in Chicago. In Chicago, most Black households reside in neighborhoods where 80–100 percent of neighboring households are Black and no or almost no neighboring households are White. In Worthington in 1990, almost no Latino household resides in a neighborhood where 80–100 percent of neighboring households are Latino and most live in neighborhoods where 80–100 percent of neighboring households are White. The case of White-Black segregation in Chicago is known for the large and expansive region of predominantly Black neighborhoods in the southern region of the city, the existence of which is the demographic foundation for the concept of hypersegregation. Nothing like this exists for Latino households in Worthington. The only blocks that are predominantly Latino in population are occupied by one or two Latino households. There are no significant clusters of contiguous blocks that are predominantly Latino. In every meaningful way, White-Latino segregation in Worthington is different from White-Black segregation in Chicago. This drives home the point that scores of the dissimilarity index obtained via conventional methodological practices used in previous research cannot be taken at face value. Instead, they must be called into question and considered carefully to avoid reaching unfounded conclusions about White-Latino segregation in new destination communities.

The unbiased scores for the dissimilarity index show clear improvement over the standard versions of the same index. The value of the unbiased version of *D* calculated using data for households in 1990 is 30.2, some 55 points lower than the value of *D* obtained using the standard version with data for households. The source of the astounding impact of bias on *D* is surprisingly easy to explain. *D* registers the White-Latino difference in percentage of households that attain parity contact with White households at the neighborhood level. Standard versions of *D* assess percent White in the spatial unit based on the combined count of all

White and Latino households. But in new destinations, Latino households are by definition a small fraction of the population so the presence of even a single Latino household in a census block will in most cases cause percent White for the block to fall below parity (i.e., below percent White for the city overall). In fact, in Worthington in 1990 pairwise percent Latino is about 1 percent, so the standard calculation would result in below-parity status being assigned to any block with fewer than 100 White and Latino households combined with a single Latino household. That accounts for all but 2 of the 1,120 blocks in Worthington in 1990. There are 70 Latino households in Worthington in 1990. Of these, 37 reside in a block where they constitute the only Latino household on the block and the block has fewer than 100 households. Under the standard calculation of *D,* all of these Latino households are designated as residing in below-parity neighborhoods despite the fact that all of their neighbors are White and their only contact with Latino households stems from self-contact. This is the source of the extreme level of bias in the result for the standard calculation of *D* for Worthington in 1990.

The unbiased version of *D* is 55 points lower than the standard version of *D* because it eliminates bias by calculating contact based on neighbors and excluding self-contact, the sole source of index bias. Thus, the unbiased version of *D* registers the difference between the percentage of White and Latino households that attain parity-level contact with White households among neighboring households. In these calculations, the 37 Latino households that reside on blocks where they are the only Latino households and have only White neighbors are correctly treated as having parity-level contact with White households (since 100 percent of their neighbors are White). There is no way to accept the standard scores for *D* as trustworthy for measuring segregation in new destinations in nonmetropolitan settings where group size is small and it is crucial to use block-level data. The standard scores for *D* are fatally flawed and egregiously misleading. In contrast, the unbiased scores for *D* are correct and trustworthy and their difference from the standard scores is easy to explain. Accordingly, our analyses are based only on scores obtained using the unbiased versions of segregation indices.

The decision to focus on unbiased index scores is consequential for more than just correctly assessing the level of segregation in new destinations. It also is important for correctly assessing how segregation is changing over time in new destinations. The case of Worthington is useful for illustrating how conclusions about trends in segregation can vary dramatically when using standard and unbiased versions of indices. The scores for *D* calculated using standard formulas with data for persons suggest a large decline of 14.4 points in White-Latino segregation from 81.3 in 1990 to 66.9 in 2010. The scores for *D* calculated using standard formulas with data for households suggest an even larger decline of 19.9 points in White-Latino segregation from 85.3 in 1990 to 65.4 in 2010. In contrast, scores for *D* calculated using the unbiased formulas with data for households suggest the exact opposite trend with the value of *D* increasing 21.2 points from 30.2 in 1990 to 51.4 in 2010. The unbiased scores can be trusted to reveal the true trend in segregation. The dramatic reversal in findings for the time trend occurs because the standard score for *D* in 1990 is inflated by 55.1 points by index bias but is "only" inflated by 14 points in 2010. Eliminating the impact of bias on the value of D thus results in a massive 40.8-point change in findings from a trend of a 19.9-point decline in segregation using the standard version of D to a 21.2 increase in segregation using the unbiased version of D.

We justify using scores for the unbiased formulation of the separation index over scores for the standard version based on the same logic. Index bias can distort standard scores and raises concerns that findings based on them are questionable and possibly misleading. That said, we should note a very big difference between the separation index and the dissimilarity index. It is that, in general, the standard version of the separation index is not as susceptible to index bias as the standard version of the dissimilarity index. And, equally importantly, the impact of bias on the separation index is more uniform across cases while the impact of bias on the dissimilarity index can vary greatly across cases. Consequently, when segregation is measured using the separation index, one is less likely to encounter the egregious, pathological results along the lines just discussed for trends in the dissimilarity index in Worthington. This is evident in the results for the separation index for Worthington. The scores for the standard version of the separation index are inflated by bias and are about 6–7 points higher than the scores for the unbiased versions of the index. But, in decided contrast with the dissimilarity index, the impact of bias on scores for the separation index is fairly stable over time even as the Latino percentage in the population is changing rapidly. So, both versions of the index suggest White-Latino segregation is increasing by about 23–25 points. The same trend also is observed when switching from data for households to data for persons and the reason for this is the same; the bias impact associated with using person data instead of data for households tends to be uniform across cases. Thus, in comparison with the dissimilarity index, bias for the separation index is less likely to impact findings regarding variation in segregation across communities and/or over time.

The discussion we offered above provides both a rationale for why we measure segregation using unbiased versions of segregation indices in combination with data for households rather than persons and reviews an example where the choice has practical consequences. Now we turn to the question of why we assign priority to measuring White-nonwhite segregation in new destinations using the separation index over the dissimilarity index. Here the case of White-Latino segregation in the new destination community of Worthington, MN is again useful. The unbiased dissimilarity index based on households rises from a medium level (30.2) to a high level (51.4) from 1990 to 2010. In contrast, the unbiased separation index begins at a very low level (3.7) in 1990 and rises to a medium level (27.7) by 2010. There is clear discordance between the scores for the two indices; the raw score difference is similar at both points in time, 26.5 points in 1990 and 23.7 points in 2010, but the relative comparison changed dramatically as the dissimilarity index is larger by a factor of 8.2 in 1990 but only by a factor of 1.9 in 2010. We explain below that we gain most of the information we need from the scores for the separation index, but we gain additional interesting information from the contrast between scores for the separation index and the dissimilarity index.

In Worthington in 1990, the value of the unbiased dissimilarity index for White-Latino segregation based on households is 30.2 while the unbiased separation index based on households is only 3.7. This value of the dissimilarity index is in the medium range. But the low value of the separation index indicates that White-Latino segregation in Worthington involves a pattern of highly dispersed unevenness. Because the dissimilarity index is insensitive to whether uneven distribution is dispersed or polarized, its value provides no basis for inferring which pattern prevails. Examining the separation index brings clarity. Under polarized unevenness, the value of the separation index would be in the range of 24–30 (at or above 80 percent of the value of the dissimilarity index). But, instead, its observed value of 3.7 is very close to zero. This provides a definitive signal that White-Latino segregation in Worthington follows a pattern of dispersed unevenness where White and Latino households alike reside in neighborhoods that are quantitatively close to parity regardless of whether they are technically below or above parity. The low value of the separation index also strongly indicates that in the early stages of Latino migration and settlement in Worthington in 1990 Latino households do not reside in homogeneous neighborhoods. This is consistent with the close review of block-level outcomes for Latino households discussed earlier which noted 37 of 70 Latino households lived in blocks where all of their neighboring households were White. We additionally note here that every Latino household that resides in a block with five or more households has more White neighbors than Latino neighbors.

The value of the dissimilarity index increases from 30 to over 50 in the later decades, thus moving into the high range. But just as we could not know from the value of the dissimilarity index whether the initial pattern of uneven distribution in 1990 was polarized or dispersed, we cannot know whether the increase in the value of the dissimilarity index reflects a change in the underlying pattern of segregation. If one only knows the value of the dissimilarity index, the logical possibilities range from group separation declining (i.e., uneven distribution becoming more dispersed) to group separation increasing (i.e., uneven distribution becoming more polarized). To know what is occurring, one must examine values of the separation index. The *S* index indicates that White and Latino households have become more residentially separated, with the average group difference in neighborhood proportion White rising from 3.7 to 27.7 in just two decades, as directly measured by the separation index.

A key point here is that the value of the separation index is telling the story of primary interest – namely, whether groups are living together and experiencing similar neighborhood contexts or living apart and potentially experiencing unequal neighborhood contexts. For this concern, additionally learning the value of the dissimilarity index adds little to no relevant information because its relationship to this aspect of uneven distribution is inherently ambiguous. Once the value of the separation index is known, the extent of group separation is known. Values of the dissimilarity index can range from being approximately equal to the value of the separation index or higher, possibly much higher. Knowing that the value of the dissimilarity index is on the low end of this range indicates that below-parity neighborhoods skew toward having higher levels of Latino presence (i.e., depart from parity by larger amounts), a hallmark of polarized unevenness. Knowing that the value of the dissimilarity index is on the high end of its possible range indicates that below-parity neighborhoods include a mixture of not only neighborhoods with higher Latino presence but also a larger number of below-parity neighborhoods that are quantitatively close to parity, a hallmark of dispersed unevenness.

Note that once the value of the separation index is known at a single point in time, additionally knowing whether its level occurs under a pattern of dispersed or polarized unevenness does not have important implications for the question of whether segregation is conducive to racial stratification in neighborhood outcomes, it will be the same under either pattern. However, when the level and trend of change in the separation index are known, additionally knowing the level and trend in the dissimilarity index can provide a basis for speculating about the trajectory of segregation. When the value of the separation index is increasing, finding that values of dissimilarity are higher and/or rising faster might be seen as a leading indicator of future progression toward a pattern of neighborhood polarization and group separation. When the value of the separation index is decreasing, the finding that values of the dissimilarity index are higher and/or declining more slowly might be seen as a trailing indicator of a fading pattern of neighborhood polarization and group separation (see also Chap. 4).

We present polarization charts for White-Latino segregation in Worthington in 1990 and 2010 in Fig. 5.1 to visualize the nature of uneven distribution in this new destination community and clarify how it is registered by the separation index and the dissimilarity index. The charts depict the observed distributions of White and Latino households across levels of presence of White households among neighboring households in 1990 and 2010. The chart for 1990 shows that all households, White and Latino alike, had more White neighbors than Latino neighbors (i.e., percent White among neighbors was greater than 50) and that the overwhelming majority of both White and Latino households – specifically, 97.8 percent and 87.1 percent, respectively – were living in neighborhoods where at least 90 percent of the neighboring households were White. As a result, average levels of contact with White households among neighbors was very high; 99.1 percent for White households and 95.4 percent for Latino households. The difference between these two values yields the value of the unbiased separation index of 3.7.

The unbiased dissimilarity index of 30.2 in 1990 also reflects a simple group difference in contact with White households among neighbors. But it summarizes the patterns in a crude way that exaggerates the underlying quantitative differences on contact with White households. To review from our discussion in Chap. 2, the dissimilarity index registers contact as either 0 or 100 based on whether contact matches or exceeds parity. Since uneven distribution is highly dispersed, not polarized, the contact scores registered by the separation index are generally very close to parity for both groups. So, the typical rescaling of those contact scores to extreme values of 0 and 100 (scaled from 0 to 1) when calculating the dissimilarity index exaggerates the group difference. To the best of our knowledge, no rationale has ever been offered to justify rescaling contact in this way before comparing group differences in contact with White households. In part this is because few researchers were aware that the dissimilarity and separation indices, along with other indices of uneven distribution, reflected group differences in contact with White households

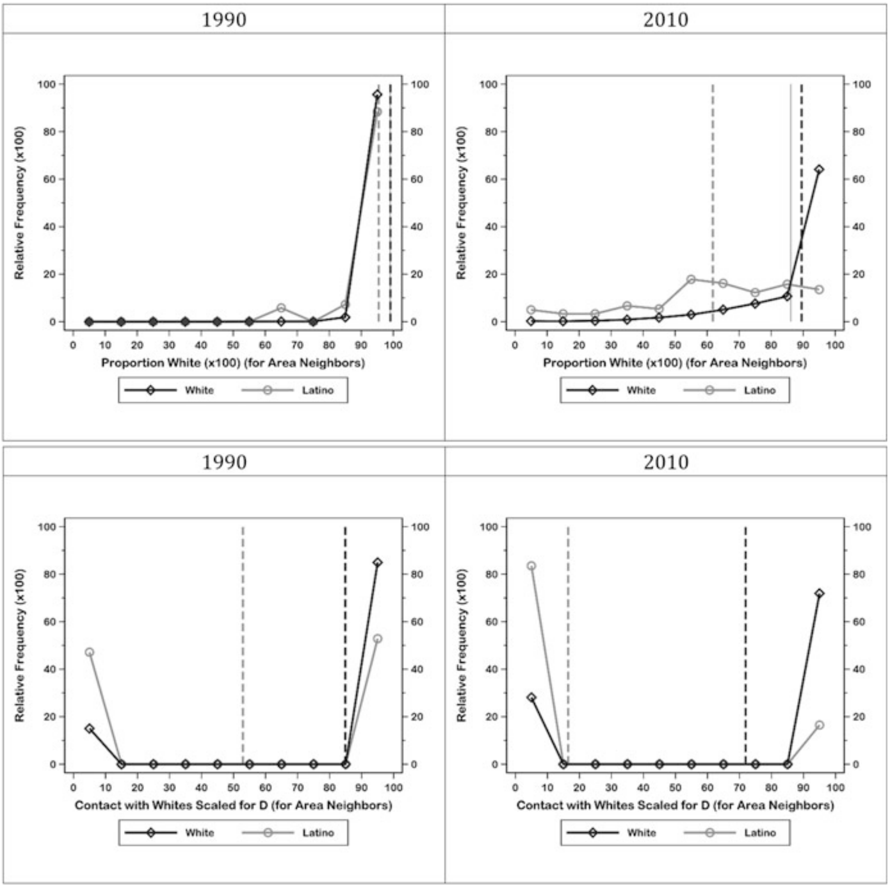

Fig. 5.1 Observed distributions of White and Latino households by proportion White among neighbors

with the difference in index scores tracing solely to how original contact scores are registered by the index. For the separation index, contact scores are registered as observed and thus take values over the full logical range of 0 to 100. For the dissimilarity index, contact scores are rescaled with all intermediate scores being assigned to the extreme values of either 0 or 100.

In light of this, the polarization chart for 1990 provides a visual insight into how the dissimilarity index comes to take much higher values than the separation index when uneven distribution is dispersed instead of polarized. Close review of patterns of contact for Latino households provides further insight into how separation registers information about group differences in contact with White households in a way that is most relevant for the potential implications of residential segregation for racial stratification. Of the 70 Latino households in 1990, 37 reside in above-parity neighborhoods; all of these households have only White neighbors. The remaining 33 Latino households reside in below-parity neighborhoods. Not one has more Latino neighbors than White neighbors, as the lowest value for percent White among neighbors for these households is 63 percent. Furthermore, the median value of contact with White households among neighbors for Latino households residing in below-parity neighborhoods is 95 percent. Thus, close inspection of residential outcomes for Latino households shows that even when focusing only on those that reside in below-parity neighborhoods, Latino households in Worthington live alongside White households in neighborhoods that are overwhelmingly White. Consequently, Latino households in Worthington experience essentially the same neighborhood contexts as White households experience and thus White-Latino inequality on location-based outcomes is simply not possible. This aspect of segregation is accurately reflected in the very low value of the separation index of 3.7. The fact that the value of the dissimilarity index of 30.2 is more than 8 times higher does not require any reconsideration of the conclusion. We would characterize the high value of the dissimilarity index as a curious byproduct of its crude construction if not for the fact that so many people rely solely on this measure to evaluate segregation.

A final point about Worthington in 1990 is that the low value of the separation index is not at all a necessary outcome. The median value for number of households on a census block is 13. So, if Latino households in Worthington were distributed in the same way as Black households are distributed in Chicago, 80 percent of Latino households would reside in blocks that are at least 65 percent Latino. That pattern is absolutely feasible. It would involve 56 Latino households residing in 6 blocks of typical size (i.e., 13 households) with 9 Latino households and 4 White households. Discussion in Chap. 2 of this work and also Fossett (2017) review cases where high values of the separation index are in fact observed under similar demographic settings. The fact that this kind of pattern is seen for Black households in Chicago and in some nonmetropolitan settings but not for Latino households in Worthington is due to differences in the social dynamics of residential distribution, not to any technical limitations of the separation index.

