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# COVID-19 and the resilience of European firms: The influence of pre-crisis productivity, digitalisation and growth performance

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**ABSTRACT:**

We analyse how the COVID-19 crisis impacted firms' employment levels and digitalisation efforts differently depending on their pre-crisis productivity, digitalisation and growth performance. We match the EIB Investment Survey with firm-level financial statements from the ORBIS database for 27 EU Member States and the United Kingdom. Following the sales decline during the crisis, we show that: (1) Higher productivity firms are less prone to reduce the number of employees both in the short and in the long term; (2) High-growth enterprises are also less prone to reduce the number of employees in the long term; (3) Firms in highly digitalised sectors are less likely to reduce the number of employees; (4) Firms are more likely to increase their use of digital technologies, especially those that were already more digitalised before the crisis.

**JEL CODES:** L22, 047

**KEYWORDS:** HGE, labour productivity, digitalisation, COVID-19.

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## 1. Introduction

The rapid spread of the COVID-19 pandemic had a massive impact on many sectors of the economy. This episode provides an opportunity to investigate whether it also had a heterogeneous impact on firms depending on their productivity level, and their past growth performance (Flachenecker et al., 2020; Benedetti Fasil et al., 2021). Resources should be reallocated from low- to high-productivity firms during crisis periods (Caballero and Hammour, 1994). Indeed, previous research has shown that firms respond to crises by boosting productivity (Dosi et al., 2000, 2012; Bugamelli et al., 2018). One way for firms to achieve higher productivity levels is by increasing their digitalisation activities. The COVID-19 pandemic has led many firms to digitalise and assess its advantages (Apedo-Amah et al., 2020). Hence, COVID-19 is a disruptive shock that may accelerate the digital transition.

Our research addresses two main questions. First, we explore the impact of COVID-19 on employment in the short and long term. Second, we analyse the expected impact of the pandemic on digitalisation. We focus on two categories of firms: the most productive firms and high-growth enterprises (HGEs). Our main database is the European Investment Bank Group Survey on Investment and Finance (henceforth EIBIS). EIBIS is uniquely equipped to investigate the impact of COVID-19 according to the firm's productivity level, the potential uptake in digitalisation, and the role of HGEs. Our sample includes firm-level data for all EU-27 member states and the UK and focuses on the EIBIS 2020 wave. We first apply coarsened exact matching to enhance the comparability of firms that were hit negatively by the COVID-19 pandemic and those that were not. We then estimate cross-sectional probit regressions to test our different hypotheses.

Our results show that the most productive firms have been less prone to reduce the number of employees due to the COVID-19 pandemic, both in the short and in long term. HGEs do not significantly differ in the probability of reducing employment in the short term, but they are less prone to reduce employment in the long term, in comparison with non-HGEs. When analysing the long-term impact of COVID-19 on

digitalisation, we find that already digitalised firms have a higher likelihood of raising their digitalisation efforts than non-digitalised firms. Additionally, we also analyse asymmetric reactions across sectors. Our results show that firms operating in sectors hit hard by COVID (in terms of negative turnover changes) have a higher probability of reducing employment in the short and long term. Conversely, firms in highly digitalised sectors have a lower probability of reducing their employment.

From an academic point of view, we contribute to the strand of literature that analyses the firm-level impact of an unexpected shock such as the COVID-19 pandemic according to the productivity level (Bloom et al., 2021; Andrews et al., 2021a, 2021b). This literature has stressed the employment reallocation impact of the pandemic in the short term (Andrews et al., 2021a, 2021b) but also the presence of a negative 'within-firm' productivity and positive 'between-firm' effects since less productive sectors, and less productive firms within them, contracted (Bloom et al., 2021). In this paper, we take a broader perspective and assess the impact of the pandemic on firms' strategies concerning employment and digitalisation. Our results confirm the larger resilience in terms of employment of more productive firms during the crisis (in the short term), but also in the long term. Lastly, we contribute to the literature on the adjustment of HGEs during crisis periods (Flachenecker et al., 2021).

From a policy point of view, there is interest in fostering and supporting the development of HGEs (Flachenecker et al., 2020) as well as increasing productivity and innovation in the EU, thus narrowing the productivity gap between the EU and the US (European Commission, 2021). The COVID-19 pandemic may lower productivity growth and hinder the convergence of productivity within the EU if efficient firms do not survive in the post-pandemic period. Our analysis points out that enhancing the productivity level of laggard firms is an important policy issue, especially in countries with many firms far from the technological frontier. Finally, policy-makers have promoted digitalisation due to its potential to transform industries (EIB, 2021). Our results suggest that the digitalisation gap between digital and non-digital firms may widen due to COVID-19.

The rest of the paper consists of three sections and concluding remarks. The next section reviews the main theoretical and empirical works related to our questions and describes our main hypotheses. Section 3 describes our data, key variables, descriptive statistics and empirical methodology. Our main estimation results are discussed in Section 4. Section 5 concludes and discusses policy implications.

## 2. Literature review and hypotheses

### 2.1. COVID-19 and the effect on employment

The COVID-19 pandemic has been a supply-demand shock with heterogeneous impacts across sectors (Mason, 2020; Gu et al., 2020; Stiglitz, 2020). Some theoretical models of managerial incentives and competition argue that productivity tends to converge during economic downturns as reduced margins pose a threat of liquidation for less efficient firms (Schmidt, 1997). Different reasons may explain this. First, the crisis lowers the opportunity cost of adjusting production (Hall, 2005). Second, managers shift their attention from growth to efficiency (Koenders and Rogerson, 2005) due to higher bankruptcy risks. Third, a crisis changes the costs of layoffs (Mortensen and Pissarides, 1994; Berger, 2012). Finally, it alters the incentives for a firm to invest in their employees' human capital as a consequence of the shift to efficiency (Jaimovich and Siu, 2012).

However, there is also evidence that crises do not push firms' productivity to converge (Bugamelli et al., 2010; Dosi et al., 2017). Bugamelli et al. (2010) observe a high dispersion of firms' performance after the introduction of the euro since it induced more within-firm changes (restructuring) rather than a relative reallocation of shares of output and employment across firms. Economic downturns such as COVID-19 may put at risk the youngest firms and, consequently, the most dynamic ones (Benedetti-Fasil et al., 2020; Coad, 2021), e.g. due to financial constraints (Hadlock and Pierce, 2010) or market distortions that alter creative destruction (Foster et al., 2016; Harris and Moffat, 2016). Stronger financial restrictions may affect younger and smaller firms

more due to their lack of collateral and experience, while market distortions may cause innovative young companies to have more difficulties establishing themselves in the market.

Furthermore, leader and laggard firms may differ in their reaction during the COVID-19 crisis due to their different intrinsic characteristics (Coad, 2011). On the one hand, laggard firms tend to imitate, are characterized by steeper hierarchies and tend to focus on improving efficiency rather than growth.[1] On the other hand, low-productivity firms have the advantage of having the possibility to access frontier production technologies, the opportunity to invest in more recent capital vintages, the ability to learn from leaders' mistakes, as well as the freedom to choose between technological trajectories in the absence of being "locked-in" to any particular trajectory. Leader firms are more innovative, often characterised by flat hierarchies, and smaller while aiming to grow.

Hence, given the heterogeneous nature of leaders and laggards, COVID-19 may have exerted a different impact on these two respective firm types. Recent evidence gives support to this assumption. Andrews et al. (2021a, 2021b) have stressed the reallocation impact of the pandemic in the short term in terms of employment. Bloom et al. (2021) find a positive "between" effect from two channels – low-productivity firms shrank, and the least productive firms within these sectors suffered most- while there is a negative "within" effect since firms had higher costs to operate during the pandemic. Similarly, HGEs are usually small young firms that may have large financial needs to finance their occasional growth spurts but also with stronger cash flow, are more innovative and more flexible to adapt (Coad et al., 2021).[2] However, their overall economic importance is in crisis periods (Flachenecker et al., 2021). Hence, our hypotheses with respect to employment are as follows:

[1] Coad (2011) provides a literature review of the different characteristics of both leader and laggard firms.

[2] HGEs are pointed out to be younger, smaller, more innovative, more internationalized and present in different sectors (Moreno and Coad, 2015), implying that the association between productivity and HGE-status is not clear-cut ex-ante (Du and Temouri, 2015; Guillamón et al., 2017).

