Productivity and HGEs: resilience and recovery from the COVID-19 pandemic

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ABSTRACT:

The impact of crises on firm performance has been studied widely. This paper explores the relationship between firms' reaction to COVID-19 (in employment) and the adoption of digital technologies, taking into account their productivity, digitalisation level and high-growth episodes before the crisis. We match the EIB Group Survey of Investment and Investment Finance with ORBIS database for 27 EU Member States and the United Kingdom. We find that firms with higher productivity levels are less prone to decrease the number of employees in the short and long term due to the pandemic. High-growth enterprises are less likely to expect a reduction in the number of employees in the long term. Moreover, firms in highly digitalised sectors have a lower probability to reduce the number of employees. Finally, our results suggest that COVID-19 leads firms to increase their use of digital technologies, especially those that were already more digitalised.

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1. Introduction

There exists a sizeable economic literature focusing on the cleansing effect of economic crises (Caballero and Hammour, 1994; Dosi et al., 2000, 2012; Osotimehin and Pappadà, 2017; Bugamelli et al., 2018). The exogenous nature of the COVID-19 shock provides an opportunity to investigate its potentially heterogeneous impact on firms depending, taking into account e.g. their productivity level or their past growth performance (Flachenecker et al., 2020; Benedetti Fasil et al., 2021; Muzi et al., 2022). Moreover, the unexpected COVID-19 pandemic caused operational and organisational disruptions, forcing firms to apply new organisational strategies through digitalisation (Apedo-Amah et al., 2020) such as introducing remote working arrangements, using 3-D printing to produce parts affected by supply chain disruptions, and implementing 'big data' analytics and artificial intelligence (EIB, 2021).

As such, the COVID-19 pandemic allows us to explore which firms have deepened their digitalisation level, and to which extent, as a reaction to this new economic reality. Several reasons support the claim that firms that had adopted certain digital technologies were more resilient to the COVID-19 shock. First, COVID-19 was an asymmetric supply and demand shock that affected contact-intensive businesses more than sectors where firms relied more on digital business models (Benedetti-Fasil et al., 2021). Second, evidence shows that digital adoption exerts a positive effect on productivity (Falk and Hagsten, 2015) and on the development of technological innovations (Hempell and Zwick, 2008) which might allow digitalised firms to react faster and better to adverse shocks than non-digitalised firms.

Our research addresses these broad questions. First, we evaluate how pre-COVID 19 productivity affected firms' actual (i.e. short-term) and expected (i.e. long-term) changes in employment levels. Secondly, we investigate whether (and to what extent) the COVID-

19 crisis has increased firms' propensity to increase their digitalisation activities. Thirdly, we analyse whether the subgroup of high-growth enterprises (henceforth HGEs) reacted differently to COVID-19. Our main database is the European Investment Bank Group Survey of Investment and Investment 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 data of the EIBIS 2020 wave which was conducted between March and May in 2020. Our sample includes standard variables (e.g. firms' employment, turnover, investment and investment finance), as well as questions about the firms' responses and expectations in relation to COVID-19 along several dimensions (e.g. about employment). Using this dataset, as a first step, we apply coarsened exact matching (CEM) to enhance the comparability between firms that were hit negatively by COVID-19 pandemic and those that were not. To investigate our hypotheses, we apply cross-sectional probit regressions.

Using firms' reported adjustments in employment levels as a proxy for the reaction to COVID-19, we find that more productive firms are less prone to reduce their workforce due to the COVID-19 pandemic. Conversely, HGEs' short-term response concerning employment is not different from that of other firms, but in the long term, they are less likely to reduce the number of employees in comparison to non-HGEs. Hence, rapid-growth episodes were not enough to ensure resilience in terms of employment during COVID-19, but this result is mainly driven by the innovative nature of HGEs. When analysing the long-term impact of COVID-19 on digitalisation, we find that already-digitalised firms are more likely to continue their digitalisation activities due to the pandemic compared to non-digitalised firms. Finally, at sectoral level firms in highly digitalised sectors are less likely to reduce their employment.