The polarization chart for 2010 shows a significant change in the pattern of White-Latino segregation. The Latino presence among all households increased to 12.9 percent and, due to larger Latino household size, to an even larger 22.5 percent of total population. Latino presence in the White-Latino comparison is 13.9 percent for households and 25.1 percent for persons. Thus, the parity threshold for contact with White households using data for households fell from 99.1 in 1990 to 86.1 in 2010. This substantial change in the racial-ethnic composition of the community, characteristic of all new destinations, does carry implications for patterns of contact, but it does not have any implications for changes in how group differences in contact determine values of the separation index and the dissimilarity index. This is illustrated in Fig. 5.2 which presents polarization charts for unbiased contact in 1990 and 2010 when the White and Latino households in Worthington are randomly assigned across the blocks where White and Latino households reside. The upshot of the charts is that patterns of contact with White households shift down from a very high level in 1990 (91.1 percent) to a somewhat lower level in 2010 (86.1 percent) but the distributions of contact with White households that occur under random assignment are the same for White and Latino households in both decades. Therefore, the expected group difference in level of contact with White households is zero (0.0) in both decades for both the separation index and the dissimilarity index.

Returning to the polarization chart for observed distributions of White and Latino households in 2010 in Fig. 5.1 we note that the percentage of households living in neighborhoods where 90–100 percent of neighboring households are White dropped significantly for both White and Latino households, but most dramatically for Latino households. The polarization charts in Fig. 5.2 depict expected group distributions for contact with White neighbors under random distribution and clarify that the changing demographic composition of the community accounts for only some of the change. A major part of the change is that observed distributions depart more from expected distributions in 2010 compared to 1990, leading to increasing group separation because highly dispersed unevenness was giving way to a pattern of

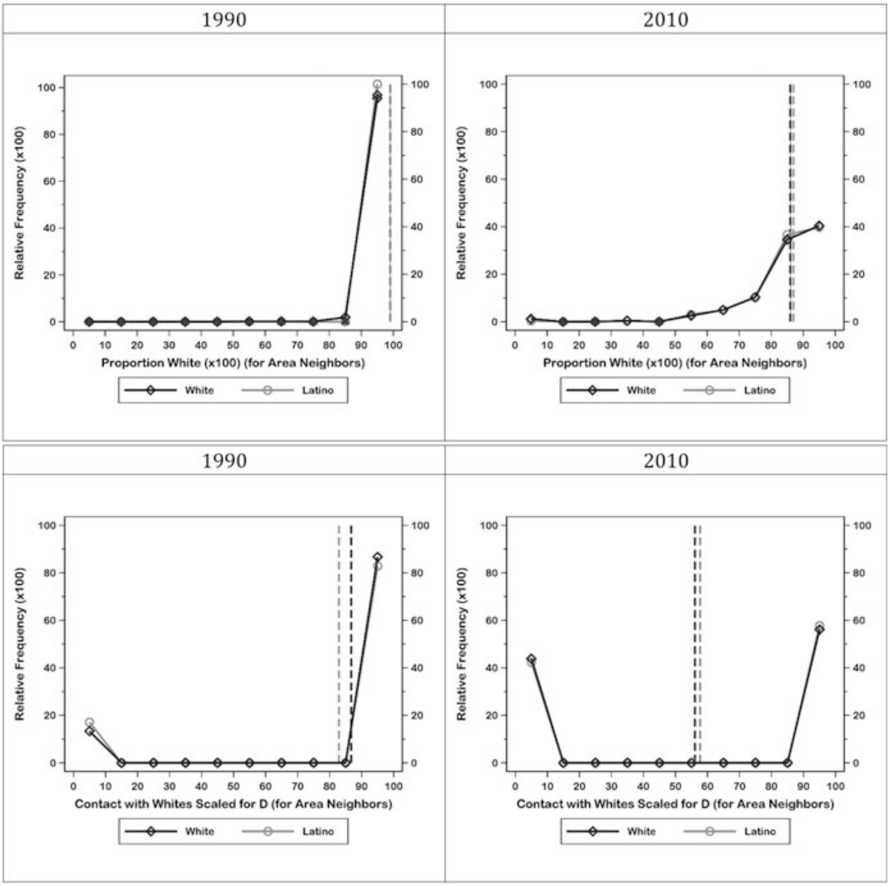

Fig. 5.2 Expected distributions of White and Latino households by proportion White among neighbors under random distribution (per bootstrap simulation)

emerging polarized unevenness. In 1990, the observed distributions of White and Latino households by level of contact with White neighbors closely follows the distributions expected under random assignment, producing a very low value for the separation index and a higher value of the dissimilarity index, which reflects a benign pattern of dispersed unevenness.

In 2010 the expected distributions of contact with White households among neighbors under random distribution in Fig. 5.2 shift left toward lower levels for both White and Latino households. But unlike in 1990 when the percentages of White and Latino households in the 90–100 category are very close to the percentages expected under random distribution, in 2010 the percentage of Latino households is far below the expected level and the percentage of White households is far above the expected level. Additionally, the percentages of Latino households living in neighborhoods with White presence among neighbors at 70 percent or lower (Latino presence at 30 percent or higher) increase beyond expected levels by large margins. This reflects a rapid transition from dispersed unevenness to polarized unevenness, which is reflected in the separation index rising from 3.7 to 27.7. The dissimilarity index also rises from 30.2 to 51.4. But the most notable change is the convergence of values for the dissimilarity index and the separation index from a ratio of over 8 in 1990 to a ratio of only 1.9 in 2010. This indicates that, while the level of segregation in 2010 is in the medium range, it rose rapidly in just two decades and uneven distribution moved strongly in the direction of becoming more polarized. These important changes in the nature of White-Latino segregation in Worthington can only be captured by examining values of the separation index and using unbiased versions of segregation indices.

All of this highlights the value of using new methods to measure segregation and also the value of examining scores for the separation index over the dissimilarity index. Following conventional practices used in previous research, we would measure White-Latino segregation in Worthington in 1990 using person data and obtain a value of 81.3 for the dissimilarity index. Since this high value would be comparable to values seen for exemplars of high-segregation such as White-Black segregation in Chicago, many would be tempted to assume White-Latino segregation in Worthington therefore involves a high level of group separation with Latino households residing in all-Latino neighborhoods and White households residing in all-White neighborhoods. Taking note of the separation index value of 15.3 based on person data provides a first indication that the nature of White-Latino segregation in Worthington is very different from White-Black segregation in Chicago.

Based on understanding the technical properties of the two indices, two factors can potentially explain why the separation index takes a much lower value than the dissimilarity index. One is that, because the separation index is much less susceptible to bias, the value of the dissimilarity index is higher because it is inflated by index bias. The other is that the segregation pattern involves dispersed unevenness instead of polarized unevenness. As it happens, both play a role. Correcting for bias, which includes switching to data for households instead of persons, reduces the score for the dissimilarity index 51.1 points from 81.3 to 30.2. By comparison, correcting for bias reduces the score for the separation index 11.6 points from 15.3 to 3.7. The score of 81.3 for the standard version of the dissimilarity index calculated using person data can only be described as grossly misleading. The score of 30.2 for the unbiased version of the dissimilarity index is correct. But prevailing habits for interpreting values of the dissimilarity index would lead to misleading conclusions about whether Latino households live with or apart from White households. The values of the separation index, especially the value of the unbiased version, make it very clear that in 1990 Latino households live alongside White households in this new destination community and necessarily experience the same neighborhood contexts that White households experience.

5.12 Summary

In their review of the research on new destinations, Flippen and Farrell-Bryan (2021) described new destination migration as one of the most "striking demographic trends of recent decades" (2021: 27.2). Residential patterns can be a telling indicator of emergent racial and ethnic relations, and their trajectories also tell a story of how these relations are changing over time. A handful of scholars have recognized this and contributed research on residential segregation in new destinations, but these efforts have faced multiple challenges that are shared by segregation research on nonmetropolitan communities (see Chap. 4). The demographic conditions of many new destinations make conventional approaches to segregation measurement prone to inflated index bias and can also lead to high scores on the more popular dissimilarity index when in fact the two groups in the analysis are not living in fundamentally different neighborhoods. Additionally, the choice between measuring segregation of persons versus households becomes critical because the index scores are already more prone to upward bias. Finally, it is important to measure segregation at the level of the census block when studying segregation of new destinations because these areas often have smaller populations, especially in the case of the newly emerging group.

While some of these issues are simply underexamined and therefore have gone unaddressed, index bias is a problem that researchers have been aware of but have been unable to fix until Fossett (2017) developed the formula correction that directly removes the source of the bias from the calculation of the segregation index. With this correction for index bias in addition to our empirically-driven choices to rely on the separation index for segregation measurement and to measure segregation of households rather than persons, we contribute to the literature on residential segregation in new destinations with refined and superior analyses of patterns and trends of segregation in new destinations, including how these areas compare to established areas of settlement and how they change over time. We also extended beyond Latino new destinations to further develop our understanding of Asian new destinations and begin asking questions about the possibility of Black new destinations. Even though Latino new destinations are far more common and better understood as a social phenomenon, areas across the United States where Asian and Black populations are newly emergent going into the twenty-first century give us the opportunity to observe how these groups experience new settlement into predominately White communities by the way they are residentially distributed initially and over time.

Our empirical analyses in this chapter can be summarized by three key findings. First, residential segregation is lower in new destinations as compared to established areas of settlement for all three minoritized groups. In the case of both Latino and Asian new destinations, residential segregation is at very low levels in 1990, which is the starting point of the analysis. However, we also find that White-Latino and White-Asian residential segregation is rising in new destinations and reaches moderate levels by 2010. White-Black segregation in new destinations follows a different pattern initially and over time, beginning at moderate levels and fluctuating to slightly lower levels in 2010. These findings contradict some of the conclusions that have been drawn in the literature, as we would have expected based on past studies to find higher levels of segregation in new destinations. But the theoretical arguments on racial conflict and place stratification that frame previous studies may still stand, as we do find segregation increasing over time for Latino and Asian households in new destinations. It is possible that as these groups become more visible and more permanent in their new communities, they could face increasing conflict with and separation from White residents.

We also find discordance between the dissimilarity index and the separation index when measuring residential segregation in new destinations, with the dissimilarity index consistently suggesting higher levels of segregation occurring than the separation index. This is indicative of a form of uneven distribution in new destinations that we refer to as dispersed unevenness, where the two groups in the analysis are living in neighborhoods that have different average levels of proportion White, but the differences are not large enough to produce patterns of segregation that we would think of as prototypical segregation. However, for Latino and Asian new destinations this discordance between the separation index and the dissimilarity index is changing over time as scores on the separation index increase, suggesting that residential segregation in Latino and Asian new destinations is shifting from patterns of dispersed unevenness to patterns of polarized unevenness, where now Latino and Asian households are living in fundamentally different neighborhoods than White households in the community.

We have documented that the impact of bias on segregation index scores can be very high when scores are computed using standard computing formulas and this is true both when indices are calculated using data for households and data for persons. We have documented how researchers can use refined formulas introduced in Fossett (2017) and measure segregation of households rather than persons to obtain index scores that are free of index bias. Happily, it is a relatively simple matter to obtain unbiased index scores when indices are calculated using data for households because the adjustments to calculations are simple and do not require detailed data beyond the basic household counts used in calculating index scores with standard formulas. Unfortunately, the situation is more complicated when index scores are calculated using data for persons. In this situation the sources of index bias are more complex and adjustments to calculations must accordingly be more complicated.

Furthermore, additional detailed data on race distributions of households by size across residential areas are needed to implement the adjustments (see Chap. 2 for further discussion).

In conclusion of this chapter, we have accomplished two goals. First, we have provided a sound analysis of residential segregation patterns and trends in new destinations to support future research in this area using methods that produce reliable and trustworthy measures of residential segregation even under conditions that researchers have avoided because of the problems that they presented for conventional methodological approaches. Second, we have demonstrated in this chapter (and described in more detail in Chap. 2) the measurement tools and guidelines needed to successfully study residential segregation in new destinations or in any communities where one group is small or newly emerging. The analyses presented here document that application of the formulas for unbiased index scores can yield scores much lower than the scores obtained when using standard index formulas. Researchers who are accustomed to seeing high scores for segregation indices may wonder if the unbiased scores are in some sense too low and perhaps unnecessary. We are confident in advocating the use of unbiased scores to gain the best understanding of the state of segregation in new destinations and its implications for life chances and race relations. Our approach overcomes many of the limitations that have hindered research in this area. We hope that researchers will adopt these methods and continue to develop our sociological understanding of demographic changes and residential patterns in new destinations.

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Chapter 6
The Micro-Level Dynamics of Racial and Ethnic Residential Segregation

6.1 Overview

Segregation is often viewed and studied as a macro-level phenomenon, described in terms of aggregate patterns across areas. Empirical analyses of segregation are typically conducted at the macro-level as well, explaining changes and variations in segregation through contextual-level factors such as population size, region, or percent White. This approach was popularized by the work of Douglas Massey and Nancy Denton (e.g. 1987, 1993) and continues to be used in more recent studies that use census summary file tabulations (e.g. Iceland, 2014; Iceland et al., 2014; Frey, 2018). Indeed, this is the approach that we have taken in previous chapters, albeit while taking precaution to only include aggregate-level predictors that do not lead us to an ecological fallacy (Fossett, 1988). However, there is an established body of literature that recognizes segregation as an outcome of micro-level processes of locational attainments and residential mobility. This work was spearheaded by Richard Alba and John Logan in the early 1990s in a series of articles that modeled segregation-relevant outcomes, such as neighborhood percent White, using household or individual-level predictors such as income, education, and nativity (Alba & Logan, 1991, 1992, 1993), which led to more locational attainment studies in the following decades (e.g. Pais et al., 2012; South et al., 2008; Yu & Myers, 2007). This work is fundamentally important for testing the dominant theoretical frameworks

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employed in segregation research, which largely emphasize that segregation is driven by micro-level characteristics and processes and center the barriers and opportunities in residential mobility. Additionally, the locational attainments approach can be linked with outcomes that are essentially consequences of segregation such as educational disparities, health disparities, and unequal exposure to crime.

Despite the contributions to come out of this past literature, this approach to studying segregation through analyzing locational attainments has fallen just short of linking the neighborhood outcomes of individual households to overall patterns of segregation. The reason for this lies in how we measure segregation, which ultimately affects how we think through drawing the link between micro- and macro-level approaches to studying segregation. Fossett (2017) emphasizes that one of the most important benefits to reformulating segregation indices as a difference of group means is that we are also called on to reconceptualize segregation, thinking of it not as an aggregate-level phenomenon but as an outcome of processes of locational attainments happening below the surface. With new methodologies described in Chap. 2 and with access to data that permits micro-level analyses, we can take on an entirely new approach to studying segregation that does not break from tradition but rather advances it, drawing a direct link between the study of locational attainments and aggregate-level patterns of segregation by simply reformulating the segregation index. By analyzing segregation through modeling individual or household-level neighborhood outcomes, the locational attainments approach to studying segregation can be directly and quantitatively linked to Fossett's (2017) reformulation of segregation indices, which situates segregation as an aggregation of individual outcomes (i.e. the difference-of-means approach). We have been successful in empirically demonstrating this approach in our recent work (Crowell & Fossett, 2018, 2020, 2022).

This final empirical chapter presents our most complex analysis of segregation thus far by rightly analyzing segregation as a dynamic and multilayered social phenomenon – one that is inherently sociological as individual actors make residential moves that are determined by both individual preferences and resources as well as structural-level factors that shape the extent to which households can convert those resources and desires into locational attainments. Disparities in these dynamics can lead to racially and economically segregated communities. In previous chapters, we examined contextual factors that correlate with patterns of segregation across areas as others have done in the past. Those analyses, while useful and informative, are ultimately simple and largely descriptive. In this chapter, we conduct a multivariate analysis of segregation that can account for a multitude of household-level factors that lead to group inequalities in residential outcomes, which at the aggregate level manifest as segregation.

While we discuss some of the dominant theoretical frameworks in this chapter, our goal is not to frame this methodological approach as the solution to engaging specifically with what has been theorized, but rather to provide a new methodological toolkit that opens up new avenues for theorizing about and analyzing segregation. What can we build on to our existing frameworks? Or perhaps the more exciting question is: What new theories and understandings can we develop about residential segregation? This chapter presents an analysis of White-Black, White-Latino, and White-Asian segregation in 25 of the largest metropolitan areas in the United States, modeling locational attainments in a way that directly and exactly predicts overall levels of segregation for any given area. The research design is determined by existing theory, but the methods are almost entirely novel to segregation research. We at times draw on our previously published research in this area, the first empirical demonstrations of these new methods, but in this chapter we take the liberty to go further into what is possible for the future of segregation research – what methodological innovations we can implement and what new questions we can ask to advance our understanding of residential segregation.