**Hypothesis 1a:** More productive firms before the pandemic are less likely to reduce their employment in the short and long term due to the COVID-19 shock.

**Hypothesis 1b:** HGEs are more likely to increase their employment in the short term and less likely to reduce it in the long term due to the COVID-19 shock.

The effect of the COVID-19 crisis has varied across sectors. Whereas firms including HGEs in sectors such as tourism or hospitality have endured steep sales drops, online retailers have flourished (Benedetti-Fasil et al., 2021; Canton et al., 2021).[3] As such, we posit that the degree of digitalisation, both on the firm- as well as on the sectoral level, provided valuable flexibility to adjust to the new conditions and avoid cutting jobs. Therefore, our hypotheses with respect to digitalisation are:

**Hypothesis 1c:** Firms (including HGEs) in more digitalised sectors are less likely to reduce their employment in the short and long term due to the COVID-19 shock in comparison to those firms in less digitalised sectors.

**Hypothesis 1d:** More digitalised firms are less likely to reduce their employment in the short and long term due to the COVID-19 shock in comparison with less digitalised firms.

[3] Scale-ups are a subgroup of HGEs characterized by their application of digital technologies and their innovative business models. Conversely, HGEs are present across sectors (Daunfeldt et al., 2016).

## 2.2. COVID-19 and the adoption of new digital technologies

One potential explanation of the permanent gap between leader and laggard firms is the divergence in technological adoption (Bersch et al., 2019). New digital technologies (NDTs henceforth) can foster productivity growth and unleash winner-takes-all dynamics through lower marginal costs and easier upscaling (Brynjolfsson and McAfee, 2011; Bartelsman et al., 2015). NDTs facilitate the replication of informational goods and business processes at near-zero marginal cost, and they enable the top-quality provider to obtain a certain monopolistic power since providers capture most, or all, of the market. At the same time, only a small market share accrues to the next-best provider. Furthermore, globalization fosters the global nature of frontier firms which increases the returns to investing in non-rival technologies via expanded market size (Acemoglu and Linn, 2004). Consequently, they cause a widening of the performance gap between the leader and laggard firms.

In this line, digitalisation is one of the drivers of future growth (Benedetti Fasil et al., 2021). ICTs affect firms' organizational structure and commercial strategy, by providing them with new ways of selling products and services (e-commerce) or by giving easy, fast access to data about customers. For instance, using the EIB database, Cincera et al. (2020) find that ICT and acquisition of new skills are more important for explaining productivity gains than R&D investment and organizational improvements.

During crises, firms have incentives to accelerate their technological transformation (Hershbein and Kahn, 2018). Hence, crises offer an opportunity to deploy NDTs more rapidly and across a wider range of products and services. Indeed, the unprecedented situation due to the COVID-19 pandemic obliged firms to redefine their strategy (Pantano et al., 2020; Ebersberger and Kuckertz, 2021).

Therefore, COVID-19 has intensified the adoption of NDTs by firms.[4] Hence, it is interesting to understand if this change is expected to persist in the future (Apedo-Amah et al., 2020). Furthermore, due to the potential capacity of NDTs to increase firms' productivity, we explore whether different firm categories, including leader/laggard firms and HGEs, have a different probability to adopt those technologies in the future.

We posit three distinct hypotheses regarding the adoption of NDTs:

> **Hypothesis 2a:** HGEs and more productive firms are more prone to continue the adoption of NDTs due to the COVID-19 pandemic.

As stated by Ferrando et al. (2019), this may be since HGEs differ in their capacity to technologically innovate but also in their success in combining diverse intangibles – the capacity to handle computerised information, to carry out innovative activities and to develop economic competencies (Corrado et al., 2009)– in production processes. Therefore, we may expect firms that are more digitalised or that are in highly digitalised sectors already to have certain digital competencies that make them more likely to continue investing in these NDTs after the COVID-19 pandemic. Hence:

> **Hypothesis 2b:** Firms (including HGEs) in more digitalised sectors are more prone to continue their digitalisation process in comparison with those in less digitalised sectors.
>
> **Hypothesis 2c:** More digitalised firms are more likely to continue their digitalisation process compared to less digitalised firms.

[4] Marques Santos et al. (2021) report evidence on how the innovation process has changed between the pre-Covid period and during 2020. Their results show that in comparison with the pre-Covid period, only the probability of developing product and process innovations is lower while the probability of developing marketing innovations has increased.

## 3. Database, descriptive statistics and empirical methodology

We detail the database assembled for the sake of the analysis, define the key variables, present the main descriptive statistics and outline the empirical methodology.

### 3.1. Database

The main data are a combination of the EIB Group Survey on Investment and Finance (EIBIS) merged with the Bureau van Dijk (BvD) ORBIS database. EIBIS is an EU-wide survey that gathers qualitative and quantitative information on investment activities by non-financial corporates, both SMEs and larger corporates, their financing requirements and the difficulties they face. Our sample is based on the 27 EU Member States and UK that are representative for each member state, using a stratified sampling methodology, (Brutscher et al., 2020). All interviewed firms are drawn from the BvD ORBIS database, which allows the survey answers to be linked to firms' financials and other administrative information.[5] The survey has been compiled since 2016 and until 2020. More than 12,000 firms have participated in multiple waves of the survey, resulting in more than 62,000 observations.

The merged EIBIS – ORBIS dataset allows for obtaining firm information for the period before the survey (more than 200,000 observations are available for surveyed firms from 2013 to 2020 for years when they are not participating in the survey). Hence, whenever possible, we use the EIBIS database and supplement it with ORBIS in a few cases where EIBIS data is missing.

Finally, the Structural Business Statistics (Eurostat) provides information on annual sales during the years 2019 and 2020 at sector and country levels. This information allows us to estimate the annual sales growth per sector and categorize them

[5] Detailed methodology on the survey is available https://www.eib.org/en/publications-research/economics/surveys-data/eibis/about/index.htm

according to their change in turnover, i.e., i) if they are declining (a drop of sales more than -10%), ii) intermediate (drop between -10% and 0%) or iii) growing (positive growth of over 0%). In a second step, we classify individual firms according to these three different sectoral categories. In case of lack of information for a particular sector and country, we consider the European average for this sector.

We acknowledge that causality is difficult to infer given our data limitations. Our analysis relies specifically on the EIBIS 2020 survey wave, a wave that includes COVID-19-specific information, e.g. regarding the pandemic's effect on employment dynamics or longer-term investment in digitalisation. Hence, we can only rely on cross-sectional estimation techniques and cannot use the panel dimension of the EIBIS dataset. Moreover, owing to the elevated correlation across firm characteristics, one must be cautious when analysing the magnitude of the impact of each variable. However, the results are broadly robust across estimations.

### 3.2. Key variables

HGEs are defined according to the OECD-Eurostat definition (Petersen and Ahmad, 2007). HGEs have an average annualized employment growth greater than 10% per year over the past three years and have at least 10 employees at the beginning of the growth period.[6] EIBIS compiles most information from the previous financial year. Therefore, variables such as labour productivity and being an HGE, for instance, refer to the year 2019. However, our key variables related to the Covid-19 pandemic, i.e. the expected impact of the pandemic in the short and long term, refer to expectations made in 2020. Hence, our empirical analysis will mainly focus on the cross-section of firms of the EIBIS 2020 wave.

To measure the short-term impact of COVID-19, the EIBIS survey wave 2020 includes the following question: "*Thinking about the impact of coronavirus, have you had to put staff temporarily on leave, make staff redundant or unemployed or reduce the number of hours they work compared to before the coronavirus pandemic?*". Firms have 7 different answers: "*a.*

[6] Most of the studies in the literature use either sales or employees as growth indicators, since they do not seem to affect the results and they are moderately correlated (see Moreno and Coad, 2015).

*Yes, up to a quarter; b. Yes, up to half; c. Yes, up to three quarters; d. Yes, three quarters or more; e. No, but we will start to take these actions in the next three months; f. No, and we don't need/intend to take any of these actions; g. No, we have increased staff numbers and/or the number of hours our staff work*". We group these nine possible answers into four categories: 1) High impact if the firm responded that the reduction of the staff was up to half, up to three quarters or three quarters or more; 2) a low impact if it responded that the reduction of the staff was up to a quarter or they were going to start in the next three months; 3) no impact if the firm responded that the employees did not decrease; 4) and finally a positive impact if it increased its workforce.