This study contributes to the strand of literature that analyses how firms with heterogeneous productivity levels react to an unexpected shock such as the COVID-19 pandemic (Bloom et al., 2021; Andrews et al., 2021a, 2021b; Van den Bosch and Vanormelingen, 2022; Muzi et al., 2022). 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 negative 'within-firm' and positive 'between-firm' productivity effects due to the contraction of less productive sectors, and of less productive firms (Bloom et al., 2021). This means that at the aggregate level, the increasing weight of more productive firms mitigated the effect of the general decline in firm-level productivity. Other studies of COVID-19 show that high-productivity firms were more successful in maintaining their employment levels (Kozeniauskas et al., 2022) and surviving (Muzi et al., 2022). Our results confirm a larger resilience of more productive firms during the crisis, particularly in the long term. Lastly, we contribute to the literature on the adjustment of HGEs during crises (Flachenecker et al., 2021).

In the European Union, targeted policy measures support the development of HGEs (Flachenecker et al., 2020) as well as supporting productivity and innovation (European Commission, 2021, 2022). Such efforts could be jeopardised by the COVID-19 pandemic. Our analysis shows that high-productivity firms are less likely to decrease their employment in the long term, hence confirming the importance of increasing the productivity level of low-productivity firms, especially in countries with many firms far from the technological frontier. Finally, policymakers have promoted digitalisation due to its potential to transform industries (EIB, 2021). Our results suggest that the digitalisation gap between firms that already adopted digital technologies and those that did not may widen due to COVID-19.

The paper proceeds as follows. The next section reviews the main theoretical and empirical works and describes our main hypotheses. Section 3 describes our data and the key variables. Section 4 outlines the empirical methodology, while Section 5 presents our main estimation results. Finally, Section 6 concludes and discusses the policy implications.

2. Literature review and hypotheses

2.1. COVID-19 and employment

Some theoretical models of managerial incentives and competition argue that productivity should converge during economic downturns. On the one hand, the reduced margins pose a threat of liquidation for less efficient firms (Schmidt, 1997) forcing them to adjust. Moreover, a crisis lowers the opportunity cost of adjusting production (Hall, 2005), and shifts managers' attention from growth to efficiency (Koenders and Rogerson, 2005) due to higher bankruptcy risks and changes in the costs of layoffs (Mortensen and Pissarides, 1994; Berger, 2012). On the other hand, downturns alter the incentives for a firm to invest in its employees' human capital due to the shift to efficiency (Jaimovich and Siu, 2012).

However, there is also empirical evidence that crises do not necessarily lead to productivity convergence (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 the 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 et al., 2022), e.g. due to financial constraints or bargaining problems that alter the process of creative destruction (Hadlock and Pierce, 2010; Foster et al., 2016; Harris and Moffat, 2016). For instance, due to their lack of collateral and experience, financial constraints may be more binding for younger and smaller firms, in spite of them being potentially more innovative. COVID-19 may have exerted a reallocation of employment towards more productive firms. Bloom et al. (2021) find a positive "between" effect that includes two channels – low-productivity sectors shrank, and the least productive firms within these sectors declined most- while there is a negative "within" effect since firms had higher operating costs during the pandemic. High-productivity firms were more successful at maintaining employment during the COVID-19 pandemic (Kozeniauskas et al., 2022), and they were less likely to exit the market (Muzi et al., 2022). Therefore, our first hypothesis posits that:

Hypothesis 1a: Firms that were more productive before the pandemic were less likely to reduce their employment in the short and long term due to the COVID-19 shock.