6.2 Review of Theoretical Frameworks

In Chap. 1, we gave an overview of some of the dominant theoretical frameworks in the segregation literature as well as an emergent theory of residential sorting recently set forth by Maria Krysan and Kyle Crowder (2017). Consistent with previous research in this area (Crowell & Fossett, 2018, 2020, 2022; Iceland & Scopilliti, 2008), we draw on three major theoretical perspectives – *spatial assimilation, place stratification,* and *segmented assimilation* – to frame our analysis and conclusions in this chapter. These perspectives guide demographic studies focused on racial residential segregation while considering other social factors such as socioeconomic status and immigration (e.g. Iceland & Scopilliti, 2008). Each perspective holds potential relevance for the residential segregation patterns of Black, Latino, and Asian households. One innovation in our study is that we draw on this multi-perspective framework to understand how the effects of factors operating in micro-level locational attainment processes may vary in shaping segregation across different community contexts and, in particular, across low- and high-segregation settings.

We review these three perspectives here briefly, noting first that they are not mutually exclusive and in fact can both contribute independently and complement one another to provide a more complete, nuanced understanding of the complexities of racial residential segregation processes. This point is made in Crowder and Krysan's (2016) critique of the simplicity with which these theories are often applied. Furthermore, we recognize that these three theories of segregation are not exhaustive of the perspectives that could be employed to develop a theoretical framework for residential segregation and attainments. For example, Krysan and Crowder's structural sorting perspective (2017) is an important lens for understanding the nature of household residential movements and the role of networks and information in determining residential location. However, the hypotheses of this and other theories are not testable within the scope and design of our study.

The *spatial assimilation* perspective holds that as members of a minoritized racial group acculturate towards characteristics of the majority group and experience socioeconomic mobility within and across generations, they become more likely to move away from ethnically concentrated neighborhoods and into higher-status neighborhoods with a greater presence of White households (Alba & Logan, 1991; Charles, 2003; Duncan & Lieberson, 1959; Massey & Denton, 1985). As Charles (2003) explains, this perspective emphasizes group differences in social characteristics as a primary reason for residential separation. Socioeconomic differences, typically measured by income and education, determine what neighborhoods householders are able to afford, which can lead to racial residential segregation when there is racial and economic inequality and neighborhoods are stratified on housing quality and amenities. Acculturation is also key to this perspective and is often operationalized in locational attainment models as English language ability and citizenship. The origins of this theoretical perspective are based in observations of White ethnic groups in the twentieth century, who moved away from inner-city immigrant enclaves and into suburbs where U.S.-born White households resided as they experienced social and economic mobility, intermarriage, and language assimilation, accelerated by a decline in European immigration and generational shifts along with increased economic opportunity. Thus, cultural characteristics and acculturation are also emphasized as determinants of residential location.

Spatial assimilation as a conceptual framework has persisted in residential segregation research with renewed attention following the work of Alba and Logan (1991, 1992, 1993) and is often used to guide the research design of locational attainments analysis. When applied in more contemporary research, this framework has had some useful explanatory power for understanding Latino and Asian residential trends. For example, studies show that, over time and across generations, Latino and Asian households experience residential mobility and increased contact with White households. Thus, Latino and Asian households with high socioeconomic status, where English is spoken exclusively or very well, and are several generations removed from immigration have more residential contact with White households in comparison to foreign-born Latino and Asian households with lower socioeconomic status (Alba & Logan, 1993; Alba et al., 2000; Charles, 2003; Iceland et al., 2014; Iceland & Nelson, 2008; Iceland & Scopilliti, 2008; Massey & Denton, 1985; South et al., 2008; Yu & Myers, 2007). For these groups where immigration is a major factor, newer arrivals may initially rely on enclaves where there is language support and established networks for entry into the labor market and social institutions, especially for those households with low socioeconomic status. As members of these groups acculturate and experience upward mobility, they may be less reliant on enclaves, which will be especially true for their second- and third-generation descendants (Alba et al., 1999; Charles, 2003; Massey & Denton, 1985). Their social distance from White households will be reduced and they will experience higher levels of residential integration.

The impact of spatial assimilation dynamics can potentially be seen at both the macro-level and the micro-level. As noted above, spatial assimilation theory predicts the micro-level finding that co-residence with White households will be more likely with social mobility. While this perspective also predicts that aggregate-level segregation will be greater when group differences on social and economic characteristics are more pronounced, the predicted pattern must also include evidence that segregation and group differences coincide for reasons beyond being jointly determined by discrimination and constrained opportunity. That is, there must be evidence indicating that reductions in group differences will lead to reductions in segregation. The new methods of segregation analysis we use allow us to examine this issue with quantitative precision not possible in previous research.

There is the potential for complex patterns to emerge as spatial assimilation dynamics initially emerge and play out. If group disadvantage is rooted in a pervasive web of discrimination and constrained opportunities, group disparities will be large when segregation is high but spatial assimilation at the micro-level will be weak and reducing group disparities will have little or no short-term impact on reducing segregation. Alternatively, if group differences trace discrimination that was higher in the past than in the present, as might be the case for the Black population, or if it traces to a group's historical immigration experience, as might be the case for the Latino or Asian populations, group differences might be smaller than in the former case yet have a greater potential impact on reducing segregation in the present because the micro-level spatial assimilation process is stronger. In a later section we discuss how this possibility leads us to search for evidence that the impact of group disparities on segregation will vary by context.

One notable limitation of the spatial assimilation framework is that even for U.S-born, high-socioeconomic status Latino and Asian households, segregation from White households persists, albeit at lower levels (Crowell & Fossett, 2018, 2020). Additionally, the spatial assimilation framework has had little relevance for understanding Black segregation; the predominately U.S.-born Black population experiences medium to very high levels of segregation from White households even at higher matched incomes (Alba & Logan, 1991, 1992, 1993; Iceland et al., 2005; Massey & Denton, 1987; Spivak & Monnat, 2013; Yu & Myers, 2007). Therefore, other general theoretical perspectives must be considered which can address persistent racial residential segregation.

The *place stratification* perspective is an alternative to the spatial assimilation perspective, but it is complementary, rather than mutually exclusive, in positing that discrimination based on race holds an important role in maintaining levels of segregation. Where spatial assimilation takes on greater relevance when groups begin to experience a less obstructed path to social mobility and increased residential contact with White households, place stratification takes on greater relevance when segregation primarily reflects structural racism. Place stratification stresses the persisting role of racism and group conflict in the White population's efforts to maintain power, status, and privilege by restricting access to White neighborhoods (Charles, 2003, 2006; Logan, 1978). Mechanisms include direct and covert discrimination, exclusionary zoning, steering by realtors and landlords, housing loan discrimination, and covert but perceived hostility toward minoritized families in predominately White neighborhoods. Thus, place stratification operates through both individual and institutional determinants (Massey, 2020). These dynamics are hypothesized to be effective regardless of reductions in group differences on characteristics such as socioeconomic status or acculturation.

Work by Farley and colleagues in previous decades (Farley et al., 1978, 1994) lends some support to the place stratification perspective, finding that Black families perceive greater racial discrimination in the housing market while White families remain resistant to living in neighborhoods where minoritized racial groups predominate, although White preferences have become more racially progressive over time (Farley & Frey, 1994). Additionally, direct evidence has emerged over the past several decades which would indicate continuing discrimination in the housing market, particularly that which comes from audit studies. These studies generally find that although housing market discrimination may be declining, it is still significant and, furthermore, mortgage loan discrimination shows no signs of abating (Massey & Lundy, 2001; Galster, 1990; Quillian et al., 2020; Turner et al., 2013; Yinger, 1995). The place stratification perspective is widely seen as relevant for understanding the continuing high levels of segregation for Black households but could also explain why Latino and Asian households may remain at some level of uneven distribution even though levels of segregation may be moderate or decreasing over time, as racism persists with consequences for all racially minoritized groups (Alba & Logan, 1991; Charles, 2003; Pais et al., 2012).

The final framework that informs this study is a theory positing that systems of stratification can create multiple trajectories of "assimilation," known as *segmented assimilation*. This framework holds particular relevance for understanding divergent segregation patterns by nativity and across generations and can provide insight into how locational attainment dynamics may vary by group. Assimilation can mean experiencing upward social mobility and entrance into White neighborhoods, as posited by the traditional assimilation framework that informs the spatial assimilation perspective. But it can also result in being subjected to institutional racism and discrimination, being shut out of economic opportunities, or gravitating towards ethnic communities with supportive structures for social and economic opportunities.

Segmented assimilation was first empirically explored within the context of the labor market (e.g., Portes & Zhou, 1993) but can be extended to many social outcomes that serve as indicators of social mobility and resources including residential locational outcomes (Crowell & Fossett, 2020; Iceland & Scopilliti, 2008). The implications of this framework for understanding the segregation patterns of the groups considered here is that we may not observe uniform patterns of locational attainments but may in fact find attainment patterns that run counter to what the spatial assimilation hypothesis would have us expect (South et al., 2005). For example, in our past research on the Minneapolis-St. Paul Metropolitan Statistical Area, we found that U.S.-born Black households were more likely to be segregated from White households than foreign-born Black households, counter to what we found for Latino and Asian households (Crowell & Fossett, 2020). From the segmented assimilation perspective, we argue this pattern results because Black households experience a trajectory of assimilation that is more strongly impacted by institutionalized racism and particularly an established legacy of Black residential segregation. This implies that in contrast to the traditional spatial assimilation perspective, the social and economic resources that would ease entrance into

White neighborhoods give way to other more structural dynamics including barriers that emerge from racialization and racism.

6.3 Framing Cross-context Segregation Patterns

Finally, we consider the possibility that spatial and segmented assimilation and place stratification dynamics may vary in relative salience and importance across metropolitan areas. To the extent that they do so, it will require us to take more care in assessing the quantitative importance of the different processes. Most importantly, group differences in socioeconomic characteristics and in locational attainments will have implications for reducing segregation that vary across low- to high-segregation contexts. If group differences in the effects of household social and economic characteristics on locational attainments were constant across metropolitan areas, it would be a simple matter to assess the impact of group disparities on resources and social characteristics on aggregate-level segregation. The impact of group disparities would be a simple function of the magnitude of the disparities. However, if the effects of household characteristics vary between low- and high-segregation contexts, the impact of group differences on those characteristics will vary across contexts, possibly in complex and sometimes counterintuitive ways.

Thus, we anticipate the following complexities: The role of spatial assimilation for segregation may loom largest in situations where segregation and group differences are in the middle range, spatial assimilation and place stratification dynamics are both salient, and group disparities are sizeable. In contrast the role of spatial assimilation for segregation may ironically be smaller in high segregation contexts. Group differences may be larger in such cities creating the potential for important consequences for segregation. But the differences may in fact be less consequential for segregation because place stratification dynamics and other limiting factors such as those that are central to the structural sorting perspective (Krysan & Crowder, 2017) are stronger than spatial assimilation dynamics, reinforcing observed higher levels of segregation. Similarly, the role of spatial assimilation for segregation may be higher than expected in low-to-medium segregation contexts. If group differences on social and economic characteristics are in a lower range, the consequences for segregation could rival and match the consequences in medium segregation contexts where spatial assimilation dynamics are also stronger.

These theories all carry weight in understanding the many determinants of segregation, substantiated by extensive empirical research. We do not here seek to test these theories anew or challenge the claims made by any of them. Instead, we suggest that segregation research that engages with any or all of these theories can more directly test the hypotheses posited by them by adopting our methodological approach, which permits a more thorough and dynamic demographic analysis of residential segregation. Thus, throughout this chapter we highlight opportunities and possibilities for engaging with existing questions or addressing new ones using our framework, leaving the reader to think broadly about what theories, outcomes, and sources of data they can bring in.

6.4 Previous Research in Locational Attainments Analysis and Segregation

The tradition of understanding segregation through the individual locational, or residential, attainments of households and how they vary by certain sociologically meaningful characteristics such as race or income dates back to the 1980s, exemplified by the work of Douglas Massey and Brendan Mullen (1984) and Douglas Massey and Nancy Denton (1985). This type of analysis gained more popularity in the 1990s through a series of studies published by Richard Alba and John Logan (1991, 1992, 1993) and has been a mainstay of segregation research into the twenty-first century through work by Scott South and colleagues in addition to several other researchers who have developed an interest in wanting to understand segregation in an increasingly multicultural society where multivariate analyses are really needed to answer questions about where people live, who they live among, and why (South et al., 2011; Yu & Myers, 2007).

Alba and Logan's innovating 1993 article is most often cited as an exemplar of how locational attainment analyses can be linked to segregation outcomes and inform dominant theories about segregation. In their study, they used group-specific micro-models to test theories of spatial assimilation and place stratification where the outcome was a measure of racial composition which, when measured as non-Hispanic White, can indicate low or high segregation as racial residential segregation is inherently about the level of residential contact that minoritized racial groups have with the majority group. Under this approach, independent variables in the model such as income or nativity are used to assess the spatial assimilation model, where positive effects on indicators of social mobility would be interpreted as spatial assimilation. Place stratification effects are interpreted through variations in the intercepts, or the "starting points" for each group in regard to the racial composition of their neighborhoods after all effects are controlled for.

Alba and Logan's model modernized segregation analysis to situate dynamics of segregation at the level of household locational attainments and the inequalities that shape those movements. A second major contribution of their work was their inclusion of contextual effects, circumventing the limitations of public census data that we have also reviewed throughout this book to construct correlation matrices that account for cross-area variation in contexts and their correlations with individual-level characteristics. Their work began to reframe our understanding of how the two major veins of segregation research, micro-level locational attainments and aggregate-level segregation patterns, are intricately related and demonstrated an empirical approach to drawing out this link (Alba & Logan, 1991, 1992, 1993).

While these studies argue that there is evidence of spatial assimilation dynamics and that therefore segregation may decrease as minoritized groups make gains in socioeconomic status, they also often reiterate the persistent role of place stratification which complicates what would otherwise be a simple explanation for segregation. That is, segregation can never be fully eradicated if structural racism continues to be embedded in our society and shapes housing neighborhood patterns along racial lines. Studies come to this conclusion indirectly, pointing to the unexplained component of variation in their models and bolstering their argument with existing qualitative and survey evidence that housing discrimination is still occurring. It is undoubtedly true that segregation is a product of structural racism in addition to other factors that are emphasized by the spatial assimilation model or hypotheses that focus on ethnic preference. But identifying the role of structural racism in a model of segregation has been a difficult challenge.

Additionally, even if these studies restrict their conclusions to the spatial assimilation hypothesis that is directly addressed by their models, the link between the modeled neighborhood outcomes and the pattern of segregation that exists in the area in which these neighborhoods are embedded has remained elusive. For example, many locational attainment studies model neighborhood proportion White. This decision is in recognition of the location-based resources and amenities associated with predominately White neighborhoods where White residents leverage their collective power and privilege to protect opportunity and status (Logan, 1978; Trounstine, 2018). But this choice is also made because we often use neighborhood proportion White as the building block of racial residential segregation measurement. When locational attainment models are predicting neighborhood proportion White as an outcome, they are ultimately predicting the key component for measuring segregation in the area overall. This is both conceptually true and also a methodological fact, as most indices of segregation, including the ever-popular dissimilarity index, are constructed based on neighborhood proportion White and represent group differences in residential contact with White households.

Scholars who have done this work are rightly recognizing that segregation is a collective outcome of individual residential moves that are shaped by preferences, resources, and barriers, but ultimately they have been establishing only indirect links to how these individual dynamics form and transform segregation patterns overall in a given area. We contribute directly to this literature in a substantial way by taking advantage of Fossett's (2017) difference-of-means reformulations of segregation indices which permit the disaggregation of segregation indices into individual outcomes that can then be modeled using the conventional locational attainment approach. We cannot overstate how this approach draws the locational attainments and segregation literature together with a simple, quantitative link that is established using a different, but mathematically equivalent, formula for any of the widely accepted traditional measures of segregation. Thus, we spend the remainder of this chapter describing our methodological approach and presenting empirical findings from an analysis that draws on a variety of different methodological techniques to capture the complexity of residential segregation, which is in part the product of multifaceted dynamics occurring at a micro-level. One primary benefit of what we are able to find with these new methodological innovations is that we can speak directly to the prevailing theoretical frameworks in the segregation literature, as we have done in some of our recent work (Crowell & Fossett, 2018, 2020, 2022).