To measure the long-term impact of COVID-19, the EIBIS survey wave 2020 includes the following question: "*Do you expect the coronavirus outbreak to have a long-term impact on any of the following: c. The increased use of digital technologies; d. Permanent reduction in employment*." We generate two further Corona-impact proxies out of the answers: 1) a dummy that identifies firms that expect to reduce their workforce due to Covid-19 in the long term, and 2) a dummy that indicates if the firm will continue the process of digitalisation.

The EIBIS database allows us to further define three variables that relate to digitalisation. The first considers firm investment in R&D, software and IT, and training. The second is based on a firm's level of digitalisation, using a dummy variable to capture either i) partial or ii) full digital adoption.[7] Thirdly, we define a sector as highly digitalised if it has an above-average investment per worker in *Software, data, IT networks and website activities.*

[7] Partial and total digitalization refers to firms that have implemented in parts of the business or entirely a particular digital technology, respectively. Digital technologies are: 3D printing, robots, internet of things, cognitive technologies, drones, augmented or virtual reality and platform technologies.

### 3.3. Descriptive statistics

We provide a short overview of some key descriptive statistics. We start by analysing whether HGEs and non-HGEs have adjusted their workforce differently due to the COVID-19 shock, and how this relates to their level of productivity. The EIBIS questionnaire includes specific questions on how firms have been impacted by the COVID-19 pandemic in terms of employment, both in the short (first months of the pandemic) and long term (as an expected impact). Concerning the relationship between the short-term impact of the COVID-19 crisis on the workforce (Table 1, upper part), more than 54% of firms declare to have reduced the number of employees due to COVID-19. However, the share of HGEs that increased thir workforce is slightly larger than the share of non-HGEs (3.6% vs. 2.7%). Furthermore, a somewhat lower share of HGEs (10.6%) than non-HGEs (12.8%) fall into the most negatively affected category in terms of employment.

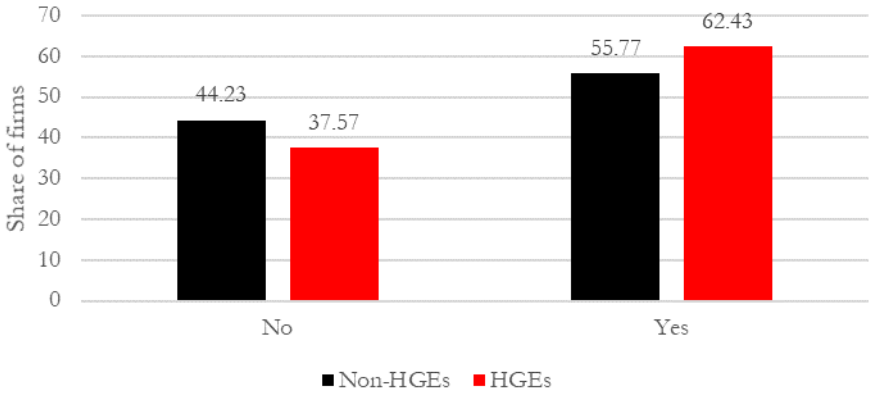
**Table 1. Short-term and long-term impact of Covid on employment.**

| | Non-HGE | HGE |
|---|---|---|
| **Employment reduction in the short term** | | |
| High impact (reduction at least of 25%) | 29.4 | 27.8 |
| Low impact (reduction of less than 25%) | 25.3 | 26.6 |
| No, and we don't need | 41.8 | 41.0 |
| No, we have increased | 2.7 | 3.6 |
| **Expected employment reduction in the long term** | | |
| No | 54.6 | 57.9 |
| Yes | 45.3 | 42.1 |

Note: The columns show the % of firms on each category. Data corresponds to year 2019 (Wave 2020).

Observing firm expectations to reduce employment in the long-term (Table 1, bottom part), more than 40% of both HGEs and non-HGEs declare that they expect to suffer a long-term impact. This highlights the remarkable impact that the pandemic might exert in the long run.

**Graph 1. Firms that expect a digital increase due to the Covid-19 (%). Wave 2020.**




NDTs are among the key elements that may have facilitated the adaptation of firms during the COVID-19 pandemic. Regarding how Covid-19 is affecting the potential future digital transition, Graph 1 shows the share of firms that declare to expect an increase in digitalisation. As we can observe, most firms expect to increase digitalisation due to Covid-19. Interestingly, we observe that a larger share of HGEs responds positively (62.43%) in comparison with non-HGEs (55.77%).

### 3.4. Empirical methodology

We present the methodology implemented to test our hypotheses, in particular focusing on the impact of the COVID-19 pandemic, both in the short and long term, according to productivity levels, digitalisation activities and pre-crisis growth performance.

First, we apply Coarsened Exact Matching (CEM) to alleviate potential endogeneity concerns (see Online Material Appendix 1 for more details). CEM is a non-parametric methodology that establishes a covariate balance between treated and control units. This methodology selects firms with relatively similar characteristics that have been impacted

by the COVID-19 pandemic and those that they have not.[8] Additionally, including the lagged HGE mitigates slightly endogeneity concerns.

Second, we estimate our main equations. Our baseline equation is the following:

$$Prob(impact)_{i,t} = \alpha_1 + \beta_1 HGE_{it-1} + \beta_2 LabProd_{it-1} + \cdots \\ \ldots + Digit_{it-1}\beta_3 + x_{1it-1}\beta_4 + \epsilon_{1i,t} \qquad (1)$$

where the dependent variable *impact* refers to different dummies that capture the firm-level adjustment due to COVID-19 along different dimensions. For the short term impact of Covid-19 on employment, our dependent variables are the following:
i) *impactHL*, which takes the value of 1 for the group of firms that reported a high drop in employment (i.e., a staff reduction greater than 50%) and zero for those with a moderate impact (a staff reduction lower than 50%; ii) *impactLN* which is equal to 1 if firms suffered a moderate impact on employment and zero for those that declare that Covid-19 did not change their workforce and that no change is expected; iii) *impactNG* which takes the value of 1 for firms that did not change their workforce and do not expect to do it and zero for those that grew in terms of employment.
To estimate the long-term impact of Covid-19, we consider two dependent variables: a dummy which identifies firms that expect to reduce their workforce due to COVID-19 (*LTimpact*) and another dummy that indicates if the firm will continue the process of digitalisation (*LTdigit*).

Concerning our key variables, *HGE* identifies high-growth enterprises between the years 2017-2019, *LabProd* is the log labour productivity and *Digit* is a vector which is composed of three dummies: *DigitSector*, which is a dummy variable that identifies those sectors with a higher investment per worker in *Software, data, IT networks and website activities*; *full digitalisation,* which identifies full digital adoption; and *partial digitalisation* which equals

[8] Non-observable characteristics of firms affected by the COVID-19 pandemic may differ from those of firms not affected by the pandemic in the short-term. This can cause a coefficient bias in the results.

1 in case of partial digital adoption. Hence, we can capture the digitalisation level at the firm and sector levels.

$x_1$ is a set of explanatory variables, $\beta$ are the estimated coefficients and $\varepsilon_i$ are the random errors. All equations include control variables such as firm size, firm age and a dummy identifying if the firm is a subsidiary. Additionally, a set of variables captures the intangible assets accumulated in the company. In particular, we include dummies identifying the degree of innovativeness, and the share of investment in R&D, software and training. Finally, we include country and sector dummies with the only exception of those equations that include the variable *Digitsector*.

Equation (1) includes a dummy variable if the sector was declining (sales drop in the sector larger than -10%) or growing (positive sales growth) during the year 2020 and firm's global expectations in terms of expected availability of internal funds, external funds, business prospects and overall economic climate. The latter variables control for the influence of the economic climate on the expected long-term impact of COVID-19. Finally, in our estimation of the impact on long-term digitalisation, we include the previous level of digitalisation (partial or full level).[9]

The equations are estimated with a probit econometric model using robust standard errors and we test our hypotheses 1a, 1b, 1c, 1d, 2a, 2b and 2c using the EIBIS 2020 data.

[9] For an overview of the definition of the variables, please see Table A-1 in the Appendix.

## 4. Results

This section presents the main results of our estimations. We explore the impact of COVID-19 on employment, first in the short-term, and second in the long term. Third, we analyse the expected impact of COVID-19 on digitalisation.