Similarly, HGEs are younger, smaller, more innovative and more internationalised than non-HGEs (Moreno and Coad, 2015). Mason (2020) shows that HGEs were significantly more affected by the COVID-19 crisis due to their dependence on venture capital, whose number of deals dropped during the initial phase of the pandemic. However, Flachenecker et al. (2021) show that HGEs continued to contribute significantly to economic activity during the global financial crisis, and this is true especially for larger HGEs. Their results highlight the potentially heterogeneous impact of a crisis on HGEs, but generally support the view that HGEs boost overall economic recovery thanks to their employment generation capacity. Hence, our hypothesis is as follows:

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 varied across sectors. Whereas firms in sectors such as tourism or hospitality have endured steep sales drops, digitalised sectors such as online-retailers have flourished (Benedetti-Fasil et al., 2021). Additionally, digitalised and innovative firms have a higher survival probability post-COVID (Muzi et al., 2022). The main reason is that digital technologies facilitate the development of technological innovations which facilitate the emergence of HGEs (Hempell and Zwick, 2008). This is confirmed by Benedetti-Fasil et al. (2021), who show that firms with high-growth expectations value digitalization as a driver for their growth process more than firms with lower growth expectations. As such, we posit that the degree of digitalisation (at the firm-level and the sectoral-level) provided firms with valuable flexibility which enabled them to adjust to the new economic conditions more rapidly, and thus helped to mitigate the negative employment effect. Therefore, our hypotheses are:

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

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

Crises offer an opportunity to deploy New Digital Technologies[1] (NDTs) across a wider range of products and services and accelerate technological transformation (Hershbein and Kahn, 2018).[2] The COVID-19 pandemic has caused firms to reorient their digital strategy (Pantano et al., 2020; Ebersberger and Kuckertz, 2021), possibly with long-lasting consequences (Apedo-Amah et al., 2020).

The adoption of digital technologies can be hampered by the lack of incentives and capabilities at the firm-level that subsequently slows down a broad diffusion of technology and knowledge (Andrews et al., 2018). However, more productive firms with

[1] We consider the following digital technologies as NDT: 3D printing, Augmented/virtual reality, advanced robotics, big data/artificial intelligence, drones, digital platforms, internet of things.

[2] Marques Santos et al. (2021) report evidence on how the innovation process has changed between the pre-COVID period and during 2020. 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.

previous investments in intangible assets and digitalisation tend to accumulate tacit knowledge that allows them to implement existing technologies and innovations more easily than less-productive firms. In this context, HGEs tend to be on average more digitalised than non-HGEs (Teruel et al., 2022, figure 4c).

Therefore, we posit that:

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

The adoption of NDTs can unleash winner-takes-all dynamics through lower marginal costs and easier upscaling (Brynjolfsson and McAfee, 2011; Bartelsman et al., 2015). Furthermore, globalization fosters the global nature of frontier firms that increase the returns to investing in non-rival technologies via expanded market size (Acemoglu and Linn, 2004). Moreover, firms in more technological and knowledge-intensive sectors have a higher capacity to develop technological innovations, since they are also more successful in combining diverse intangible assets in their production processes. Therefore, we may expect that firms that are more digitalised, or that are operating in highly digitalised sectors, already have obtained digital competencies that make them more likely to continue investing in these NDTs after the COVID-19 pandemic.

Based on these reflections, we propose two distinct hypotheses:

> **Hypothesis 2b:** Firms (including HGEs) in more digitalised sectors are more likely 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.

3. Databases and descriptive statistics

3.1. Databases

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. The survey covers the 27 EU Member States and the UK and produce a representative sample of firms 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.[3] 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 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; we use only a subset of this information). 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 the sector and country levels. This information allows us to estimate the annual sales growth per sector, and to categorize the sectors according to their change in turnover, i.e. i) if they are declining (a drop of sales superior to -10%), ii) intermediate (drop between -10% and 0%), or iii) growing (positive growth of over

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

0%). In the second step, we classify individual firms according to these three different sectoral categories. In case of a lack of information for a particular sector and country, we consider the European average for this sector.

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 at least 10 employees at the beginning of the growth period.[4] EIBIS compiles most information from the previous financial year. Therefore, in 2020, variables such as labour productivity and HGE status, 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 focus on the cross-section of firms of the EIBIS 2020 wave.