6.5 Data

For the analyses in this chapter we rely on the restricted-use microdata files from the 2010 decennial census and the 2012 American Community Survey (ACS) 5-year estimates, linked together by census block identifiers. While the decennial census is a full count of the U.S. population and collects basic demographic information including race, age, gender, marital status, and household structure, the American Community Survey is an annual demographic survey conducted by the U.S. Census Bureau that collects much more detailed social, economic, and demographic information on households and persons living within the household. Each annual survey collects data on approximately 1 percent of the population, and unique samples permit the data to be pooled over 5 years to create a 5 percent nationally representative sample. The benefit of using the decennial census data is to create a measure of neighborhood racial composition that is not subject to sampling error which can be modeled and aggregated to construct a measure of segregation for the community overall. A limitation of the decennial census, however, is that it collects sparse information of persons and households, so that information relevant for testing theories that focus on how group differences on social characteristics such as education and income can contribute to residential segregation is not available. The American Community Survey does include detailed information on socioeconomic indicators, military participation, nativity, language, and other characteristics that allow us to understand much about the diversity of the U.S. population. Many of the variables identified as relevant to segregation theories, particularly spatial assimilation theory, are available in the ACS. Because the ACS is also a U.S. Census Bureau product, the data can be linked to the decennial census files using geographic identifiers. Thus, the dataset is created by merging the decennial census with the ACS using census block identifiers, creating a unique dataset that relies on a sample but draws on complete census data for the dependent variable.

Using the decennial census for the construction of the dependent variable is critical, as trying to measure segregation based on sample data can introduce bias in the segregation score. Bias that is due to small population counts can be overcome by using the unbiased segregation indices that we have used throughout this book, but it is not a solution for overcoming the measurement problems that arise from sampling error. This issue is one that has begun receiving attention, particularly as interest in economic segregation continues, because household income is a variable that can only be found in the sample survey data. Napierala and Denton (2017) identified several ways in which the dissimilarity index, and implicitly other measures of segregation, can overstate levels of segregation when using the ACS or other sample-based data. They, in addition to other scholars (e.g. Wei et al., 2023), have explored ways to account for sampling error in segregation measurement, but the issue remains largely unresolved. For this reason, we bypass the issue altogether by measuring segregation, and constructing the dependent variable that comprises the components for measuring segregation, using the decennial census.

Importantly, we also clarify our reason for relying on the restricted-use microdata files of both the decennial census and the ACS. One of the major challenges in segregation research is the limited availability of detailed social and demographic data that includes neighborhood-level geographic identifiers. There is a justifiable reason for this, because the sort of detailed information on individuals and households that we may want to access to conduct locational attainment analyses could make it easy to identify individuals if the data also comes with fine-grained information about their residential location. Thus, when it comes to public-use data, researchers have a choice: access detailed information about persons or households without information on their neighborhoods, or access information on the neighborhoods where people live but with limited data on those persons or their households. The first option is available in the form of public-use microdata, which provides researchers with deidentified individual responses to the ACS and some geographic information that rarely goes below the county level. The second option comes in the form of summary tabulations, providing population estimates from cross-tabulations of two or at most three variables at a time at levels of geography that can go as low as the block group level.

The tradeoffs that must be made using public-use data have throttled any sort of large-scale attempts at detailed segregation research, especially for conducting analyses on locational attainments. Researchers can turn to other data sources, but often this means resorting to smaller samples in comparison to the American Community Survey. Fortunately, none of these less-than-ideal alternatives have to be considered if instead one can access the restricted-use microdata files for the decennial census, the ACS, and other survey data collected and distributed by the U.S. Census Bureau. With approval from relevant agencies, these data can be accessed at Federal Statistical Research Data Centers around the country and simultaneously provide the key components needed to perform the sort of analyses that we present here: detailed social and demographic information on persons and households, and information on the neighborhoods where they live. For this chapter and other studies that we have done in the past, we accessed these restricted-use files to construct the merged dataset described above. The caveat to using these data is that disclosure of results must first undergo review, so when necessary we acknowledge the information that is not provided because data and results were not approved for disclosure.

6.6 Sample

In this chapter we present results from a selection of metropolitan areas, relying on 25 of the largest metropolitan areas in the United States with some selections made based on the representation of certain minoritized racial groups. In Table 6.1 we list

Table 6.1 Group percentages by race of householder in 25 metropolitan areas, 2010

Metropolitan area	White	Black	Latino	Asian
Atlanta-Sandy Springs-Marietta	55.5	31.9	6.7	4.0
Baltimore-Towson	63.9	27.6	3.1	3.7
Boston-Cambridge-Quincy	79.6	6.1	6.8	5.3
Chicago-Joliet-Naperville	62.6	17.0	14.2	5.0
Dallas-Ft. Worth-Arlington	58.3	15.6	19.7	4.6
Denver-Aurora-Broomfield	73.7	5.4	15.9	3.0
Detroit-Warren-Livonia	70.9	22.3	2.7	2.6
Fresno	44.3	5.4	50.3	7.5
Houston-Sugarland-Baytown	47.9	17.8	27.0	5.9
Los Angeles-Long Beach-Santa Ana	42.7	8.0	32.6	14.3
Miami-Ft. Lauderdale-Pompano Beach	43.3	16.7	36.7	1.9
Minneapolis-St. Paul-Bloomington	84.6	6.4	3.4	3.9
New York City-Northern New Jersey-Long-Island	55.3	16.0	18.4	8.5
Philadelphia-Camden-Wilmington	69.2	19.7	5.6	4.0
Phoenix-Mesa-Glendale	69.2	4.6	20.4	2.8
Pittsburgh	88.8	7.9	0.9	1.5
Portland-Vancouver-Hillsboro	82.7	2.6	6.9	4.6
Riverside-San Bernardino-Ontario	48.9	7.7	35.3	5.6
Sacramento-Arden-Arcade-Roseville	64.7	7.0	14.7	9.6
San Diego-Carlsbad-San Marcos	59.9	4.9	22.9	9.2
San Francisco-Oakland-Fremont	52.5	8.7	15.1	20.2
Seattle-Tacoma-Bellevue	74.9	5.3	6.0	9.6
St. Louis	77.9	17.3	1.8	1.8
Tampa-St. Petersburg-Clearwater	74.1	9.9	12.2	2.2
Washington-Arlington-Alexandria	54.8	25.8	9.3	7.9

these 25 metropolitan areas in addition to group percentages by racial group. While in previous chapters we have emphasized an increasing need to focus on nonmetropolitan residential segregation, the data that we use in this chapter cannot sustain analysis in nonmetropolitan communities and also present issues with confidentiality disclosure that would have prevented us from being permitted to release any results from the restricted-use data environment. Each of these 25 metropolitan areas consists of four subsamples: White, Latino, Black, and Asian householders over the age of 15.

We had previously explained our justification for measuring segregation of householders and households rather than all persons, operating on the assumption that persons are more likely to change residence as a single household unit rather than experience residential mobility individually and independent of one another. Additionally, measuring segregation of persons when household size varies by race and ethnicity can create distortions in the measure of segregation because racial groups with on average larger households will register as having more residential contact with one another when in fact it is because they live in relatively larger groups together within the same household.

6.7 Analysis Design

The central analyses of this chapter are regression models of locational attainments, where we regress neighborhood proportion White on selected characteristics of the householder including income, education, citizenship, and language, which are key independent variables within the spatial assimilation framework. The dependent variable in these models is the individual-level score, or p_i, that is used to calculate the separation index. To review, the separation index (S) is a measure of evenness that can be interpreted as the average group difference in neighborhood proportion White. Using the difference-of-means approach, the separation index is calculated by assigning each household a score, p_i, which in this case is simply the household's neighborhood pairwise proportion White. The separation index is calculated by taking the difference in the average score on p_i for White households and for the other group in the analysis. Using regression, the separation index can be estimated through group-specific models that predict p_i (described more below).

The independent variables for these models are factors relevant to spatial assimilation theory, including the following:

Socioeconomic – For socioeconomic indicators, we include measures of education and income. Education is a six-category measure that ranges from "less than high school" to "graduate degree." Income is measured as household income to which we apply a natural log transformation.

Acculturation – We include several indicators of acculturation, the first of which is a combined measure of nativity and citizenship constructed with dummy variables: U.S.-born citizen, naturalized citizen, and non-citizen. We also include a binary variable for those who are recent immigrants, defined as somebody who has arrived in the U.S. in the last 15 years. Finally, we include a measure of English-language usage which is a four-category variable that ranges from "speaks English not at all" to "speaks English very well/speaks only English."

Controls – In addition to indicators of socioeconomic status and acculturation, we also include controls for age, household family structure, and military participation.

This starting point is not unlike traditional locational attainments analysis, resembling Alba and Logan's models where positive effects of variables such as income, education, or nativity on neighborhood proportion White would indicate spatial assimilation while group differences in the intercept may be interpreted as place stratification effects (Alba & Logan, 1991, 1992, 1993). We extend beyond the conventional approach, however, with innovations that are threefold. First, the dependent variable is a direct component of an overall index of segregation which allows us to essentially model segregation at a micro-level. This allows us to link theories of segregation tested in our models with levels of segregation at the aggregate-level, aligning theory with purpose.

Second, following our regression estimations, we are able to perform regression standardization and decomposition, a core method of demographic analysis, and assess the relative roles of group differences in characteristics and group differences in the rates at which they can convert those characteristics, or resources, into residential contact with White households in producing an overall level of segregation for the area. This innovation in particular gives us the ability to more directly address place stratification dynamics in segregation outcomes. Third, using standardization we are able to isolate the effect of specific variables, such as income and education, on overall levels of segregation. This allows us to engage with multiple debates about the intersecting factors that shape racial segregation outcomes, like socioeconomic status. Importantly, because we conduct these analyses by pairing (e.g. White-Black, White-Asian, White-Latino), we can also speak to how place stratification, spatial assimilation, and other perspectives vary in relevance depending on the context and characteristics of the minoritized racial group in question.

To estimate the regression models, we use fractional regression. We have used fractional regression to analyze segregation outcomes in previous chapters, but the particular qualities of this modeling technique are especially important here. Fractional regression is a nonlinear model that restricts predicted values with the boundaries of 0 and 1, inclusively. This is important for modeling most measures of segregation at the micro-level because the individual scores are often bound between 0 and 1. For example, the dependent variable for modeling the outcome relevant for constructing the separation index is pairwise proportion White in the householder's neighborhood, adjusted to remove self-contact. This variable ranges continuously from 0 to 1, which is not appropriately handled by other estimation methods, such as ordinary least squares regression and binary logit regression (Kieschnick & McCullough, 2003; Papke & Wooldridge, 1996). The appeal of fractional regression is that it constrains the predictions to a logit curve but, unlike other nonlinear approaches, permits predictions to fall on the endpoints of 0 or 1, which are substantively meaningful in our analysis as there are observed cases of households located in neighborhoods that are either entirely White or do not have any White households at all.

For each metropolitan area, we analyze White-Black, White-Asian, and White-Latino segregation. In order to conduct regression standardization and decomposition, we must estimate a separate model for each group in the pairing (e.g., one model for White householders and one model for Black householders in the analysis of White-Black segregation). Because the measurement of neighborhood proportion White is a pairwise proportion, which means that only the two groups in the pairing are included in the calculation, this outcome is measured three separate times for White householders depending on the pairing. Neighborhood proportion White will vary for White householders depending on if the other group in the analysis is Black, Asian, or Latino. Thus, in total we estimate six models for each metropolitan area, resulting in 150 models altogether. This is admittedly an unwieldy amount of regression models to present in a single chapter, so we limit our presentation of findings to summaries of trends observed across all regression models.

Following the estimation of our regression models, we apply regression standardization and decomposition analysis techniques. This approach can be conceptually understood as asking two general questions. Within each segregation analysis pairing (i.e., White-Black, White-Asian, and White-Latino) we ask: How much residential contact would the minoritized racial group have with White households if they had the same distribution of characteristics, or resources, as White households?, and How much residential contact would the minoritized racial group have with White households if they had the same rates of return as White households on their own resources? The first question is answered by standardizing predicted outcomes for each group to White characteristics, capturing the effect of group differences that is relevant to spatial assimilation theory. The second question is answered by standardizing predicted outcomes for each group to the coefficients from the model estimated for White householders, capturing the effect of disparities in the rates of return that each group receives on their own resources in the form of residential contact with White households. Disparities in rates of return can reflect many things, with the place stratification framework emphasizing discrimination while other theoretical models, such as Krysan and Crowder's structural sorting model, may emphasize the role of disparate social networks. In addition to these separate components, we calculate a "joint" component that represents the codependency of group differences in resources and rates of return. This captures the expectation that group differences in characteristics would likely change if the two groups were matched on rates of return, or vice versa.

The predicted values are generated from the estimated group-specific regression models. Residential contact with White households for the minoritized racial group standardized to White characteristics is estimated by generated predicted values for White households out of the regression model estimated for the minoritized racial group, capturing the observed distribution on the independent variables for White householders and the estimated coefficients for householders belonging to the minoritized racial group. Residential contact with White households for the minoritized racial group standardized to White rates of return is estimated by doing the opposite – we generate predicted values for householders of the minoritized racial group using the regression model estimated for White householders. We summarize this procedure using the formulas below:

$\overline{Y}_{G1_{Re}G2_{Ra}}$ = the observed mean for Group 1 (i.e., the mean of predicted values $(\widehat{y}_i)$ for White households under the attainment model for White households)

$\overline{Y}_{G2_{Re}G2_{Ra}}$ = the observed mean for Group 2 (i.e., the mean of predicted values $(\widehat{y}_i)$ for households of the minoritized racial group under the attainment model for households of the minoritized racial group).

$\overline{Y}_{G1_{Re}G2_{Ra}}$ = the mean of Group 2 standardized to the resources of Group 1 (i.e., the mean of predicted values $(\widehat{y}_i)$ for White households under the attainment model for households of the minoritized racial group)

$\overline{Y}_{G2_{Re}G1_{Ra}}$ = the mean of Group 2 standardized to the rates of return of Group 1 (i.e., the mean of predicted values $(\widehat{y}_i)$ for households of the minoritized racial group under the attainment model for White households).

Upon estimating both the unstandardized and standardized predicted values, we can proceed to the next step in the exercise, which is to decompose the observed segregation index into the contributions made by group differences in characteristics, or resources that can be converted into movement into neighborhoods with White households, and the group differences in rates of return on those resources. This is accomplished using the general formulas presented below:

$\bar{Y}_{G1_{Re}G1_{Ra}} - \bar{Y}_{G2_{Re}G2_{Ra}}$ = (S) observed overall segregation
$\bar{Y}_{G1_{Re}G2_{Ra}} - \bar{Y}_{G2_{Re}G2_{Ra}}$ = (S_{Re}) the "resources" component
$\bar{Y}_{G2_{Re}G1_{Ra}} - \bar{Y}_{G2_{Ra}G2_{Re}}$ = (S_{Ra}) the "rates" component
S – (S_{Re} + S_{Ra}) = (S_J) the joint impact component

This decomposition allows us to understand more about the micro-level dynamics that shape segregation and engage with prevalent theories about segregation. For example, if the "resources" component makes up the larger share of the overall segregation score, then we would attribute segregation to the group differences in resources that are relevant for having residential contact with the majority group. This conclusion would be consistent with spatial assimilation theory, which argues that segregation is due to these group differences and will diminish over time as characteristics of the minoritized racial group converge with the majority group through acculturation and social mobility. However, if the component that represents group differences in returns on those resources contributes the larger share to overall segregation between the two groups in the analysis, then we would find support for the place stratification perspective, or perhaps other unaccounted for factors that result in White households and households who belong to minoritized racial groups converting their resources into residential contact with White households at disparate rates.

6.8 Profile Standardization

One technique that we highlight in this chapter which segregation researchers may find attractive is an extension of regression standardization where, rather than standardizing predicted values on observed distributions across independent variables, the predicted values are instead standardized on specific characteristics while only a selection of variables are permitted to vary. This technique in a sense allows one to isolate the effects of a single variable or set of factors on overall levels of segregation. For example, one could generate predicted values out of the White and Black estimated models in an analysis of White-Black segregation where all of the characteristics of the White and Black householders are specified at certain values except for household income and education for Black households. The predicted values that emerge at each income level while all other characteristics are held constant can tell us what the average difference is in neighborhood proportion White between White and Black householders at various income levels for Black households that roughly represent working-, middle-, and upper-class households. These differences produce the relevant segregation index (i.e., the separation index), and allow us to model segregation by race at different income levels while holding other factors constant. In this chapter, we demonstrate this technique to analyze the separate effects of income and education on White-Black, White-Latino, and White-Asian segregation.