### 4.1. The short-term impact of the COVID-19 crisis on firms' employment

We start by disentangling the short-term impact of the COVID-19 crisis on employment, testing hypotheses 1a, 1b, 1c and 1d. Table 2 displays the results of the probability of firms' being subject to a high impact versus a low impact (columns (1)-(4)), a low impact versus a negligible impact (columns (5)–(8)), and a negligible impact versus a positive impact (columns (9)–(12)).

The main results are the following. First, more productive firms are less prone to reduce employment. As expected, we partly confirm hypothesis 1a since productive firms have been in a better position to resist the economic shock in the short term and they were able to maintain or even increase their workforce in the short term. This confirms similar results found in Bloom et al. (2021) and Andrews et al. (2021a, 2021b).

Furthermore, being an HGE in the year 2019 does not have a significant relationship with changes in the workforce during the COVID-19 crisis. The only exception is that HGEs seem to have a lower probability of having a neglible impact in comparison with increasing the number of workers. However, since HGEs differ in labour productivity, it is also interesting to analyse if more productive HGEs behave differently. Our results show that the interaction term between HGEs and labour productivity is positively and significantly related to the likelihood of suffering a negligible impact in comparison with growing during the pandemic. However, in order to derive the overall impact, we have to add the coefficient for HGEs and its interaction term with labour productivity (-3.74 +

0.363) which yields a negative effect. Therefore, we partially confirm hypothesis 1b in the short term, by controlling for the labour productivity level.

As expected, firms in sectors highly affected by COVID-19 have a higher probability of a high reduction in their workforce. Interestingly, the sectoral classification does not seem to influence the other two remaining impact categories. Hence, firms in sectors relatively more affected by the COVID-19 pandemic have been more negatively hampered in the short term.

Finally, firms in more digitalised sectors were less likely to decrease their employment size during the first months of the COVID-19 pandemic. Hence, we confirm hypothesis 1c. Conversely, we are not able to confirm hypothesis 1d since the estimated coefficient of being more digitalised on the company level is not statistically significant on the probability to reduce the number of employees in the short term. Therefore, our results show that COVID-19 has generated a different shock to sectors depending on their degree of digitalisation.

**Table 2. Short-term impact of the COVID-19 pandemic on employment. Matched sample. Wave 2020.**

| | **Impact high vs. low** (Probability of suffering a high impact in comparison with a low impact) | | | | **Impact low vs. Negligible** (Probability of suffering a low impact in comparison with a negligible impact) | | | | **Impact negligible vs. Growth** (Probability of having a negligible impact in comparison with growing) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** | **(9)** | **(10)** | **(11)** | **(12)** |
| $HGE_{t-1}$ | 0.005 | -0.136 | -0.120 | 0.001 | 0.004 | -0.225 | -0.239 | -0.002 | -0.046 | -3.74*** | -3.77*** | -0.043 |
| | [0.069] | [0.846] | [0.844] | [0.069] | [0.065] | [0.784] | [0.783] | [0.065] | [0.128] | [1.440] | [1.443] | [0.129] |
| $LabProd_{t-1}$ | -0.064* | -0.065* | -0.071** | -0.074** | -0.070** | -0.072** | -0.071** | -0.073** | 0.049 | 0.015 | 0.011 | 0.047 |
| | [0.033] | [0.034] | [0.034] | [0.033] | [0.030] | [0.030] | [0.031] | [0.030] | [0.067] | [0.068] | [0.069] | [0.068] |
| $HGE_{t-1} \times LabProd_{t-1}$ | | 0.014 | 0.012 | | | 0.022 | 0.023 | | | 0.363** | 0.365*** | |
| | | [0.081] | [0.081] | | | [0.076] | [0.075] | | | [0.141] | [0.142] | |
| $CovidNeg_{t-1}$ | 0.125** | 0.125** | | | 0.07 | 0.07 | | | 0.053 | 0.047 | | |
| | [0.052] | [0.052] | | | [0.052] | [0.052] | | | [0.125] | [0.125] | | |
| $CovidPos_{t-1}$ | -0.16*** | -0.16*** | | | 0.008 | 0.007 | | | -0.004 | -0.01 | | |
| | [0.060] | [0.060] | | | [0.052] | [0.052] | | | [0.108] | [0.108] | | |
| $DigitSec_{t-1}$ | | | -0.124** | | | | -0.091* | | | | 0.078 | |
| | | | [0.056] | | | | [0.050] | | | | [0.121] | |
| Full $digitalisation_{t-1}$ | | | | 0.027 | | | | -0.093 | | | | -0.001 |
| | | | | [0.071] | | | | [0.065] | | | | [0.132] |
| Partial $digitalisation_{t-1}$ | | | | -0.029 | | | | 0.041 | | | | -0.003 |
| | | | | [0.043] | | | | [0.042] | | | | [0.091] |
| Innovation $company_{t-1}$ | -0.079* | -0.116 | -0.082* | -0.080* | -0.002 | 0.087 | -0.0004 | -0.003 | -0.199** | -0.186 | -0.192** | -0.197** |
| | [0.047] | [0.093] | [0.047] | [0.047] | [0.046] | [0.091] | [0.046] | [0.046] | [0.094] | [0.221] | [0.094] | [0.094] |
| Innovation $country_{t-1}$ | 0.004 | -0.033 | -0.010 | -0.010 | 0.106 | 0.194* | 0.106 | 0.105 | 0.150 | 0.192 | 0.178 | 0.147 |
| | [0.098] | [0.125] | [0.097] | [0.098] | [0.092] | [0.118] | [0.092] | [0.092] | [0.196] | [0.276] | [0.202] | [0.196] |
| Global $Innovation_{-1}$ | 0.037 | | 0.024 | 0.025 | -0.089 | | -0.086 | -0.085 | -0.023 | | -0.011 | -0.024 |
| | [0.094] | | [0.094] | [0.094] | [0.090] | | [0.090] | [0.090] | [0.225] | | [0.229] | [0.229] |
| $R\&D_{t-1}$ | 0.082 | 0.081 | 0.068 | 0.043 | -0.034 | -0.035 | -0.020 | -0.030 | -0.291 | -0.326 | -0.343 | -0.290 |
| | [0.133] | [0.133] | [0.133] | [0.133] | [0.127] | [0.127] | [0.127] | [0.127] | [0.234] | [0.233] | [0.233] | [0.232] |
| $Software_{t-1}$ | -0.078 | -0.079 | -0.093 | -0.098 | 0.253*** | 0.253*** | 0.260*** | 0.245*** | 0.01 | 0.023 | 0.008 | 0.006 |
| | [0.092] | [0.092] | [0.092] | [0.092] | [0.090] | [0.090] | [0.090] | [0.090] | [0.222] | [0.220] | [0.219] | [0.221] |
| $Training_{t-1}$ | 0.092 | 0.092 | 0.090 | 0.088 | 0.018 | 0.018 | 0.028 | 0.020 | 0.308 | 0.287 | 0.281 | 0.309 |
| | [0.108] | [0.108] | [0.108] | [0.108] | [0.102] | [0.102] | [0.102] | [0.102] | [0.258] | [0.258] | [0.256] | [0.257] |
| Constant | 1.196*** | 1.209*** | 1.320*** | 1.300*** | 0.539 | 0.557 | 0.613* | 0.685** | 0.925 | 1.299 | 1.321* | 0.983 |
| | [0.381] | [0.390] | [0.387] | [0.364] | [0.364] | [0.369] | [0.367] | [0.347] | [0.777] | [0.792] | [0.791] | [0.762] |
| Pseudo-$R^2$ | 0.133 | 0.133 | 0.121 | 0.120 | 0.078 | 0.078 | 0.077 | 0.077 | 0.130 | 0.134 | 0.132 | 0.127 |
| Observations | 4,254 | | | | 5,258 | | | | 3,392 | | | |

*Note: *** p<0.01, ** p<0.05, * p<0.1 Dummy reference of innovation is non-innovator. Robust standard errors. Note (2): Age, Size, country, sector and expectation dummies are included. Note (3): columns (1)-(4) consider firms suffering a high employment reduction (high impact) vs. those suffering a low employment reduction (low impact); columns (5)-(8) consider firms suffering a low employment reduction vs. those havinga negligible employment reduction; columns (9)-(12) consider firms having a negligible employment reduction vs. those growing.*

### 4.2. The long-term impact of the COVID-19 crisis on firms' employment

We now analyse factors associated with the expected long-term impact on employment due to COVID-19 (hypotheses 1a-1d). Table 3 displays the main regression results. We confirm hypothesis 1a since the estimated coefficient for productivity is statistically significant and negative. Therefore, firms that are more productive are less likely to

reduce their employment in the long term due to the Covid-19 shock. Keeping in mind potential endogeneity concerns, our results suggest that the most productive companies are expected to be more resilient to the COVID-19 crisis in terms of avoiding negative employment effects.