In order 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. 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 reduction 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 reduction 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) a

[4] 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).

negligible decrease if the firm responded that the employees did not decrease; 4) and, finally, positive growth if it increased its workforce.

In order 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 COVID-19 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.

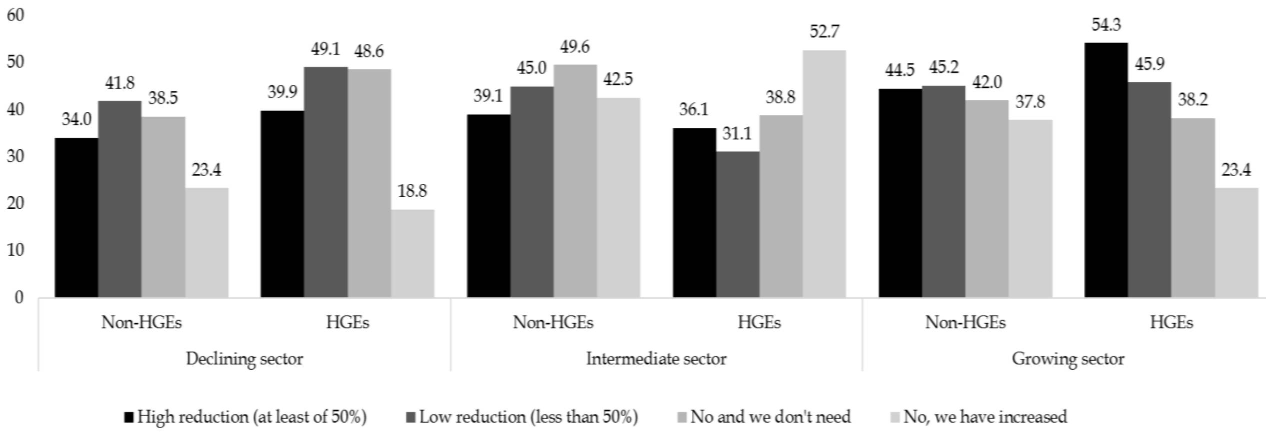
The EIBIS database allows to further define three sets of variables related to digitalisation. The first set considers (as three separate variables) the firm's share of investment in software and IT networks and website activities. The second is based on a firm's level of digitalisation, using a dummy variable to capture either i) partial or ii) full digital adoption.[5] 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.*

3.3. Descriptive statistics

In the following, we provide a short overview of some key descriptive statistics. We start by analysing how both HGEs and non-HGEs have adjusted (or planned to adjust) their workforce due to the COVID-19 shock, and how this relates to their level of productivity.

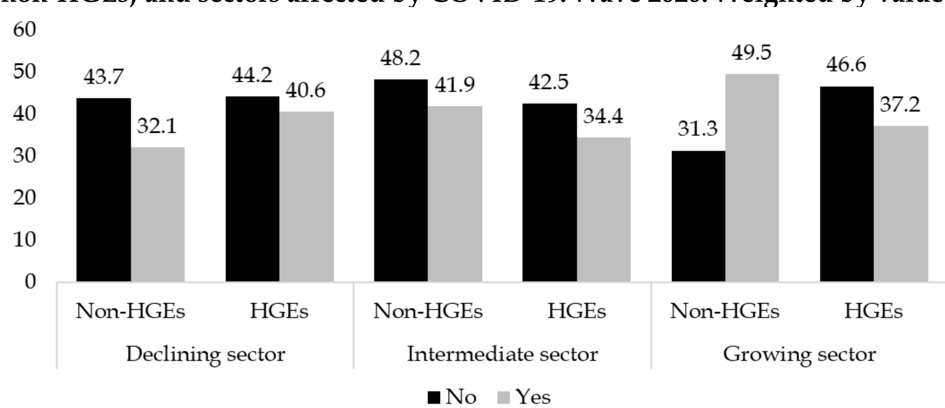
[5] Partial and total digitalisation refers to firms that have implemented in parts of the business or entirely a particular digital technology, respectively. Digital technologies are 3D printing, robots, internet of things, cognitive technologies, drones, augmented or virtual reality and platform technologies.