6.8.1 Locational Attainment Analysis of Segregation

We begin by summarizing results from the 25 metropolitan areas included in the micro-model analysis of locational attainments. Table 6.2 presents observed levels of White-Black, White-Asian, and White-Latino segregation across the 25 metropolitan areas measured by the separation index, which has been corrected for index bias. These areas represent some of the largest and most diverse metropolitan areas across the United States, making them ideal for conducting the sort of analyses that are the primary feature of this chapter, where we ask how segregation is affected by variations in group differences in resources in addition to other factors related to structural racism. Descriptive statistics of group characteristics in these areas, such as income, education, nativity, and household structure are presented in Table 6.3, but we do not review them here other than to say that in most areas the distributions look generally similar, with higher percentages of foreign-born householders in the Latino and Asian populations and varying levels of socioeconomic status that range from highest levels for White and Asian householders and lowest levels for Black and sometimes Latino householders.

We move directly to reviewing results from the micro-models of locational attainments, where we regress pairwise neighborhood proportion White on characteristics of the householder, running separate regression models for each group. For the sake of brevity, we omit the full set of 150 regression models. In Figs. 6.1, 6.2, 6.3, 6.4, 6.5, and 6.6, we summarize the estimated regression coefficients using box plots by group and pairing across the 25 metropolitan areas in the analysis, where group refers to the racial group in the analysis and pairing refers to the combination for calculating pairwise segregation scores (e.g. White-Black, White-Latino, or White-Asian).[1] The box plots allow us to assess not only trends but also variability in the estimated effects across areas. Given that each metropolitan area has unique historical trajectories and processes of attainment, there is non-trivial variation in the

[1]Each pairing consists of a model for White households, with the dependent variable calculated based on the two groups involved. This results in three predicted outcomes for White households per area, one for each pairing.

Table 6.2 Separation index for White-Black, White-Latino, and White-Asian segregation in 25 metropolitan areas, 2010

Metropolitan area	W-B	W-L	W-A
Atlanta-Sandy Springs-Marietta	52.2	28.0	19.1
Baltimore-Towson	57.7	10.4	12.9
Boston-Cambridge-Quincy	42.5	35.2	14.7
Chicago-Joliet-Naperville	69.6	36.4	16.7
Dallas-Ft. Worth-Arlington	44.7	33.6	18.3
Denver-Aurora-Broomfield	28.5	23.7	5.5
Detroit-Warren-Livonia	68.1	17.5	13.9
Fresno	30.1	31.8	17.8
Houston-Sugarland-Baytown	53.1	38.1	25.8
Los Angeles-Long Beach-Santa Ana	55.0	46.3	30.4
Miami-Ft. Lauderdale-Pompano Beach	56.8	47.0	7.8
Minneapolis-St. Paul-Bloomington	31.3	12.7	12.3
New York City-Northern New Jersey-Long Island	69.0	47.4	28.4
Philadelphia-Camden-Wilmington	59.8	35.8	15.9
Phoenix-Mesa-Glendale	15.2	30.9	6.5
Pittsburgh	46.6	1.4	12.1
Portland-Vancouver-Hillsboro	13.4	11.4	9.0
Riverside-San Bernardino-Ontario	22.6	27.5	17.4
Sacramento-Arden-Arcade-Roseville	24.8	16.3	22.3
San Diego-Carlsbad-San Marcos	25.5	31.7	23.0
San Francisco-Oakland-Fremont	42.6	27.4	26.0
Seattle-Tacoma-Bellevue	18.3	9.4	15.7
St. Louis	61.8	6.0	9.6
Tampa-St. Petersburg-Clearwater	41.4	21.2	5.4
Washington-Arlington-Alexandria	52.7	23.9	14.4

Table 6.3 Selected descriptive statistics for regression analysis in 25 metropolitan areas

Variable	White	Black	Latino	Asian
% HS diploma or equivalent	94.2%	86.5%	65.5%	89.2%
% College degree	43.1%	23.6%	16.0%	57.7%
% Military	13.7%	9.7%	4.3%	3.0%
Median household income	$71,277	$41,187	$44,421	$73,736
% U.S. citizen	97.2%	94.3%	66.0%	71.2%
% Recent immigrant*	29.9%	38.0%	33.6%	37.7%
% Speaks English fluently	97.0%	96.7%	54.5%	61.3%
Median age	52	47	42	49
% Married couple HH	52.5%	30.8%	52.0%	65.6%
% Recent mover	88.1%	84.1%	84.5%	83.5%

Note: *Denominator is immigrants to the U.S. only

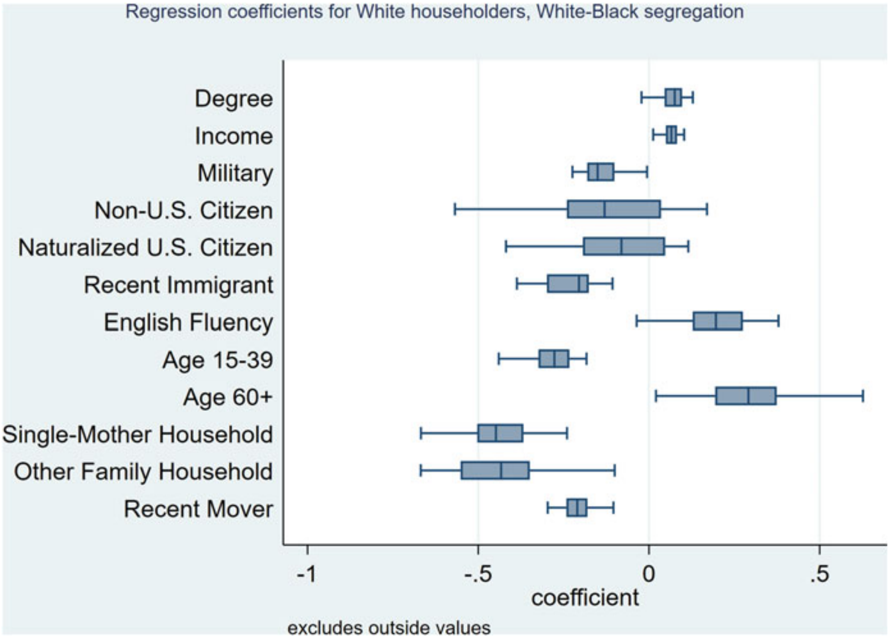

Fig. 6.1 Regression coefficients for White householders in White-Black comparison

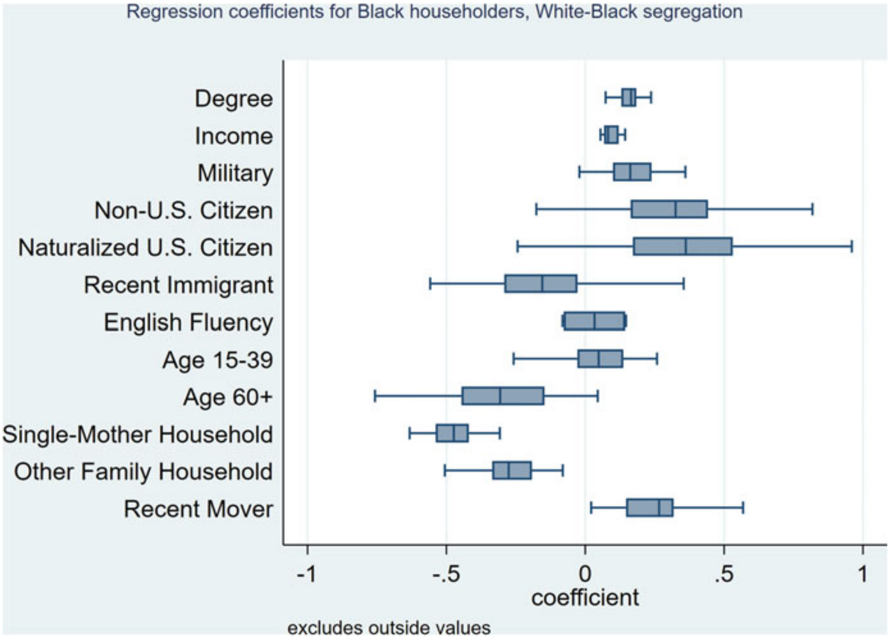

Fig. 6.2 Regression coefficients for Black householders in White-Black comparison

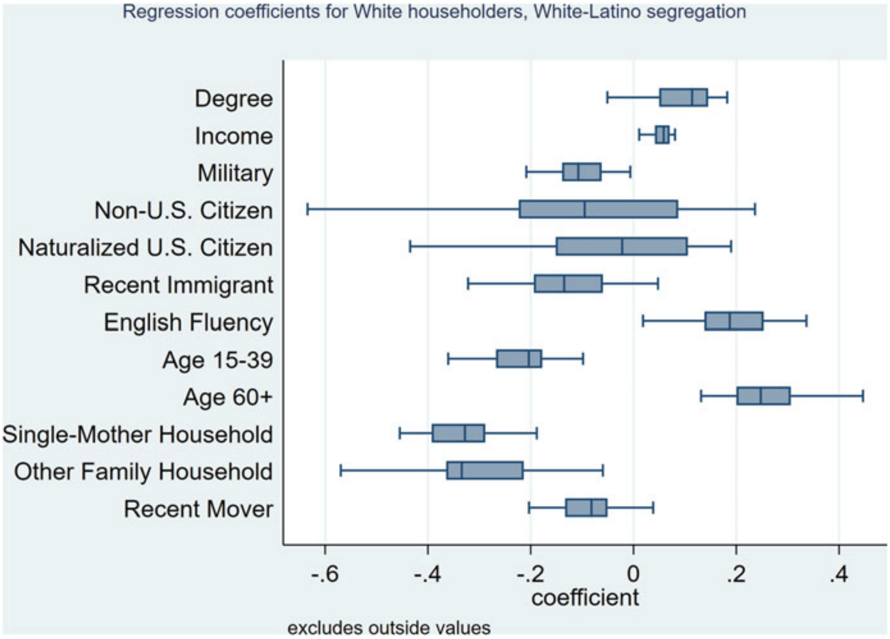

Fig. 6.3 Regression coefficients for White householders in White-Latino comparison

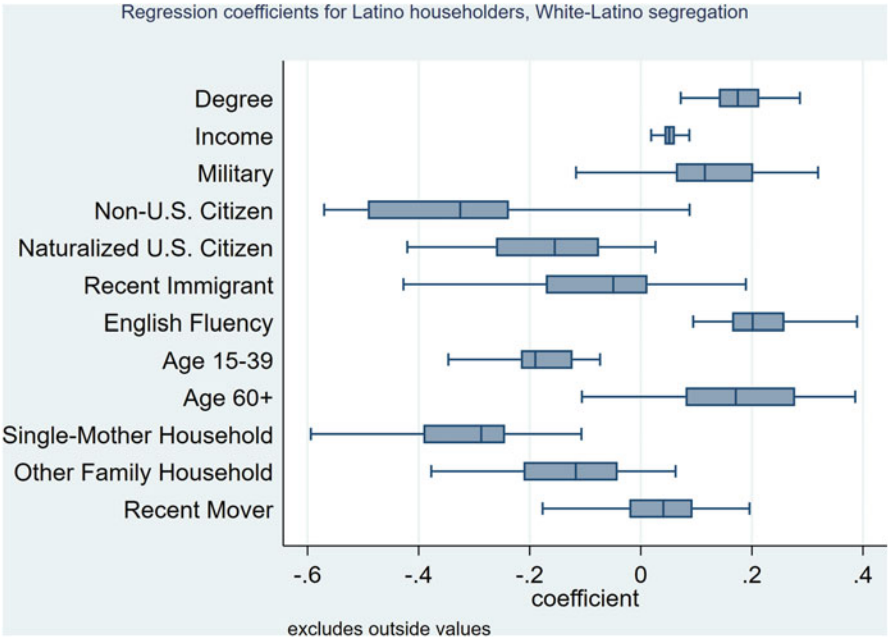

Fig. 6.4 Regression coefficients for Latino householders in White-Latino comparison

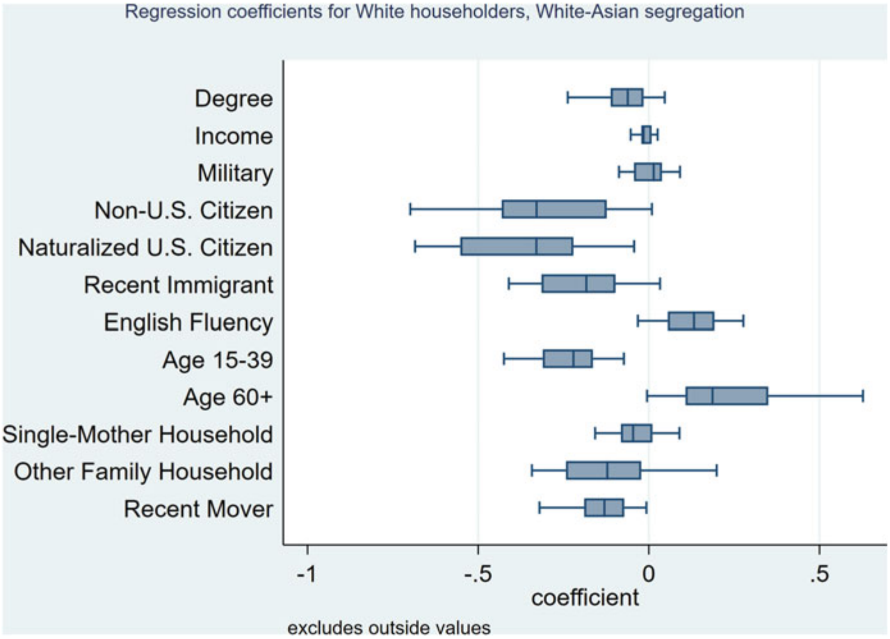

Fig. 6.5 Regression coefficients for White householders in White-Asian comparison

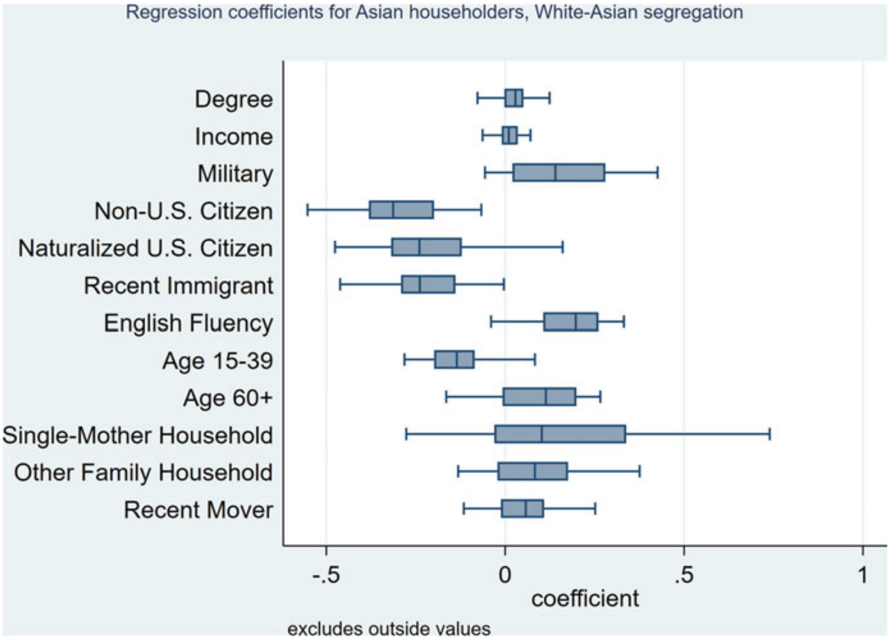

Fig. 6.6 Regression coefficients for Asian householders in White-Asian comparison

regression coefficients. For this reason, we aim to convey the typical pattern of effects found in the micro-models and limit our interpretations of these findings to the implications of the directions of the coefficients. Deeper conclusions will be drawn out from the standardization and decomposition results presented in the next tables.

The distributions of estimated coefficients in the figures document some distinct patterns aligning with the spatial assimilation hypothesis. We summarize our findings by stating that, in general, income and education are positive predictors of residential contact with White households for all groups, although these effects are very small and more mixed for Asian households. However, for Black and Latino households the effects are always positive, which means that higher incomes increase the neighborhood residential contact that Black and Latino households have with White households. From the disaggregated data we found that these positive effects of socioeconomic status were especially consistent for Black locational attainments that determine levels of White-Black segregation and were largely consistent for Latino locational attainments that determine levels of White-Latino segregation.