**Table 3. Long-term expected negative impact of COVID-19 pandemic on employment. Matched sample. Wave 2020.**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $HGE_{t-1}$ | -0.054 | -0.422 | -0.047 | -0.062 | -0.052 |
| | [0.061] | [0.724] | [0.061] | [0.061] | [0.062] |
| $LabProd_{t-1}$ | -0.091*** | -0.094*** | -0.074*** | -0.080*** | -0.092 |
| | [0.028] | [0.028] | [0.028] | [0.028] | [0.028] |
| $HGE_{t-1} \times LabProd_{t-1}$ | | 0.036 | | | |
| | | [0.070] | | | |
| $CovidNeg_{t-1}$ | | | 0.187*** | | |
| | | | [0.044] | | |
| $CovidPos_{t-1}$ | | | -0.072 | | |
| | | | [0.053] | | |
| $DigitSector_{t-1}$ | | | | -0.216*** | |
| | | | | [0.044] | |
| Full digitalisation $_{t-1}$ | | | | | 0.029 |
| | | | | | [0.060] |
| Partial digitalisation $_{t-1}$ | | | | | 0.010 |
| | | | | | [0.038] |
| Innovation company $_{t-1}$ | -0.027 | -0.026 | -0.021 | -0.019 | 0.024 |
| | [0.041] | [0.041] | [0.041] | [0.041] | [0.041] |
| Innovation country $_{t-1}$ | 0.041 | 0.040 | 0.054 | 0.068 | 0.031 |
| | [0.085] | [0.085] | [0.085] | [0.085] | [0.086] |
| $Global\ Innovation_{t-1}$ | -0.106 | -0.106 | -0.086 | -0.072 | -0.107 |
| | [0.082] | [0.082] | [0.082] | [0.082] | [0.083] |
| R&D $_{t-1}$ | -0.102 | -0.104 | -0.081 | -0.075 | -0.108 |
| | [0.121] | [0.122] | [0.122] | [0.121] | [0.122] |
| Software $_{t-1}$ | -0.042 | -0.043 | -0.016 | 0.024 | -0.041 |
| | [0.082] | [0.082] | [0.082] | [0.082] | [0.083] |
| Training $_{t-1}$ | 0.235*** | 0.234*** | 0.242*** | 0.235*** | 0.236 |
| | [0.088] | [0.088] | [0.088] | [0.088] | [0.088] |
| Constant $_{t}$ | -0.048 | -0.018 | -0.200 | -0.090 | 0.059** |
| | [0.321] | [0.329] | [0.323] | [0.319] | [0.031] |
| Pseudo-$R^2$ | 0.143 | 0.143 | 0.146 | 0.141 | 0.141 |
| Observations | 7,765 | | | | |

*Note: *** p<0.01, ** p<0.05, * p<0.1 Dummy reference of innovation is non-innovator. Robust standard errors. Note (2): country and sector dummies included. The estimation with the DigitSector does not include sector dummies. Age, size, country, sector and expectation dummies are included.*

Hypothesis 1b focuses on the relationship between having a high-growth spurt before the pandemic and the probability of reducing the workforce in the long term. The

coefficient is negative but not statistically significant. However, in an extension of our analysis which does not control for the R&D and innovation efforts (Table 4) our coefficient for HGEs becomes negative and statistically significant. This suggests that it is mainly innovative HGEs that expect not to be negatively affected in the long-term. Overall, hypothesis 1b is partially confirmed, highlighting the role of innovativeness for this specific group of firms.

**Table 4. Determinants of the probability of the expected impact on the long-term employment reduction by not controlling for their innovativeness. Matched sample. Wave 2020. Robust standard errors. Wave 2020.**

| | LTimpact | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $HGE_{t-1}$ | -0.088* | -0.109** | -0.110** |
| | [0.051] | [0.055] | [0.055] |
| $LabProd_{t-1}$ | | -0.120*** | -0.121*** |
| | | [0.023] | [0.023] |
| Full $digitalisation_{t-1}$ | | | -0.008 |
| | | | [0.051] |
| Partial $digitalisation_{t-1}$ | | | 0.037 |
| | | | [0.033] |
| From 2 to 5 $years_{t-1}$ | -0.006 | -0.481 | -0.486 |
| | [0.407] | [0.467] | [0.469] |
| From 5 to 10 $years_{t-1}$ | 0.067 | -0.005 | -0.006 |
| | [0.091] | [0.104] | [0.104] |
| From 10 to 20 $years_{t-1}$ | 0.088* | 0.050 | 0.048 |
| | [0.052] | [0.056] | [0.056] |
| More than 20 $years_{t-1}$ | 0.031 | 0.019 | 0.019 |
| | [0.038] | [0.040] | [0.040] |
| $Employ_{t-1}$ | 0.010 | 0.014 | 0.013 |
| | [0.011] | [0.012] | [0.012] |
| $Subsidiary_{t-1}$ | -0.061 | -0.020 | -0.019 |
| | [0.037] | [0.040] | [0.040] |
| Constant | -0.240*** | 0.989*** | 0.985*** |
| | [0.0789] | [0.253] | [0.254] |
| Pseudo-$R^2$ | 0.0551 | 0.0568 | 0.0568 |
| Observations | 11,015 | 9,592 | 9,573 |

*Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets. Country and sector dummies included.*

In the following, we turn our attention to hypothesis 1c. Firms in sectors with a higher share of digitalisation are in a better position to remain or even increase the number of employees in the future. Hence, hypothesis 1c is confirmed with respect to the long-term

perspective. Therefore, we find that digitalisation matters at the sectoral level both in the short and long term.[10]

Furthemore, our results in Table 3 show that firms belonging to a sector with a sales drop larger than 10% between 2019 and 2020 are more likely to reduce their workforce permanently. These results highlight the importance of deploying the economic policies necessary in order to recover from the current crisis and improving the expectations at the sectoral level in order to promote employment growth in the long term.

Finally, the level of digitalisation at the firm level is not significant; hence, we are not able to confirm hypothesis 1d (Table 3 (column (5)). A potential explanation of the different incidence between the results at the firm- and sector-level is due to the dominance of the digitalization sectoral characteristics over the digital effort at the firm level and because both variables indicate a different form of digitalisation. Therefore, the level of digitalisation at the sectoral level matters for the long-term employment outlook. Additionally, in the case of sector-level digitalisation, we cannot use sector dummies. Thus, digitalisation might capture a sector-specific COVID impact (e.g. more impacted sectors are not so digitalised, like the hospitality sector).

### 4.3. The impact of the COVID-19 crisis on firms' digitalisation

We analyse the factors associated with the expected intensification of the digitalisation process due to COVID-19 (hypotheses 2a-2c). We turn our attention to the probability of increasing the digitalisation level in the long term due to COVID-19.

[10] The interaction between being an HGE and belonging to a digitalized sector is not significant (results available upon request).

We test if HGEs and more productive firms are more likely to increase the digitalisation level due to COVID-19 (hypothesis 2a). Table 5 shows that being a HGE and their labour productivity before the COVID-19 pandemic does not have any statistically significant impact. However, global innovators and innovators at the company level are more likely of intensifying the use of NDTs.