Graph 1. **Average labour productivity expressed in thousands of euros (year 2019) according to short-term crisis adjustment. Classification according to HGEs (and non-HGEs) and sectors affected by COVID-19. Wave 2020. Weighted by value added.**



Concerning the relationship between the short-term reaction to the COVID-19 crisis and labour productivity (graph 1), firms belonging to growing sectors have higher productivity in comparison with those in declining sectors. Second, in general, HGEs are more productive than non-HGEs, except HGEs that belong to intermediate sectors that show a relatively lower productivity. Finally, firms that have increased the number of employees generally exhibit lower average productivity levels.

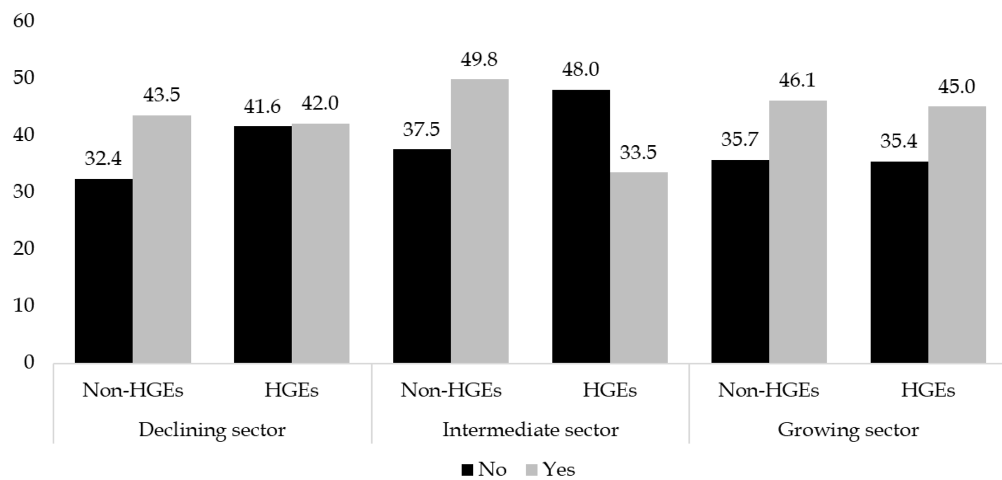
Graph 2. Average labour productivity expressed in thousands of euros (year 2019) according to the expected long-term employment reduction due to COVID-19. Classification according to HGEs (and non-HGEs) and sectors affected by COVID-19. Wave 2020. Weighted by value added.



Concerning the long term (graph 2), firms that expect to reduce their employment in the long term tend to have lower labour productivity levels, with the exception of non-HGEs operating in growing sectors. Finally, labour productivity in growing sectors is larger than in declining sectors.

Our analysis of digitalisation expectations (graph 3) shows that firms declaring to intensify their use of NDTs in the long term have higher productivity levels. However, HGEs in sectors less affected by the pandemic exhibit lower productivity. Finally, non-HGEs expecting to digitalise more in the long term are the most productive. To sum up, the preliminary results seem to indicate a certain technological "neo-dualism" since higher productivity correlates with a long-term digitalisation plan.

Graph 3. Average labour productivity expressed in thousands of euros (year 2019) according to the long-term digitalisation expectations of firms. Classification according to HGEs (and non-HGEs) and sectors affected by COVID-19. Wave 2020. Weighted by value added.



4. Econometric framework

This section presents the econometric methodology to test our hypotheses, in particular focusing on firm-level adjustments in the context of the COVID-19 pandemic, both in the short and long term, according to productivity levels, digitalisation activities and growth episodes.