Also, as expected, English language ability and citizenship are typically positive predictors of residential contact with White households for Latino and Asian households, determining levels of White-Latino and White-Asian segregation. However, in the case of nativity and citizenship, these dynamics do not entirely hold true for Black households, where foreign-born Black householders generally experience greater residential contact with White households as compared to U.S.-born Black householders in nearly all of the metropolitan areas, resulting in a typical estimated coefficient that is positive for naturalized and non-citizens as compared to U.S.-born citizens. This deviation from the spatial assimilation pattern for Black households could possibly be situated in the literature on segmented assimilation which posits assimilation is not necessarily a straightforward process of upward mobility in tandem with more contact with White households, particularly for groups who experience the negative effects of racialization in the United States (Crowell & Fossett, 2020, 2022; Iceland & Scopilliti, 2008; Portes & Zhou, 1993). We conclude our discussion of the broad findings from the regression results by noting that results for White households across individual models were inconsistent and widely variable, demonstrating weaker effects that are consistent with past findings in the literature and reflecting the high levels of residential contact that White households have with one another (Pais et al., 2012; South et al., 2008).

6.9 Standardization and Decomposition Analysis

Continuing our analysis of micro-level residential segregation dynamics, we next discuss the results of performing regression standardization and decomposition analyses on the previously estimated models of locational attainments. The first step in this process is to generate predictions of neighborhood proportion White for each group in the pairing (e.g. White and Black householders in an analysis of White-Black segregation) using each group-specific model. Using the example of White-Black segregation, this produces four predictions as outlined in the methodology section above. Two predicted values represent the observed residential contact that each group has with White households, and the other two represent the predicted residential contact that the minoritized racial group would have with White households if they had the same resources or alternately the same rates of return on those resources as White householders. To put it in terms that make it clear how these predicted values are relevant for understanding the underlying factors of residential segregation, the separation index, the tool that we use to measure overall segregation, is the difference between the average residential contact that each group has with White households or, in other words, the difference between the predicted values for each group using the respective models for each group.

Using again the example of White-Black segregation, if we want to know how segregation would change if each group in the analysis were equalized on characteristics that translate into resources for locational attainment, then we would standardize predicted outcomes for each group on the characteristics of the majority group, which can be accomplished by using the model estimated for the minoritized racial group to predict values for White householders. If, however, we want to know how segregation would change if each group in the analysis were equalized on the returns that they get on their resources for locational attainment, then we would standardize predicted outcomes for each group on the rates of return, or estimated coefficients, of the majority group. This is done by generating predicted values for Black householders using the model estimated for White householders.

For each pairing, in each of the 25 metropolitan areas included in this analysis, we conducted these regression standardization exercises. It would not be feasible to present all 75 standardization results individually here, so instead we rely on summarizing the components analysis, which tells us on average the extent to which group differences in resources and group differences in returns on those resources contribute separately and jointly to the overall group difference in residential contact with White households, i.e. the separation index. In Table 6.4 we summarize these analyses by calculating the average percentage share that each component makes to the overall level of segregation measured by the separation index across all metropolitan areas by pairing. We find that for White-Latino and White-Asian segregation, the story is as complicated as past literature suggests. We find that group differences in rates of return on resources overall make the larger

Table 6.4 Summary of percentage share of each component to overall segregation, 2010

Component	White-Black	White-Latino	White-Asian
Average percentage share of resources component	9.69%	51.03%	43.84%
Average percentage share of rates component	94.69%	76.24%	76.78%
Average percentage share of joint component	−4.38%	−27.27%	−20.62%
Average level of overall segregation	43.83	26.60	16.19

contribution to White-Latino and White-Asian segregation as opposed to group differences in resources. Nonetheless, we also find that group differences in resources make sizable contributions to White-Latino and White-Asian segregation. This suggests an identifiable spatial assimilation process is at work even as place stratification is still a major factor in explaining White-Latino and White-Asian segregation. Finally, we find that the greatest moderating effect between the two components occurs with White-Latino segregation where differences in resources and in rates of return on resources interact to a greater degree in determining levels of White-Latino segregation than they do for White-Asian or White-Black segregation, highlighting the complexities underlying White-Latino segregation.

These results stand in stark contrast to White-Black segregation, where on average 94 percent of the level of segregation can be attributed to group differences in rates of return while only 10 percent on average can be attributed to group differences in resources with very little interaction between the two components. This finding suggests that even when White and Black households are matched on resources, segregation is reduced by only modest amounts because group differences in ability to convert those resources into more residential contact with White households is the dominant factor. In other words, place stratification is playing a prominent role in explaining White-Black segregation, with stronger effects than in the case of White-Latino or White-Asian segregation.

6.10 Locational Attainments Across High- and Low-Segregation Contexts

To elaborate on how locational attainment outcomes vary across communities, we summarize variations in component contributions to overall levels of segregation in a community in Table 6.5, with the metropolitan areas categorized by their level of segregation. We classify metropolitan areas using the schema laid out in Table 3.2. There is a telling pattern, which is that for all three group pairings, the contribution of group differences in rates of return to overall levels of segregation is greatest in metropolitan areas where segregation is high. In contrast, the role of group differences in resources is greatest in areas where segregation is lower. In other words, in higher segregation areas, segregation is less attributable to group differences in resources and more attributable to group differences in how those resources are converted into locational attainments. Segregation is only slightly more attributable to group differences in resources rather than rates of return in the case of White-Latino segregation in low segregation areas. Notably, for White-Black segregation group differences in rates of return is persistently and disproportionately the larger component of segregation regardless of the level of segregation in the area.

To demonstrate how segregation can be analyzed by its micro-level dynamics in specific metropolitan contexts, we highlight the Los Angeles and Portland metropolitan areas, which represent high- and low-segregation contexts, respectively. In

Table 6.5 Mean shares of resources and rates components by overall level of segregation and group pairing

	Low segregation	Medium segregation	High segregation	Very high segregation
White-Black				
% Resources	18.56%	14.78%	7.97%	7.82%
% Rates	94.69%	91.42%	95.44%	97.65%
% Joint Effect	−13.25%	−6.20%	−3.40%	−5.47%
White-Latino				
% Resources	72.89%	49.85%	37.24%	–
% Rates	72.52%	75.76%	81.28%	–
% Joint Effect	−45.41%	−25.62%	−18.51%	–
White-Asian				
% Resources	51.40%	37.91%	–	–
% Rates	74.38%	79.78%	–	–
% Joint effect	−25.78%	−17.69%	–	–

Table 6.6 Components analysis for segregation in Los Angeles and Portland, 2010

	Los Angeles			Portland		
Component	W-B	W-L	W-A	W-B	W-L	W-A
Resources	5.83	18.70	9.19	3.77	7.21	6.37
Rates	53.56	40.06	29.94	16.49	5.72	11.41
Joint	−4.38	−12.41	−8.74	−2.00	−3.50	−2.10
Dissimilarity	55.01	46.35	30.39	18.26	9.43	15.68

any given metropolitan context, regression standardization and components analysis can reveal the extent to which segregation is determined by place stratification dynamics, spatial assimilation dynamics, or both interactively. We present these results in Table 6.6. In the Los Angeles metropolitan area, regardless of the group comparison, group differences in rates of return on resources make the largest contribution to overall segregation. To clarify, in Los Angeles, place stratification plays a larger role in segregation patterns while group differences in resources make a smaller contribution. Thus, even when groups are matched on resources such as income or citizenship, they remain at least moderately segregated in Los Angeles due to place stratification factors. However, we find that for White-Latino and White-Asian segregation, there is a larger joint component, suggesting that the separate roles of place stratification and spatial assimilation covary to a greater extent for these comparisons.

Results for Portland differ in a variety of ways that reflect the need to consider the segregation context. While the contribution of group differences in rates of return to segregation is nontrivial for White-Latino and White-Asian segregation, it is now more on par with the contribution made by group differences in resources. In fact, for White-Latino segregation group differences in resources make the larger contribution. This implies that much of White-Latino and White-Asian segregation in Portland can be explained by group differences in social characteristics. However, for Black households the results remain the same as they do in many other metropolitan areas. Differences in rates of return between White and Black households are the larger determining factor in explaining segregation. Even in a low-segregation context, equalizing on resources does not drastically reduce levels of White-Black segregation because of stronger place stratification dynamics.

6.11 Estimating Segregation by Socioeconomic Status with Standardization Analysis

A benefit of micro-modeling residential segregation is that standardization techniques can be applied to not only decompose an overall segregation score but also to generate different predicted segregation outcomes based on standardizing samples on selected characteristics relevant to theories of locational attainments like income, education, nativity, and language. This can be done by holding each sample in the pairwise analysis constant on some characteristics to create a "profile" and altering one or two characteristics to generate different predicted group outcomes on neighborhood proportion White from the estimated regression models that can be used to calculate segregation scores. These scores will represent estimated levels of segregation when the two groups in the analysis are matched on all characteristics except for the characteristics of interest. This exercise allows us to see the effect of a single factor on segregation outcomes by comparing how the segregation score changes when the isolated characteristic is modified. We have previously conducted this exercise to estimate the effects of citizenship and nativity on White-Black, White-Latino, and White-Asian segregation (Crowell & Fossett, 2022) and found that segregation was lower for White-Latino and White-Asian segregation when the minoritized racial group was set to be U.S.-born versus foreign-born and that segregation was generally higher for recent immigrants and non-citizens. We found the opposite for White-Black segregation, with Black immigrant households having lower levels of segregation from White households than U.S-born Black households (Crowell & Fossett, 2022).

In this section we will use standardization to analyze the effects of education and income on White-Black, White-Latino, and White-Asian segregation, using predicted values from the regression models to compare segregation for each group comparison across different levels of education and income. For this exercise, White householders are held constant at the following profile: U.S-born, speaks English only or very well, high school education, median income of a White householder with a high school education, living in a married couple household, not a military veteran, not a recent migrant, and aged 30–59. Black, Latino, and

Table 6.7 Average predicted levels of net segregation from U.S.-born White households by education and income*

		Net segregation			
Group	Overall	Very low SES	Low SES	Middle SES	High SES
Black	43.8	48.4	43.8	35.3	34.3
Latino	26.6	22.8	18.6	11.6	11.1
Asian	16.2	12.3	11.6	10.6	10.5

*In the difference of means formulation, "overall" segregation is the majority-minority difference of means in attaining parity-level contact with White households. "Net" segregation is the expected majority-minority difference on predicted parity-level contact with White households based on a specified set of social characteristics

Asian householders are held at all of the same characteristics except for education and income. Education and income are variably set at the following values: no high school education with a household income of $15,000, high school education with a household income of $30,000, bachelor's degree with a household income of $60,000, and bachelor's degree with a household income of $100,000. We will use these values on the independent variables to generate group-specific predicted values on neighborhood proportion White that can be used to calculate the separation index by taking the difference between the predicted mean outcome for White householders at a set profile and the predicted mean outcomes for Black, Latino, and Asian households at different levels of education and income.

We begin this analysis by summarizing average levels of segregation by pairing at different levels of education and income for the minoritized racial group in Table 6.7. First, we find that average levels of White-Black segregation are somewhat reduced as Black education and income are increased, but White-Black segregation is predicted to remain at medium levels even at high socioeconomic status levels for Black households. This is consistent with our finding from the components analysis, which is that group differences on resources contribute very little to overall levels of White-Black segregation. White-Latino segregation begins at lower levels than White-Black segregation when the scores are standardized to very low socioeconomic status for Latino households and is reduced to an average low score at high socioeconomic status for Latino households. While the absolute point reduction is nearly the same as it is for White-Black segregation, the relative reduction is larger for White-Latino segregation with the predicted average score dropping from medium to low levels with increased socioeconomic status for Latino households. Finally, we observe a more mixed pattern for White-Asian segregation that indicates weak effects of Asian education and income on the predicted segregation score. This is not surprising given we observed negligible education and income effects across all areas for Asian households in our locational attainments analysis.

Because we know from our review of the estimated regression coefficients that there is some variability in the effects of education and income across areas, we also chart predicted levels of segregation by metropolitan area. In Figs. 6.7, 6.8, and 6.9, we graph the predicted levels of White-Black, White-Latino, and White-Asian

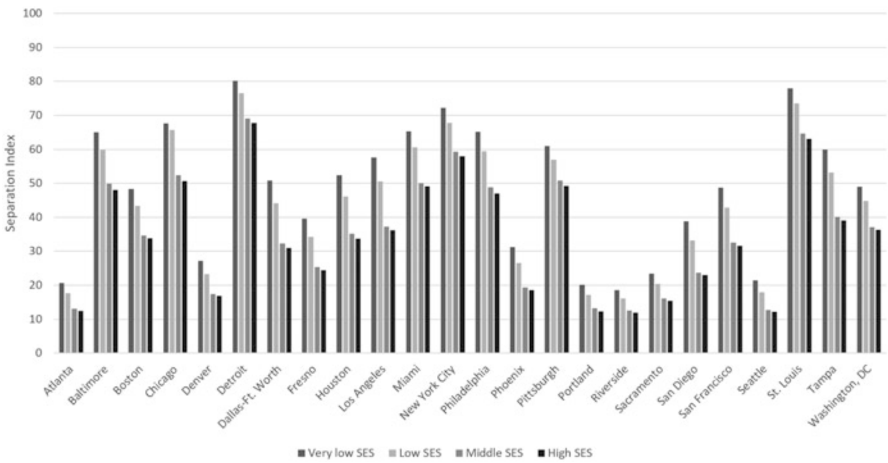

Fig. 6.7 White-Black segregation by Black socioeconomic, 25 US Metropolitan Areas

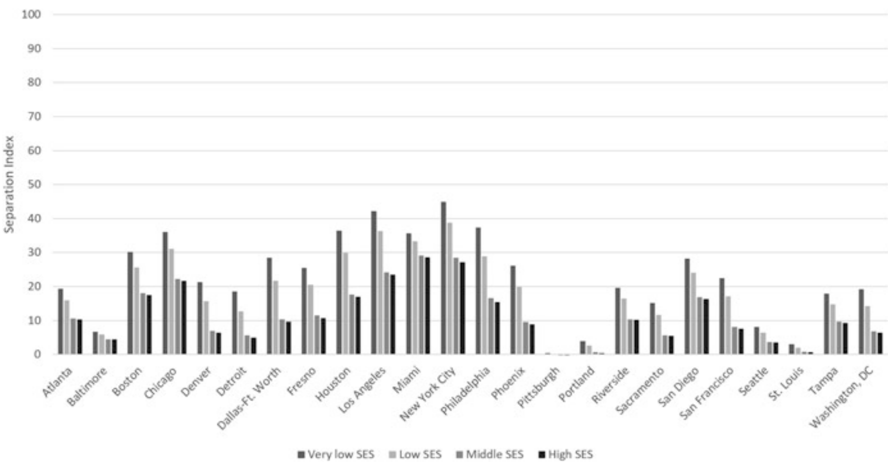

Fig. 6.8 White-Latino segregation by Latino socioeconomic status, 25 US Metropolitan Areas

segregation when White householders are standardized to the profile described above and the householders belonging to the minoritized racial group in the analysis are standardized to the profiles described above at varying levels of education and income. Across all group comparisons, it is clear that White-Black segregation remains at the highest levels even when Black households have high socioeconomic status (and White households are not set at high socioeconomic status) and are matched with White households on all other characteristics. Education and income have consistently positive effects on Black residential contact with White households, which reduces segregation as Black education and income increase. In some cases, this can result in relatively low levels of segregation, with the separation index

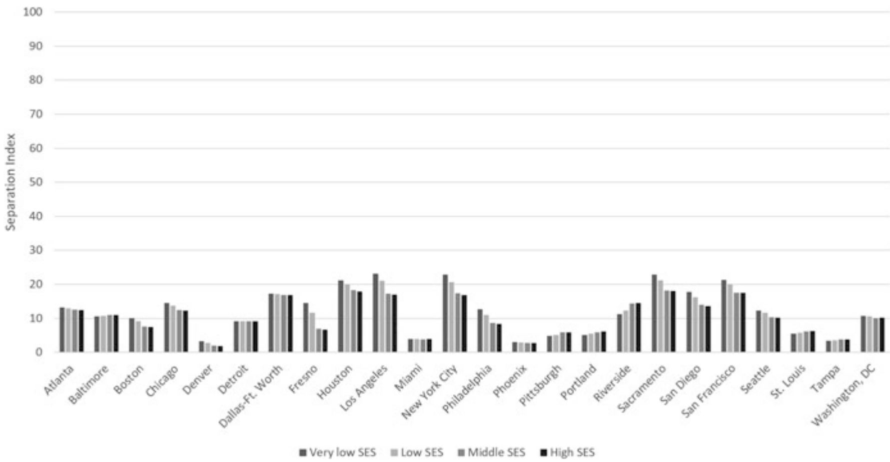

Fig. 6.9 White-Asian segregation by Asian socioeconomic status, 25 US Metropolitan Areas

score predicted to be between 11 and 13 in Atlanta, Portland, Riverside, and Seattle at the highest socioeconomic levels for Black households. But in many other metropolitan areas, White-Black segregation is predicted to remain high even at the highest levels of Black socioeconomic status, with separation index scores over 50 in Chicago, Detroit, New York City, and St. Louis.