**Table 5. Determinants of the probability of the expected impact on the long-term digitalisation. Matched sample. Wave 2020.**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $HGE_{t-1}$ | 0.008 | 0.554 | 0.007 | 0.019 |
| | [0.054] | [0.69] | [0.055] | [0.025] |
| $LabProd_{t-1}$ | 0.025 | 0.030 | 0.020 | 0.001 |
| | [0.025] | [0.026] | [0.025] | [0.055] |
| $HGE_{t-1} \times LabProd_{t-1}$ | | -0.053 | | |
| | | [0.066] | | |
| $CovidNeg_{t-1}$ | | | -0.097** | |
| | | | [0.043] | |
| $CovidPos_{t-1}$ | | | 0.007 | |
| | | | [0.046] | |
| $DigitSector_{t-1}$ | | | | 0.099** |
| | | | | [0.038] |
| Full digitalisation $_{t-1}$ | 0.168*** | 0.168*** | 0.164*** | 0.186*** |
| | [0.055] | [0.055] | [0.055] | [0.055] |
| Partial digitalisation $_{t-1}$ | 0.235*** | 0.235*** | 0.234*** | 0.242*** |
| | [0.035] | [0.035] | [0.035] | [0.035] |
| $Innovation\ company_{t-1}$ | 0.137*** | 0.137*** | 0.137*** | -0.265*** |
| | [0.038] | [0.038] | [0.038] | [0.075] |
| $Innovation\ country_{t-1}$ | 0.122 | 0.124 | 0.117 | -0.129* |
| | [0.076] | [0.076] | [0.077] | [0.076] |
| $Global\ Innovation_{t-1}$ | 0.289*** | 0.288*** | 0.286*** | -0.149 |
| | [0.077] | [0.077] | [0.077] | [0.099] |
| $R\&D_{t-1}$ | 0.087 | 0.090 | 0.080 | 0.045 |
| | [0.105] | [0.105] | [0.105] | [0.105] |
| $Software_{t-1}$ | 0.307*** | 0.308*** | 0.297*** | 0.327*** |
| | [0.074] | [0.074] | [0.074] | [0.073] |
| $Training_{t-1}$ | 0.158* | 0.159* | 0.156* | 0.162** |
| | [0.083] | [0.083] | [0.083] | [0.083] |
| Constant | -0.835*** | -0.885*** | -0.825*** | -0.830*** |
| | [0.294] | [0.300] | [0.297] | [0.292] |
| Pseudo-$R^2$ | 0.089 | 0.0889 | 0.090 | 0.086 |
| Observations | 7,762 | | | |

*Note: *** p<0.01, ** p<0.05, * p<0.1 Robust standard errors. Dummy reference of innovation is non-innovator. Note (2): Age, size, country, sector and expectation dummies included. The estimation with the DigitSector does not include sector dummies.*

Focusing on the relationship between the degree to which a sector has been affected by the pandemic, the digitalisation level of the sector (Hypotheses 2b) and the digitalisation

level of the firm (Hypothesis 2c), on the probability of digitalising due to COVID-19 pandemic. First, our results show that firms in sectors negatively affected by COVID-19 are less likely to continue their digitalisation process in comparison with those in intermediate sectors. A plausible explanation is that firms in sectors particularly affected by the pandemic might have a lower capability to introduce NDTs. Second, our results show that firms operating in digitalised sectors are significantly more prone to continue their digitalisation process. Therefore, Hypothesis 2b is confirmed. Furthermore, firms which already had introduced NDTs before the COVID-19 pandemic have a higher probability to increase the use of digital technologies in the future. This may widen the gap for less digitalised firms. Finally, an important dimension is investments in intangible assets. Our explanatory variables such as the innovation profile and investment in software and training are positively related to expected long-term digitalisation. Consequently, our results highlight the important complementarity between incorporating NTDs and investments in the internal capabilities to exploit these technologies. Both investments foster the probability of continuing investment in digitalisation.

Implementing digital technologies seems to be conditioned by certain digital and innovative capabilities already established in the company. Thus, technological adoptions may increase existing productivity gaps as it is mostly firms with high innovation capabilities that undertake them. However, investment in NDTs is not directly related to the past high-growth episodes of the company but rather to the innovative character of HGEs.

## 5. Conclusions

COVID-19 has led to massive economic disruptions. To shed light on the potential uneven impact of the pandemic, this paper analyses how productive firms and HGEs are

affected by COVID-19 in terms of employment adjustments in the short and long term, and whether these firms have potentially changed their digitalisation activities as a response to the crisis. We reach four main conclusions.

First, the COVID-19 crisis had a especially negative impact on employment for less productive firms. Those firms have reduced their workforce by more than more productive firms. This result highlights the importance of increasing the productivity of the least efficient firms.

Second, firms operating in sectors that have experienced a sales drop larger than 10% between 2019 and 2020 expect to reduce their workforce permanently due to the pandemic. Moreover, firms in these heavily affected sectors are also less likely to strengthen their digitalisation level.

Third, firms that had already implemented NDTs expect to continue their digitalisation process. This result suggests a widening gap in terms of the degree of digitalisation across firms and emphasises the importance of core internal abilities at the firm level to increase firms' competitiveness, resilience and capacity to recover from the present crisis.

Fourth, our results highlight the innovative dimension of HGEs. When we do not control for firms' innovative characteristics separately in our empirical analysis, HGEs exhibit a lower probability of reducing their employment in the long term. This implies that the innovative nature of HGEs is one of the main characteristics associated with this lower risk of reducing employment. One of the potential explanations might be that the long-term expectations are not necessarily linked with past growth episodes, but rather to how the firm develops its internal capabilities that increase competitiveness.

The main message stemming from this research is that productivity-enhancing reallocation played a role in the response to the crisis. Although firm exit slowed down significantly due to support measures from governments, firms have still adjusted their

labour force, at least in the short term. This finding is consistent with Bloom et al. (2021) and Andrews et al. (2021a). Our finding also points to the need to support innovation and firm-level productivity, not only for the sake of growth but because it provides some resilience against major crises. However, we must be cautious with our results, since the medium-term effect of the COVID-19 crisis on labour reallocation is uncertain, as government support tended to be given to lower productivity firms (Harasztosi et al., 2021). That support might have potential effects on employment that were not realised until the close of the survey used in this paper. Finally, another important policy-oriented message is that there is a need to support firms in their initial investments in digitalisation. In this regard, the implementation of the national Recovery and Resilience Plans in the context of the Recovery and Resilience Facility will provide important support to the digitalisation efforts of European economies.

We must highlight several shortcomings. First, our analysis of the impact of COVID-19 is based on the questionnaire in 2020 so we must be cautious with the relationship between the performance and characteristics of firms in 2019 and their impact in 2020. Second, while we tried to minimize endogeneity concerns by using coarsened exact matching and lagged explanatory variables, our results may not indicate causality and should be interpreted as conditional correlations.

Future research lines should analyse the capability of the firms to recover from COVID-19 by analysing their final performance in 2020 in terms of employment adjustment but also productivity. Previous results (Dosi et al., 2017) suggest a convergence in productivity levels following crises. It would be interesting to confirm this process for the COVID-19 crisis. Moreover, it would be interesting to analyse the impact of the COVID-19 pandemic on the appearance of new start-ups. Start-ups evaluate the market expectations and also search for funding sources. During the pandemic, the former may have deteriorated in some sectors and the latter became more difficult to find (Benedetti et al., 2020). Finally, an analysis of the persistence of the technological digital gap, its

underlying factors and its effects on firm performance is also a potential research extension.

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# APPENDIX 1. Main statistics