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 technique that establishes a covariate balance between treated and control units, in an attempt to create a valid counterfactual group. This methodology selects firms with relatively similar characteristics from among two groups: those that have reacted to the COVID-19 crisis by reducing their employment, and those that have not.[6]

Our baseline equation is the following:

$$\begin{aligned} Prob(y)_{i,t} = \alpha_1 + \beta_1 HGE_{it-1} + \beta_2 LabProd_{it-1} + \beta_3 DigitSector_{it-1} + \cdots \\ \ldots + \beta_4 full\_digit_{it-1} + \beta_5 partial\_digit_{it-1} + x_{it-1}\beta_6 + \epsilon_{1i,t} \end{aligned} \qquad (1)$$

where the dependent variable y refers to different dummies that capture the firm-level adjustment due to COVID-19:

- For the short term: i) *impactHL* takes the value of 1 for the group of firms that reported a high reduction in employment (i.e. more than 50% of the staff) and 0 for firms with a moderate impact (less than a 50% of the staff); ii) *impactLN* is equal to one if firms registered a moderate impact and 0 for firms that declared to not have reduced their workforce nor expect to do so; iii) *impactNG* is equal to 1 if firms did not change their workforce and do not expect to do it, and equal to 0 in case of actual employment growth.
- For the long term: i) *LTimpact* identifies firms that expect to reduce their workforce due to COVID-19; and ii) *LTdigit* indicates if the firm will continue the digitalisation process.

[6] Non-observable characteristics of firms that reacted to the COVID-19 pandemic may differ from those which did not adjust the number of employees to overcome the pandemic in the short-term. This can cause a coefficient bias in the results. Matching methods may partially mitigate this issue since the individual L1 distance for each variable shows a quite similar structure across variables (see online Appendix). The overall L1 distance is equal to 0.6688 showing the existence of a joint distribution, which is not perfectly balanced (L1 takes values between 0, indicating a full balance, and 1, indicating an imbalance).

Our key variables are:

- *HGE* identifies high-growth enterprises between the years 2017-2019
- *LabProd* as the log labour productivity
- *DigitSector* is a dummy variable that identifies those sectors with a higher investment per worker in *Software, data, IT networks and website activities*
- *full_digit* and *partial_digit* are dummies identifying if firms have adopted fully or partially NDTs

x is a set of explanatory variables, β are the estimated coefficients and ε_i are the random errors. All equations include control variables such as firm size and age and a dummy identifying if the firm is a subsidiary. Additionally, a set of variables captures the intangible assets accumulated such as the degree of innovativeness and the share of investment in R&D, software and training. We include country and sector dummies with the only exception of those equations that include the variable *Digitsector*.

Finally, 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 year 2020 and their 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. Furthermore, our estimation regarding long-term digitalisation expectations as a reaction to the COVID-19 crisis includes the previous level of digitalisation (partial or full level). Finally, we include the HGE dummy in lags in order to mitigate endogeneity concerns. [7]

Our hypotheses (1a, 1b, 1c, 1d, 2a, 2b and 2c) are tested by estimating a probit econometric model using robust standard errors, using only the EIBIS 2020 data.

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

5. Results

5.1. Firms' short-term employment adjustment due to COVID-19

First, we disentangle the short-term response of the COVID-19 crisis on employment, testing hypotheses 1a, 1b, 1c and 1d. Table 2 displays the results for the probability of showing a high decrease versus a low decrease (columns 1-4), a low decrease versus a negligible decrease (columns 5–8), and a negligible decrease versus positive growth (columns 9– 12).

The main results are the following. First, more productive firms are less likely to reduce employment in comparison with those firms with a negligible reduction (columns 5-8). Our results are in line with those of Bloom et al. (2021), Andrews et al. (2021a, 2021b) and Kozeniauskas et al. (2022) who find that low-productive firms reduce the number of employees or even disappear during crises. Our results confirm partially hypothesis 1a since the productivity level may condition the response to COVID-19, and produce a certain cleansing effect. However, the shock of COVID-19 had a sectoral nature which affected many firms regardless of their productivity level.