The patterns are similar for White-Latino segregation but at much lower levels of overall segregation, with increasing education and income for Latino households resulting in increased residential contact with White households, which leads to lower predicted levels of segregation. White-Latino segregation is almost always at low to medium levels in these metropolitan areas with the exception of New York City and Los Angeles, which both begin with separation index scores over 40 at the lowest levels of socioeconomic status for Latino households. In some cases, increasing Latino socioeconomic status while also matching Latino and White households on other characteristics practically eliminates predicted levels of White-Latino segregation, which can be seen in Pittsburgh, Portland, and St. Louis. In other metropolitan areas, some level of segregation is predicted to occur at the highest levels of Latino socioeconomic status, but the scores are often below 20 and in many cases below 10. The decomposition analysis conducted previously reflects these results, with group differences in resources having more of an impact on overall levels of White-Latino segregation as compared to White-Black segregation, while group differences in rates of return on those resources remains non-trivial.

Finally, we find that there is little comment to offer on the effects of socioeconomic status on White-Asian segregation. First, White-Asian segregation is almost always very low and only just reaches medium levels in a small handful of cities including Houston, New York City, Sacramento, and San Francisco. Second, the effect of socioeconomic status is negligible and in many metropolitan areas non-significant. Changing Asian levels of education and income while holding all other variables constant at specific values, which includes being U.S.-born and English-fluent, does little to change what are already low levels of White-Asian segregation. However, where these factors do have a notable impact, it is in the predictable direction of spatial assimilation with White-Asian segregation reducing as Asian education and income increases. This can be observed in Chicago, Fresno, Houston, Los Angeles, New York City, Philadelphia, Sacramento, San Diego, San Francisco, and Seattle. What may complicate our findings in some of these cities is the ethnic diversity of the Asian population, with "Asian" being a broad panethnic label that can include ethnic groups with distinctly different experiences by immigration, reception, economic opportunity, and culture.

What we demonstrate with this exercise is a new way to explore questions about the intersecting factors that shape racial residential segregation outcomes and further develop the conversation about the dual and interacting roles that race and socioeconomic status are playing in shaping these patterns. This analysis extends beyond what has been done because we can now model household-level effects that shape overall patterns of segregation, including the effects of income and education, in a way that directly links to segregation measurement and permits the use of regression standardization analysis. Until this point, the two dominant methods for modeling the effects of income or education on racial residential segregation were to perform a locational attainments analysis with no way to link predicted outcomes to an overall measure of segregation, or to model aggregate-level effects on segregation scores with some measure of income inequality that introduces the chance of committing an ecological fallacy by failing to recognize that segregation is also a measure of group inequality (Fossett, 1988, 2017). This approach, by contrast, overcomes both limitations and allows for a more detailed analysis of the locational attainment processes that shape segregation patterns.

6.12 Summary

In this chapter, we demonstrated entirely new methods for segregation research that are based on the innovations made by Fossett (2017) which in previous chapters allowed us to refine our measurements of segregation across different groups and area types. The difference-of-means formula for segregation measurement, which can be applied to any of the more popularly used measures of segregation, reconceptualizes segregation as an inequality of individual locational outcomes. With the starting point for segregation measurement being an individual score for a household, we can establish a direct link between the tradition of locational attainments analysis and the tradition of aggregate-level segregation analysis and develop more complex research designs for understanding the micro-level factors that affect household-level locational outcomes and overall segregation patterns.

Our findings in this chapter detail the complexities of locational attainment processes that underlie segregation patterns and demand a more dynamic analytical framework. For Latino and Asian households, spatial assimilation dynamics are consistently evident, but place stratification dynamics often predominate. For Black households, the story is straightforward in some ways and not in others. In general, group differences in resources are less important to White-Black segregation, as Black locational attainments more strongly reflect place stratification effects. We also find that the classical spatial assimilation model is less applicable to understanding Black segregation, as nativity works in the opposite direction for Black households in comparison with Latino and Asian households, consistent with our past research and suggesting a pattern of segmented assimilation (Crowell & Fossett, 2020, 2022). While a deeper analysis of Black immigrant segregation is beyond the scope of this analysis, other research has offered further insight into variation in Black immigrant segregation patterns (Scopilliti & Iceland, 2008; Tesfai, 2019).

Standardization and decomposition analysis strengthens our argument that the role of race as employed by place stratification and segmented assimilation is prominent throughout, but more consistently and to a greater quantitative degree for Black households. This puts the historically rooted barriers to residential integration for Black households into sharp relief and speaks to the apparent fact that Black families in the United States encounter a far more entrenched system of segregation and oppression than other groups, while Latino and Asian households experience weaker place stratification barriers. For Black families, social disadvantages that are intrinsically linked with segregation are far more difficult to overcome and, according to Sharkey (2013), are likely inherited in a way that is parallel to how social advantages are inherited in White families.

High-segregation areas have patterns of segregation that are more resistant to any advances made by minoritized racial groups on various aspects of social status and there is likely a feedback loop, where segregation enables neighborhood disadvantage which then makes it more difficult for racially minoritized groups to achieve and maintain those social advancements (Sharkey, 2013). Segregation in these high-segregation contexts can also be reinforced through structural sorting dynamics, as theorized by Krysan and Crowder (2017). These dynamics are shaped by information networks, where locational attainments are affected by the information that households have about other neighborhoods in the area. In a highly segregated metropolitan area, groups may have knowledge about neighborhoods that is more limited by the social networks and neighborhoods that they regularly access, a manifestation of stratification which creates the structural sorting process that Krysan and Crowder (2017) describe.

A technical note to the reader about data is warranted here, because these analyses were also possible due to our ability to access the restricted-use census microdata that is only available in Federal Statistical Research Data Centers (RDCs). The barrier for access to these data is high, which may discourage researchers from adopting our approach. But we encourage researchers who may not have access to an RDC to seek out other sources of household survey data where neighborhood geography (e.g. blocks, tracts, etc.) is available which can be linked to public-use decennial census summary files. The decennial census summary files can be used to calculate neighborhood racial composition necessary for constructing the segregation index while avoiding the pitfalls of measuring segregation with sample-based estimates (Napierala & Denton, 2017), while the survey data can provide the covariates for conducting locational attainment analyses. This approach will appropriately situate segregation as a stratification outcome driven by micro-level dynamics while establishing continuity with those locational attainment analyses in the existing literature that stopped short of drawing a direct link to overall segregation outcomes.

To conclude this chapter, these findings highlight the complex nature of residential segregation in metropolitan settings in the U.S. and demonstrate the competing roles of locational attainments that reflect group differences but are also hindered by place stratification barriers. With this analysis we are able to explore new ways of understanding these complexities using innovative methodologies for identifying and explaining the micro-level factors that shape segregation patterns and how these relationships vary in different segregation contexts. We can draw the conclusion that equalizing group differences on relevant social resources does not have a uniform effect on segregation across groups or areas and the effect is markedly lower when segregation is high, reflecting the ability of residential segregation to persist once it is firmly in place. Moreover, the analyses presented in this final empirical chapter demonstrate the possibilities for segregation research when segregation is understood as a group inequality, which can be operationalized using the difference-of-means approach to measuring segregation given by Fossett (2017) and applied throughout this book. With this final empirical chapter, we show the culmination of the various methodological advancements in segregation measurement and analysis that we promote throughout this book. Understanding and measuring segregation as an aggregation of individual-level outcomes makes it possible to correct for index bias and analyze segregation as an outcome shaped by micro-level phenomena. In the concluding chapter of this book, we review these contributions and others that should influence the way researchers measure and analyze residential segregation.

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Chapter 7
Conclusions

7.1 Summary of Purpose and Intended Contributions

We wrote this book with the central goal of documenting patterns and trends of racial and ethnic segregation across communities and over time in the United States using refined methods of measurement analysis, which can sometimes be expected to change what we thought we knew from past research and at other times add more to our understanding of established patterns. In making this our goal, we produced several contributions that happily build continuity with past research and set a foundation for future research, which we can expect to come in waves each time there is a decennial census data release. First and foremost, by using measures of segregation that are free of index bias and specifically employing the separation index, a measure of evenness that can dependably signal when *prototypical* patterns of segregation are occurring, we were able to reanalyze and describe patterns and levels of racial and ethnic residential segregation across the United States and over time in Chap. 3. We are not the first to describe patterns of segregation, here operationalized as the uneven distribution of two groups across neighborhood-level spatial units, across communities and over time in the United States. But we are the first to simultaneously use measures that are corrected for index bias, measure segregation of households rather than persons, and expand our analysis to not only metropolitan areas but also micropolitan areas and noncore counties. Our findings in Chap. 3 should be viewed as reliable benchmarks for descriptive analyses of racial and ethnic residential segregation across a broad range of communities moving forward and should also be taken instructively, as they demonstrate the application of the methodological changes that we recommend should be the standard for residential segregation measurement.

In addition to revisiting popular areas of segregation research, such as the segregation of large racial and ethnic groups in metropolitan areas, we also addressed a major shortcoming of the existing literature by measuring and analyzing

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segregation in understudied contexts including nonmetropolitan communities and Latino, Asian, and Black new destination communities in Chaps. 4 and 5. These are topics that have not gone ignored, but rather we think have been strategically avoided or studied with caution due to the fact that the measurement issues we address in this book are most prominent in scenarios characteristic of smaller and more homogenous communities. More specifically, index bias will be at its worst when using small spatial units and when the two groups in the analysis are very imbalanced in size. This includes nonmetropolitan communities where one must use census blocks in order to capture neighborhood-level homogeneity and that are often not very diverse. It also includes new destination communities, of which the majority are nonmetropolitan and also, by definition, are predominately White with a small but emerging minoritized racial population. In addition, the choice of segregation index for measuring evenness is more consequential in these contexts. As we carefully demonstrated throughout this book and review more below, the popular dissimilarity index is incapable of making the distinction between *polarized* and *dispersed* unevenness. The former is a pattern of prototypical segregation where two groups have very little residential contact with one another and there exist the conditions for there to be location-based inequalities, while the latter does not manifest as meaningful group separation across space. The dissimilarity index will be more prone to registering high scores under conditions of dispersed unevenness in communities where one group in the analysis makes up a much smaller share of the population than the other, which is often the case in nonmetropolitan communities and is always the case, by definition, in new destinations.

In being able to overcome these two measurement challenges, in addition to making a simple adjustment to measure the segregation of households rather than persons, we are able to provide a solid foundation for residential segregation research of smaller populations and in nonmetropolitan communities. The importance of this contribution is clear if one looks at the last decade of residential segregation research, which has demonstrated an increasing awareness that racial and ethnic diversity is no longer a feature one can only expect to find in metropolitan areas. Migration and natural demographic transitions have made the nonmetropolitan United States more heterogenous than ever (Johnson & Lichter, 2022). As we have argued throughout this book and as other researchers have claimed as well, these changes open up new opportunities to test prevailing theories of residential segregation and neighborhood inequalities that largely emerged through empirical studies of urban environments. Therefore, our substantive and methodological contributions to these areas of residential segregation research should be viewed as a path forward that is cleared of the obstructions created by segregation index bias.

In keeping with our intention of dialoguing with past residential segregation research to establish new directions, we also demonstrated how Fossett's (2017) innovations in segregation measurement can improve and advance how we analyze locational attainments, or household-level neighborhood outcomes. Past research on locational attainments revealed much about the micro-level factors that determine residential location and how these correlations may vary by racial group. But where the literature has fallen short is in being able to draw a direct link between household-level locational attainment outcomes and overall patterns of segregation. In Chap. 6, we explain how this is due to the conventional formulas employed to calculate popular measures of segregation. Because of Fossett's (2017) reformulation of these measures as a difference of group means, it is now possible to disaggregate any popular segregation index to a household-level outcome, which establishes the missing quantitative link between locational attainments and residential segregation. Thus, in Chap. 6 we take several liberties to demonstrate how this innovation introduces an analytical approach to residential segregation research that is commonly found in inequality studies, including regression standardization and decomposition. This approach makes it possible to more robustly test prevailing theories of residential segregation and identify the factors that are determinant of household locational attainments which shape patterns of racial residential segregation.

Finally, as we have made clear throughout this book and in this chapter so far, what should make our contributions so attractive to segregation researchers is that they establish clear continuity with past research. In many cases, what we find when applying our new methods of segregation measurement and analysis does not overturn previous findings in the literature. In cases where our findings do conflict with previous research findings, the reasons why are clear and should not be surprising, because these instances occur when studying segregation that involves communities and populations where standard measures of segregation are known to be less trustworthy as a result of the well-documented problem of index bias. Often, segregation researchers have known to avoid these cases anyways. Therefore, our contributions remove the reasons for avoidance and make it possible for researchers to expand the scope of their work. What we contribute, both methodologically and substantively, with this book should be taken as a course correction rather than starting completely from the beginning.

7.2 Establishing Continuity with Past Research

Before reviewing specific empirical developments presented throughout this book, we first want to acknowledge the foundation of work that we built on. First, key methodological contributions to segregation research dating back to Duncan and Duncan (1955) have set the standard to how we approach conceptualizing and operationalizing residential segregation as a demographic and social outcome. From work by Duncan and Duncan (1955), Zoloth (1976), James and Taeuber (1985), White (1986), Massey and Denton (1988), and Reardon and Firebaugh (2002), we have a toolbox of segregation indices that are heavily relied on to summarize and describe segregation patterns across communities. These studies put forward segregation indices such as the dissimilarity index, the Gini index, the separation index, and the Theil entropy index and showed us their various applications, refinements, benefits, and limitations. That researchers were aware from the beginning that these indices had their flaws and sought out ways to address index bias (e.g. Carrington & Troske, 1997; Winship, 1977) is exactly why we view this book as a contribution that establishes continuity with the existing literature. This is because we directly address those limitations and demonstrate how to apply the changes needed in order to advance this area of research.

Second, we acknowledge those studies that set the standard for conducting macro-level, descriptive studies of residential segregation exemplified in work by Massey and Denton (1985) and Iceland et al. (2002) which demonstrated the best conditions under which one can do segregation research using segregation indices in their original formulation without correction for index bias. These studies, which typically focus on the largest metropolitan areas and employ the dissimilarity index, developed a model for comparing segregation patterns across communities and over time using large data sources and convenient summary measures. With this book we also connect our work to this tradition by conducting the same types of analyses except with segregation indices that have been corrected for index bias and with other specifications that make it possible to identify varying patterns of uneven distribution. By correcting for index bias and addressing other issues that posed challenges for extending the scope of analysis beyond the largest metropolitan areas and populations, we have broadened the possibilities for segregation research within this tradition of macro-level analyses.

This last point brings us to also acknowledge those who pioneered segregation research in communities beyond the largest metropolitan areas in the United States, including those who have been working through the challenges of measuring residential segregation in nonmetropolitan communities and in Latino and immigrant new destination communities. This includes very early work by Hwang and Murdock (1983) and later work by Lichter et al. (2007, 2010) and Hall (2013). These studies faced numerous measurement challenges with the knowledge that standard segregation index formulas were inherently flawed in a way that becomes apparent when using small spatial units (i.e. census blocks) and measuring segregation of small populations (e.g. immigrant groups and newly emerging racial and ethnic groups). In most cases, researchers have taken safe routes through by imposing tight restrictions on case selections so that only communities with large enough populations were included or by using weighted segregation indices to down-weight the more problematic cases affected by index bias. These researchers have made important contributions to our understanding of residential segregation outcomes in nonmetropolitan settings and has raised the call for more work in this area. This book answers that call and also opens up new possibilities for research on these communities by directly remedying the measurement issues that have hindered any progress. Thus, in so many ways we see the contributions of this book to the residential segregation literature as a leap forward on the same path, encouraging established approaches to be used but with some modifications to address the problems that have severely limited what is possible to learn and know about residential segregation patterns.

7.3 Empirical Developments from the Present Work

In this section we review specific empirical findings that we have presented throughout this book. First, in Chap. 3 we measured levels of White-Black, White-Latino, and White-Asian residential segregation in addition to levels of segregation between minoritized racial groups across all community types from 1990 to 2010. Our specific methodological approach expanded what we know about patterns and trends of residential segregation in the United States by making it possible to include more communities, including many nonmetropolitan communities. For the largest metropolitan areas, we produced findings consistent with past research on a few points. First, White-Black segregation is highest among the group comparisons, follows a pattern of polarized unevenness characteristic of prototypical segregation, and is declining over time. This is true even after correcting for index bias, employing the separation index, and measuring segregation of households rather than persons. Second, White-Latino and White-Asian segregation is holding steady at the same levels over time. But this is where our findings deviate from past research.