**Table A-1. Description of variables**

| Name | Description |
|---|---|
| *impactHL, impactLN, impactNG* | Dummies if: i) the firm has suffered a high drop of their staff during Covid-19 pandemic (it responded that the reduction of the staff was up to half, up to three quarters or three quarters or more) in comparison with a low impact; ii) the firm has suffered a low negative impact (the reduction of the staff was up to a quarter or they were going to start in the next three months) in comparison with a negligible impact; iv) the firm suffered a negligible impact (the firm did not decrease the number of employees) in comparison with those that increased. |
| *LTimpact* | Dummy if the firm expects that the Covid-19 pandemic will cause a decrease in their staff in the long term |
| *LTdigit* | Dummy if the firm expects that the Covid-19 pandemic will cause a higher investment in digitalisation in the long term |
| HGE | Dummy if the firm is a HGE. HGE follows the OECD-Eurostat definition considering an enterprise with an average annualized turnover or employment growth greater than 10% per year over the past three years and having at least 10 employees at the beginning of the growth period. |
| *LabProd* | Value added per employee (in logs) |
| **FIRM CHARACTERISTICS** | |
| *From 2 to 5 years, From 5 to 10 years, From 10 to 20 years, More than 20 years* | Dummy if the firm operates from 2 to 5 years, from 5 to 10 years, from 10 to 20 years and more than 20 years (reference = less than 2 years) |
| *Employ* | Employees (in logs) |
| **INNOVATION & DIGITALISATION** | |
| *Non-innovative, Innovation firm, Innovation country* | Dummy if the firm does not innovate, has developed an innovation new to the firm or new to the market (reference = global innovator) |
| *R&D* | Share of total R&D investment |
| *Software* | Share of investment in software, data, web and IT. |
| *Training* | Share of investment in training |
| *Fulll digitalisation Partial digitalisation* | Dummy if the firm has adopted fully or partially digital technologies |
| **SECTORS** | |
| *Services, Construction, Infrastructure* | Dummy if the firm belongs to the service sector, construction or infrastructure (reference = manufactures) |
| *CovidNeg, CovidPos* | Dummy identifying sectors at the country level that decreased their turnover by more than 10% or had a positive growth between 2019 and 2020. |
| *DigitSector* | Dummy identifying sectors with a mean expenditure in digitalisation larger than the total average. |
| **OTHER FIRM'S CHARACTERISTICS** | |
| *Salary* | Ratio of wages over employees (in logs) |
| *Subsidiary* | Dummy if the firm is a subsidiary of another firm |
| **EXPECTATIONS** | |
| IntFundsIMP, IntFundsDET<br>ExtFundsIMP, ExtFundsDET<br>BussProspectsIMP,<br>BussProspectsDET<br>EconClimateIMP, EconClimateDET | Dummy if the firm perceives improvement or deterioration of:<br>Availability of internal funds<br>Availability of external funds<br>Business prospects<br>Overall economic climate |
| **COUNTRY DUMMIES are included (UK = reference)** | |

**Table A-2. Main statistics**

| Variable | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|
| HGE | 0.103 | 0.304 | 0 | 1 |
| impact | 0.556 | 0.497 | 0 | 1 |
| impactH | 0.299 | 0.458 | 0 | 1 |
| impactL | 0.556 | 0.497 | 0 | 1 |
| impactN | 0.408 | 0.492 | 0 | 1 |
| impactG | 0.027 | 0.162 | 0 | 1 |
| LTimpact | 0.203 | 0.402 | 0 | 1 |
| LTdigit | 0.418 | 0.493 | 0 | 1 |
| LabProd | 10.212 | 0.895 | 0.799 | 16.731 |
| Full digitalisation | 0.106 | 0.307 | 0 | 1 |
| Partial digitalisation | 0.484 | 0.500 | 0 | 1 |
| CovidNeg | 0. 294 | 0.454 | 0 | 1 |
| CovidPos | 0.253 | 0.435 | 0 | 1 |
| DigitSec | 0.263 | 0.440 | 0 | 1 |
| Non-innovative | 0.563 | 0.496 | 0 | 1 |
| Innovative company | 0.294 | 0.456 | 0 | 1 |
| Innovative country | 0.070 | 0.255 | 0 | 1 |
| Innovative world | 0.073 | 0.260 | 0 | 1 |
| R&D | 0.066 | 0.180 | 0 | 1 |
| Software | 0.129 | 0.225 | 0 | 1 |
| Training | 0.090 | 0.187 | 0 | 1 |
| Less than 2 years | 0.001 | 0.035 | 0 | 1 |
| From 2 to 5 years | 0.031 | 0.173 | 0 | 1 |
| From 5 to 10 years | 0.097 | 0.296 | 0 | 1 |
| From 10 to 20 years | 0.239 | 0.426 | 0 | 1 |
| More than 20 years | 0.632 | 0.482 | 0 | 1 |
| Employ | 3.653 | 1.497 | 0 | 10.820 |
| Salary | 9.958 | 0.884 | 0.799 | 16.766 |
| Subsidiary | 0.157 | 0.364 | 0 | 1 |
| IntFundsIMP | 0.123 | 0.328 | 0 | 1 |
| IntFundsDET | 0.338 | 0.473 | 0 | 1 |
| ExtFundsIMP | 0.203 | 0.402 | 0 | 1 |
| ExtFundsDET | 0.272 | 0.445 | 0 | 1 |
| BussProspectsIMP | 0.188 | 0.391 | 0 | 1 |
| BussProspectsDET | 0.444 | 0.497 | 0 | 1 |
| EconClimateIMP | 0.121 | 0.326 | 0 | 1 |
| EconClimateDET | 0.711 | 0.453 | 0 | 1 |

## Table A-3. Correlation matrix

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) | (19) | (20) | (21) | (22) | (23) | (24) | (25) | (26) | (27) | (28) | (29) | (30) | (31) | (32) | (33) | (34) | (35) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | HGE | 1.00 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 2 | impactH | -0.01 | 1.00 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 3 | impactL | 0.00 | -0.38 | 1.00 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 4 | impactN | 0.00 | -0.54 | -0.49 | 1.00 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 5 | impactG | 0.01 | -0.11 | -0.10 | -0.14 | 1.00 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 6 | LTimpact | -0.02 | 0.32 | 0.18 | -0.42 | -0.08 | 1.00 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 7 | LTdigit | 0.02 | -0.01 | 0.04 | -0.03 | 0.01 | 0.03 | 1.00 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 8 | LabProd | 0.02 | 0.03 | 0.02 | -0.04 | -0.02 | -0.03 | 0.11 | 1.00 | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 9 | Full digitalisation | 0.01 | -0.01 | -0.01 | 0.01 | 0.01 | 0.01 | 0.05 | 0.03 | 1.00 | | | | | | | | | | | | | | | | | | | | | | | | | | |
| 10 | Partial digitzalizaton | 0.05 | -0.03 | 0.04 | -0.01 | 0.00 | -0.01 | 0.13 | 0.14 | 0.00 | 1.00 | | | | | | | | | | | | | | | | | | | | | | | | | |
| 11 | CovidNeg | -0.03 | 0.09 | 0.00 | -0.09 | -0.02 | 0.11 | -0.03 | -0.02 | -0.01 | 0.02 | 1.00 | | | | | | | | | | | | | | | | | | | | | | | | |
| 12 | CovidPos | 0.01 | -0.10 | 0.01 | 0.07 | 0.04 | -0.07 | 0.03 | -0.01 | 0.03 | 0.01 | -0.38 | 1.00 | | | | | | | | | | | | | | | | | | | | | | | |
| 13 | DigitSec | -0.01 | -0.08 | 0.01 | 0.07 | -0.01 | -0.08 | 0.06 | 0.09 | 0.09 | 0.07 | -0.24 | 0.16 | 1.00 | | | | | | | | | | | | | | | | | | | | | | |
| 14 | Non-innovative | -0.04 | -0.02 | -0.02 | 0.05 | -0.04 | -0.02 | -0.12 | -0.09 | -0.08 | -0.15 | 0.03 | -0.02 | -0.10 | 1.00 | | | | | | | | | | | | | | | | | | | | | |
| 15 | Inno.company | 0.03 | 0.03 | 0.03 | -0.06 | 0.03 | 0.03 | 0.06 | 0.05 | -0.01 | 0.06 | -0.01 | -0.01 | 0.02 | -0.73 | 1.00 | | | | | | | | | | | | | | | | | | | | |
| 16 | Innov.country | 0.01 | 0.00 | -0.02 | 0.01 | 0.01 | -0.01 | 0.03 | -0.01 | 0.08 | 0.07 | -0.03 | 0.05 | 0.07 | -0.31 | -0.18 | 1.00 | | | | | | | | | | | | | | | | | | | |
| 17 | Innovative world | 0.02 | 0.01 | 0.00 | -0.01 | 0.02 | 0.00 | 0.08 | 0.09 | 0.08 | 0.11 | -0.02 | 0.01 | 0.10 | -0.32 | -0.18 | -0.08 | 1.00 | | | | | | | | | | | | | | | | | | |
| 18 | R&D | 0.04 | 0.01 | 0.00 | -0.01 | 0.02 | -0.02 | 0.06 | 0.11 | 0.12 | 0.12 | -0.03 | 0.05 | 0.11 | -0.27 | 0.05 | 0.11 | 0.31 | 1.00 | | | | | | | | | | | | | | | | | |
| 19 | Software | -0.04 | 0.04 | 0.01 | -0.04 | -0.02 | 0.00 | 0.07 | 0.06 | 0.06 | 0.02 | -0.07 | 0.07 | 0.12 | -0.01 | 0.01 | 0.01 | -0.02 | -0.07 | 1.00 | | | | | | | | | | | | | | | | |
| 20 | Training | -0.02 | 0.04 | -0.02 | -0.01 | -0.01 | 0.04 | 0.00 | 0.03 | 0.01 | -0.04 | 0.00 | 0.03 | 0.01 | 0.07 | -0.04 | -0.02 | -0.04 | -0.07 | 0.02 | 1.00 | | | | | | | | | | | | | | | |
| 21 | Less than 2 years | 0.00 | 0.00 | -0.01 | 0.00 | 0.02 | -0.01 | 0.02 | 0.01 | 0.00 | 0.03 | 0.01 | -0.02 | -0.01 | 0.00 | -0.01 | -0.01 | 0.02 | 0.01 | 0.00 | 0.01 | 1.00 | | | | | | | | | | | | | | |
| 22 | From 2 to 5 years | 0.02 | 0.00 | -0.02 | 0.01 | 0.01 | -0.01 | -0.01 | -0.10 | 0.02 | -0.03 | -0.02 | 0.01 | -0.02 | 0.00 | 0.00 | 0.01 | 0.00 | 0.03 | -0.02 | 0.01 | -0.0 | 1.00 | | | | | | | | | | | | | |
| 23 | From 5 to 10 years | 0.09 | 0.02 | -0.03 | 0.00 | 0.02 | 0.01 | -0.04 | -0.10 | 0.02 | -0.02 | 0.00 | 0.02 | -0.03 | 0.01 | 0.01 | -0.01 | -0.03 | 0.00 | -0.01 | 0.02 | -0.0 | -0.06 | 1.00 | | | | | | | | | | | | |
| 24 | 10 to 20 years | 0.05 | -0.02 | -0.01 | 0.02 | 0.01 | 0.00 | -0.04 | -0.08 | 0.01 | -0.04 | -0.03 | 0.04 | 0.01 | 0.01 | -0.03 | 0.03 | -0.02 | 0.01 | 0.01 | 0.01 | -0.0 | -0.10 | -0.18 | 1.00 | | | | | | | | | | | |
| 25 | More than 20 y. | -0.10 | 0.01 | 0.03 | -0.02 | -0.03 | -0.01 | 0.06 | 0.17 | -0.03 | 0.06 | 0.03 | -0.05 | 0.02 | -0.02 | 0.02 | -0.03 | 0.03 | -0.02 | 0.01 | -0.03 | -0.0 | -0.23 | -0.43 | -0.73 | 1.00 | | | | | | | | | | |
| 26 | Employ | 0.13 | -0.07 | 0.12 | -0.04 | 0.00 | 0.01 | 0.11 | 0.11 | 0.04 | 0.21 | 0.04 | -0.07 | 0.02 | -0.11 | 0.04 | 0.03 | 0.10 | 0.04 | -0.12 | -0.10 | 0.00 | -0.09 | -0.15 | -0.15 | 0.26 | 1.00 | | | | | | | | | |
| 27 | Salary | 0.00 | 0.05 | 0.03 | -0.06 | -0.03 | 0.00 | 0.13 | 0.88 | 0.02 | 0.14 | 0.01 | -0.02 | 0.07 | -0.08 | 0.04 | -0.02 | 0.09 | 0.12 | 0.06 | 0.04 | 0.00 | -0.08 | -0.10 | -0.10 | 0.18 | 0.11 | 1.00 | | | | | | | | |
| 28 | Subsidary | 0.02 | -0.03 | 0.06 | -0.03 | -0.01 | 0.00 | 0.08 | 0.20 | 0.06 | 0.10 | 0.00 | -0.02 | 0.03 | -0.06 | 0.02 | 0.01 | 0.06 | 0.05 | -0.02 | 0.00 | 0.00 | -0.01 | -0.03 | -0.05 | 0.07 | 0.28 | 0.21 | 1.00 | | | | | | | |
| 29 | IntFundsIMP | 0.05 | -0.01 | -0.04 | 0.02 | 0.06 | -0.07 | 0.01 | -0.01 | 0.04 | 0.03 | -0.02 | 0.00 | 0.02 | -0.05 | 0.01 | 0.04 | 0.03 | 0.05 | -0.01 | -0.01 | 0.01 | 0.04 | -0.01 | 0.03 | -0.04 | -0.01 | -0.02 | -0.01 | 1.00 | | | | | | |
| 30 | IntFundsDET | -0.03 | 0.15 | 0.06 | -0.18 | -0.05 | 0.24 | 0.02 | -0.08 | -0.01 | -0.01 | 0.09 | -0.03 | -0.06 | -0.01 | 0.01 | 0.00 | 0.01 | -0.01 | 0.00 | 0.01 | 0.00 | -0.02 | 0.03 | 0.00 | -0.01 | -0.02 | -0.03 | -0.05 | -0.27 | 1.00 | | | | | |
| 31 | ExtFundsIMP | 0.04 | 0.04 | -0.02 | -0.03 | 0.01 | -0.02 | 0.02 | -0.04 | 0.02 | 0.03 | 0.01 | -0.03 | 0.01 | -0.06 | 0.05 | 0.01 | 0.02 | 0.05 | 0.03 | -0.01 | 0.01 | 0.03 | 0.00 | 0.03 | -0.04 | -0.02 | -0.04 | -0.02 | 0.28 | -0.09 | 1.00 | | | | |
| 32 | ExtFundsDET | 0.00 | 0.04 | 0.03 | -0.06 | -0.03 | 0.12 | 0.04 | -0.04 | 0.01 | 0.00 | 0.01 | 0.01 | -0.03 | -0.02 | -0.01 | 0.03 | 0.02 | 0.00 | 0.00 | 0.01 | -0.0 | 0.00 | 0.03 | 0.01 | -0.02 | -0.04 | -0.02 | -0.01 | -0.13 | 0.30 | -0.31 | 1.00 | | | |
| 33 | BussProspectsIMP | 0.05 | 0.00 | -0.04 | 0.01 | 0.07 | -0.08 | 0.03 | -0.02 | 0.04 | 0.02 | -0.03 | 0.01 | 0.03 | -0.06 | 0.02 | 0.03 | 0.05 | 0.06 | 0.00 | 0.04 | 0.00 | 0.05 | 0.03 | 0.02 | -0.05 | -0.02 | -0.02 | 0.03 | 0.28 | -0.17 | 0.19 | -0.10 | 1.00 | | |
| 34 | BussProspectsDET | -0.03 | 0.11 | 0.08 | -0.16 | -0.05 | 0.23 | 0.02 | 0.02 | -0.02 | 0.01 | 0.11 | -0.04 | -0.07 | -0.01 | 0.03 | -0.02 | -0.01 | -0.01 | 0.03 | -0.01 | 0.00 | -0.03 | -0.01 | -0.03 | 0.04 | 0.01 | 0.03 | 0.00 | -0.20 | 0.35 | -0.11 | 0.19 | -0.43 | 1.00 | |
| 35 | EconClimateIMP | 0.01 | 0.01 | -0.01 | -0.01 | 0.03 | -0.05 | -0.01 | -0.02 | 0.02 | 0.00 | 0.01 | -0.01 | -0.01 | -0.02 | -0.01 | 0.01 | 0.03 | 0.03 | -0.02 | 0.00 | 0.01 | 0.04 | 0.00 | 0.00 | -0.02 | -0.01 | -0.02 | 0.02 | 0.26 | -0.14 | 0.17 | -0.11 | 0.40 | -0.25 | 1.00 |
| 36 | EconClimateDET | -0.02 | 0.05 | 0.03 | -0.07 | -0.02 | 0.13 | 0.07 | 0.07 | 0.00 | 0.05 | 0.02 | -0.01 | 0.01 | -0.03 | 0.02 | 0.01 | 0.00 | 0.00 | 0.04 | 0.00 | 0.00 | -0.03 | -0.01 | -0.04 | 0.06 | 0.03 | 0.07 | 0.02 | -0.21 | 0.24 | -0.13 | 0.18 | -0.31 | 0.39 | -0.58 |

**ECONOMICS** – WORKING PAPERS 2022/13

# COVID-19 and the resilience of European firms

## The influence of pre-crisis productivity, digitalisation and growth performance


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