The first indication that our approach produces different results is in finding that White-Latino segregation has been lower and more in line with a pattern of dispersed unevenness than previously understood. Across all community types, White-Latino segregation has generally followed a pattern of dispersed unevenness at the initial timepoint of 1990, but trajectories from there vary by community type. Significantly, White-Latino segregation appears to be trending towards a pattern of polarized unevenness in metropolitan areas, meaning that White and Latino households are increasingly more separated across space over time. White-Asian segregation is also quite low, but that has generally been understood to be the case. What we have learned, however, is that White-Asian segregation also tends to follow a pattern of dispersed unevenness, meaning that to the extent that unevenness is detected, it is not enough to permit location-based inequalities. White and Asian households for the most part reside in the same neighborhoods, with Asian households living in neighborhoods that have only slightly lower percentages of White households. The dissimilarity index would not make this clear, but the separation index can be relied upon to understand this important aspect of uneven distribution. As a final and related important finding from Chap. 3, by looking at the separation index and the dissimilarity index simultaneously, we are able to chart out the trajectories of patterns of uneven distribution over time based on how the two indices are changing in tandem. These findings are essential for answering questions about the changing nature of group separation and related inequalities and group interactions over time.

In Chap. 4, we went further into understanding patterns and trends of residential segregation in nonmetropolitan areas. As we reviewed above, this area of research has faced tremendous barriers due to the limitations of standard segregation indices. Thus, our findings in these communities, generated using segregation indices completely free of the troublesome issue of index bias, are foundational. In addition to what we found in Chap. 3 about the general levels of segregation observed in nonmetropolitan communities, we also found how critical it is to use the separation index to measure segregation in nonmetropolitan communities. In these contexts where the minoritized racial group is relatively much smaller compared to the size of the White population, the dissimilarity index has a high likelihood of registering high scores when in fact what is occurring is dispersed displacement from even distribution that does not at all resemble a prototypical pattern of segregation. While White-Black segregation typically looks prototypical even in nonmetropolitan communities, White-Latino and White-Asian segregation in these communities frequently registers medium-level scores on the dissimilarity index and very low scores on the separation index – indicating a pattern of dispersed unevenness. The implications here are important, because it means that, when dispersed unevenness is occurring, these groups are actually having high levels of residential contact with White households and opportunities to create location-based inequalities are quite low. But to be clear, dispersed unevenness is not a given in nonmetropolitan communities, even when the minoritized racial group is very small in number. We highlighted cases in Chap. 4 where in fact polarized unevenness occurs even when the minoritized racial group makes up less than 3 percent of the pairwise population.

For all the reasons why dispersed unevenness and related challenges with measuring segregation using the dissimilarity index are common in nonmetropolitan communities, these issues are even more pronounced in new destination communities. Given that dispersed unevenness is more likely (but not a given) when one group in the comparison is disproportionately small, new destinations are by definition communities where dispersed unevenness would be expected to be more common. Indeed, we often found this to be the case in Chap. 5, especially at the initial time point prior to the significant population growth of the minoritized racial group. This is an important finding for a number of reasons. First, scholarly interest in residential segregation in new destinations has grown over the last decade and researchers need to be prepared with the proper measurement tools to assess and evaluate levels and trends of segregation in these communities. This means not only using indices free of index bias but also considering which index is best suited to detect prototypical segregation when it is occurring. What we found is that the separation index, corrected for index bias, is well up to the task. While the dissimilarity index will pathologically give high scores when there are no visible indications of prototypical segregation occurring, the separation index will only give a high score when it is clear from reviewing spatial distributions and average levels of group contact that the two groups in the analysis are in fact having little residential contact with one another. Second, given that new destinations are by definition demographically dynamic, with one group emerging and growing rapidly over a short period of time, there is much interest in wanting to understand how segregation is shifting over time in these communities as the minoritized racial group grows. One cannot answer this question with the dissimilarity index because a high score can either signal dispersed unevenness or polarized unevenness and therefore shifts in the underlying pattern of unevenness, from polarized to dispersed or vice versa, may not be detected with the dissimilarity index. This is troubling because a shift in either direction is an important signal for how race relations in the community are changing over time as the minoritized racial group grows, with White households either being more integrated with or more segregated from the new group. The best way to accurately measure patterns of unevenness and how they change over time is to use the separation index.

An additional point from our findings on nonmetropolitan communities and new destinations, which are also often nonmetropolitan communities, is that contrary to some of the existing research, segregation is often quite low in these communities and rarely approaches the levels seen in metropolitan areas that are known for being highly segregated. This is especially the case for White-Latino and White-Asian segregation, which most often appears to demonstrate a pattern of dispersed unevenness. The somewhat exception to this point is that White-Black segregation more often follows a pattern of polarized unevenness even in nonmetropolitan communities, albeit at lower levels than in metropolitan areas. This distinction is possible to make by correcting for index bias and using the separation index, in addition to measuring segregation of households rather than persons, the latter of which contributes to the problem of index bias. Making these adjustments also produces trends over time that can be believed because one can be assured that any changes in segregation scores are the result of real shifts in population distributions across neighborhoods rather than resulting from changes in factors that contribute to index bias. Thus, we are able to conclude that segregation is rising in some nonmetropolitan communities and for some specific groups. For Latino households, this is occurring in new destinations, which is in direct contrast to other nonmetropolitan communities as well as metropolitan areas. This is also the case for Asian new destinations. Only for Black households do we see segregation generally declining in all community types, including nonmetropolitan communities and Black new destinations.

The final set of major empirical findings that we would like to review come from our micro-level analyses of segregation in Chap. 6, where we disaggregated the separation index using Fossett's (2017) formula to predict the household-level neighborhood outcomes that underlie segregation patterns and are used to calculate the separation index. With the separation index reconstituted as a measure of group inequality on residential contact with White households, we can model neighborhood proportion White at the household level with household characteristics as predictors of the outcome and employ the methods often used in inequality studies including regression standardization and decomposition. This approach to analyzing segregation is in alignment with the level of theorizing that prevails in segregation research, where theories of spatial assimilation and place stratification emphasize resources and barriers, respectively, that affect minoritized group contact with White households. What we found was support for both theoretical perspectives, although the relevance of each theory varies by group, with Black households experiencing more pronounced place stratification effects than Latino or Asian households. Latino and Asian households also experience some place stratification effects, especially in high-segregation contexts, but they are also more likely to see returns on their gains in socioeconomic status and acculturation in increased residential contact with White households.

7.4 Methodological Developments

Finally, we review the methodological advancements in segregation research that we feature throughout this book through the empirical analyses summarized in the previous section. These technical contributions to segregation research, described in detail in Chap. 2, deserve to be mentioned again here to emphasize the impact that they can and should have on future segregation studies. Our key methodological contributions were developed from the work of one of the authors of this book, which can be found in full technical detail in *New Methods for Measuring and Analyzing Segregation* by Mark Fossett (2017). But the empirical applications of these methods are the impetus for this book as they demonstrate how our understanding of residential segregation patterns and trends might change, or sometimes hold strong, if we make the necessary adjustments to the tools we use to measure and analyze segregation.

The first of these contributions is the difference-of-means formulation of common segregation indices including the dissimilarity index and the separation index. Standard formulas for calculating these indices assume that what the researcher has on hand are census tabulations, and therefore these formulas are designed for convenient use with tabulated data aggregated to some neighborhood-level spatial unit such as a census tract. These formulas mask the individual (i.e. household)-level neighborhood outcomes that make up these tabulations and are ultimately used to construct a segregation index. Fossett's (2017) revised formulas are mathematically equivalent but reconfigured so that it is clear how these segregation indices are an aggregation of individual-level outcomes. In calculating a segregation index using location-based scores assigned to individual households, many other advancements are possible, including the ability to identify and remove the source of segregation index bias.

Thus, correcting for index bias is a major feature of this book. Removing the source of index bias involves subtracting the reference household from the calculation of the group proportion for the group that that household is a member of, so that no household is counted as its own neighbor. By making this simple and effective adjustment, index bias is no longer an issue and we are able to generate new measures of segregation that both correct results from past research and open up new areas of research in communities and on populations where index bias was too problematic to produce trustworthy segregation scores. These include nonmetropolitan communities and smaller minoritized group populations such as those found in new destination communities. There were also cases where correcting for index bias had no or minimal effect on the scores that were produced, including large metropolitan areas where the conditions that lead to index bias are not present. These cases do not cause us any concern, because it leads us to make the following main point about index bias. To the extent that index bias is a problem, using the unbiased scores will completely eradicate the problem and produce scores that can be believed according to the intention of the index being used. When correcting for index bias does not change the score, there is no downside to using the unbiased index regardless. The point, therefore, is that one should always use the unbiased formulas because it never makes segregation measurement worse and, in many cases, it will be an improvement.

While index bias is a problem that segregation researchers are well aware of, there are issues particular to the dissimilarity index that researchers may be less familiar with despite this index being the workhorse of segregation research. We make another methodological contribution to the study of segregation by demonstrating how the dissimilarity index is incapable of distinguishing between *polarized* and *dispersed* unevenness. While the former refers to a pattern that we expect to find when the dissimilarity index is high – a pattern of prototypical segregation with little residential contact between the two groups – the latter is a pattern that does not look like prototypical segregation because the two groups are in fact having high levels of residential contact with one another. Under conditions of dispersed unevenness, the dissimilarity index may still take on a high score. Throughout Chaps. 3, 4, and 5 we show how relying solely on the dissimilarity index to measure residential segregation can cause the researcher to miss variations in underlying patterns of uneven distribution that produce sociologically meaningful divergences in outcomes. Dispersed unevenness is a pattern of uneven distribution that does not produce the conditions under which location-based inequalities can occur.

As an example of why this distinction between dispersed and polarized unevenness matters, consider how the concept of redlining has in recent years gained more attention as researchers have explored ways to link historical redlining to present-day location-based outcomes including health and educational disparities and racial wealth gaps. During the 1930s and 1940s, the racial makeup of the neighborhood was often an explicit reason to rate a neighborhood as hazardous for lending (color-coded as red). Neighborhoods mostly composed of Black, Mexican, or Chinese households often fell under this category, while predominately White and affluent neighborhoods were rated as the best locations for homeowner loans. However, redlining would have only been possible under conditions of polarized unevenness where neighborhoods could be distinctly identified as having predominately White households or having predominately racially minoritized households. If one were to use the dissimilarity index to identify the spatial distributions that could make redlining possible, there would be communities misidentified as having those conditions because *D* can take on a high score when either dispersed unevenness or polarized unevenness is occurring, despite the former not being a pattern that would support the practice of redlining.

In contrast, the calculation of the separation index makes it impossible to register a high score unless polarized unevenness is occurring. To review, the separation index is the simple difference in the average residential contact that each group has with White households. A high score on *S* is a direct measure of a large difference in contact, where White households have high levels of contact with White households and the minoritized group households have low levels of contact with White households. When visualized on a map of population distributions across neighborhoods, these large differences in residential contact with White households will always appear as a pattern of polarized unevenness where there are neighborhoods that are distinctly identifiable as being predominately White or being predominately of the minoritized racial group. When this pattern occurs, it is entirely possible to deny resources to neighborhoods where minoritized racial groups live and direct resources to predominately White neighborhoods, thereby revealing a link between residential segregation and location-based inequalities. The point, therefore, is that in order to identify sociologically meaningful patterns of residential segregation, it is better to use the separation index over the dissimilarity index. Similar to our argument for correcting for index bias, there is no downside to using the separation index instead of the dissimilarity index. The two indices will agree when polarized unevenness is occurring. When they disagree, it will always be when the dissimilarity index is showing higher levels of uneven distribution than the separation index, and this is a strong signal that dispersed unevenness is occurring. This distinction is critically important to be able to make as a researcher, and it can only be made by using the separation index.

Another methodological advancement featured in this book is one that we have contributed to the literature in previous empirical studies (Crowell & Fossett, 2018, 2020, 2022) and present again in Chap. 6, which is the ability to model segregation as a household-level outcome in the tradition of locational attainments research. What makes our approach different from past locational attainment studies is the difference-of-means formula that we use to calculate the separation index (and can also be used to calculate the dissimilarity index). These formulas disaggregate the index into an individual (i.e. household)-level score based on some neighborhood outcome such as neighborhood proportion White. Previous studies by other researchers have also modeled these outcomes, but without the ability to link them to aggregate measures of segregation for the larger community (i.e. the metropolitan area). By reformulating the index as a difference of group means, we are not only able to directly link locational attainments to segregation outcomes, but we are also opening up the opportunity to employ methods of analysis that are popular in inequality studies.

One of these methods is regression standardization and decomposition, where predicted values on the separation index can be generated based on matching the two groups in the analysis on group characteristics or rates of return on those characteristics using the covariates in the model and the estimated coefficients from the model. The separation index can then be decomposed into the contributions made by group differences on those two components, which allows us to better understand how segregation is driven both by differences in group characteristics (such as income, education, and nativity) and unequal rates of return on those group characteristics. These two components correspond to the two prevailing theories of residential segregation, with the former falling within the spatial assimilation framework and the latter within the place stratification framework. While the methods we use here are not new by any means, they are in many ways new to the study of residential segregation because they were not possible without the difference-of-means approach to calculating segregation indices introduced by Fossett (2017). Like all of the other methodological developments we have contributed so far, this one also establishes continuity with existing research conventions because it advances the locational attainments approach to studying segregation that has been popular in the literature over the past several decades.

Finally, in this book we demonstrated one more methodological adjustment to the study of residential segregation, which is to measure the segregation of households rather than persons. Although we did not give this issue as much attention, we do discuss it in Chap. 2 and demonstrate the impact that it can have using a case study in Chap. 5 where we analyzed segregation outcomes in Latino and Asian new destinations. The problem with measuring the residential segregation of persons instead of households comes back to the issue of index bias. While we now have the formula correction to remove index bias, it cannot be dealt with completely unless one is using households as the microunit rather than persons. This is because the source of index bias is that the reference individual is counted as their own neighbors and therefore same-group residential contact is overcalculated. This logic extends to the problem of counting persons who share a household as neighbors because one cannot assume that these individuals could be randomly redistributed across neighborhoods to achieve even distribution. In reality, individuals who share a household would likely move together as a single unit. Thus, the only way to fully eradicate index bias is to use households as the microunit of analysis rather than persons. This problem is especially pronounced in communities with the demographic characteristics that make index bias worse in general, including nonmetropolitan communities and new destination communities where the minoritized group is significantly smaller than the White population.

7.5 Future Directions for Residential Segregation Research

In the introductory chapter of this book, we explained that the purpose of this book was not necessarily to provide current data on residential segregation patterns and trends. Given that 2020 census products are being released at the time that this book is being written, that would not be a credible claim. Instead, what we have provided with this book are corrected and more comprehensive baselines for contemporary racial and ethnic residential segregation patterns in the United States leading up to the present, which will put the literature on the correct course to understand how these patterns are shifting going forward. Thus what we ultimately hope readers will take from this book are new ways to analyze segregation that will overcome many of the problems that have hindered this area of research and also open up opportunities to ask new research questions in an area that has been constrained to a narrow focus on certain communities and populations.

As the 2020 census summary files become available, we will see a new wave of residential segregation studies aiming to understand how our communities have changed in an increasingly multiracial and diverse society. As is tradition in this literature, efforts to provide broad summaries of residential segregation patterns across metropolitan areas and beyond will be made with attention given to how these patterns have changed over the decades. Interest in residential segregation in nonmetropolitan communities and destinations that are new for Latino, Asian, and immigrant populations will stay strong as these communities grow and the migrants who have settled in them over the past three decades continue to establish a presence through family, economic, and social life. Variations in household movements across neighborhoods by group and neighborhood characteristics will also continue to hold our attention because they are key to asking questions about the barriers and opportunities that can either weaken or reinforce residential segregation patterns. And there will be new and understudied questions that will come up about populations that have not received enough attention, often due to their small numbers. These include ethnic subgroup populations disaggregated from panethnic categories, multiracial populations, and immigrant populations.

For all of these focus areas in the study of residential segregation, the empirical results and methodological techniques that we provide in this book will be critically important. The issue of index bias will confound any results that come from these studies unless it is dealt with directly by removing the source of index bias in the formula and studying the segregation of households instead of persons. The choice of segregation index for measuring uneven distribution will have serious implications when studying any types of communities where the two groups in the analysis are majorly imbalanced in size. And any interest in how locational attainments drive segregation patterns will be best served by using the difference-of-means approach to calculate the segregation index so that the score can be disaggregated to individual-level outcomes and modeled as locational attainments. Thus, we encourage researchers who study residential segregation to use the results and techniques provided here to refine our understanding of residential segregation patterns, explore new questions about different communities and populations, and move the literature forward.

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