Second, being an HGE in the year 2019 does not have a significant relationship with changes in the workforce during the COVID-19 crisis (i.e. in the subsequent year 2020). Concerning the relationship between high-growth spurts and labour productivity, our results show that the interaction term between HGEs and labour productivity is only positively and significantly related to the likelihood of increasing the number of employees during the pandemic (columns 10-11). Therefore, we partially confirm hypothesis 1b for the short term, while taking into account productivity levels.

Firms in sectors that actually displayed a positive growth during COVID-19 have a lower probability of a large employment reduction (columns 1-2). Interestingly, this sectoral classification does not seem to influence the other two remaining response categories, i.e. moderate versus negligible decrease and negligible decrease versus growth.

Table 2. Probability of having a high versus moderate reduction, a moderate versus a negligible reduction or a negligible reduction versus a positive growth in the short-term due to COVID-19 pandemic. Matched sample. Wave 2020.

	High vs. low decrease (Probability of having reduced a high reduction in comparison with a low reduction)				Low vs. negligible decrease (Probability of having a low reduction in comparison with a negligible reduction)				Negligible decrease vs. Growth (Probability of having a negligible decrease in comparison with growing)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
HGE_{t-1}	0.007	-0.014	-0.001	0.013	-0.035	-0.201	-0.214	-0.037	0.023	-2.982**	-3.038**	0.024
	[0.070]	[0.855]	[0.854]	[0.070]	[0.066]	[0.802]	[0.800]	[0.066]	[0.128]	[1.421]	[1.418]	[0.128]
$LabProd_{t-1}$	-0.036	-0.036	-0.039	-0.038	-0.056*	-0.057*	-0.058*	-0.056*	0.020	-0.008	-0.010	0.016
	[0.036]	[0.037]	[0.036]	[0.035]	[0.031]	[0.032]	[0.032]	[0.031]	[0.072]	[0.074]	[0.074]	[0.071]
HGE_{t-1}×$LabProd_{t-1}$		0.002	0.001			0.016	0.018			0.294**	0.300**	
		[0.082]	[0.082]			[0.077]	[0.077]			[0.140]	[0.140]	
$CovidNeg_{t-1}$	-0.088	-0.088			-0.073	-0.073			0.205	0.198		
	[0.070]	[0.070]			[0.068]	[0.068]			[0.167]	[0.168]		
$CovidPos_{t-1}$	-0.183***	-0.183***			0.054	0.054			-0.027	-0.030		
	[0.066]	[0.066]			[0.058]	[0.058]			[0.122]	[0.121]		
$DigitSec_{t-1}$			-0.523				1.346*				-1.486*	
			[0.808]				[0.748]				[0.819]	
Full $digitalisation_{t-1}$				0.050				-0.095				0.094
				[0.072]				[0.067]				[0.140]
Partial $digitalisation_{t-1}$				-0.026				0.042				-0.017
				[0.044]				[0.043]				[0.092]
Innovation $company_{t-1}$	-0.092*	-0.080	-0.092*	-0.087*	0.010	0.047	0.008	0.006	-0.176*	-0.221	-0.168*	-0.171*
	[0.048]	[0.094]	[0.048]	[0.048]	[0.046]	[0.092]	[0.046]	[0.046]	[0.098]	[0.216]	[0.097]	[0.097]
Innovation $country_{t-1}$	0.020	0.033	0.010	0.011	0.126	0.163	0.126	0.127	0.222	0.200	0.245	0.216
	[0.101]	[0.128]	[0.101]	[0.102]	[0.093]	[0.119]	[0.093]	[0.094]	[0.202]	[0.265]	[0.205]	[0.202]
Global $Innovation_{-1}$	-0.012		-0.009	-0.005	-0.037		-0.039	-0.035	0.033		0.048	0.023
	[0.094]		[0.094]	[0.095]	[0.091]		[0.091]	[0.091]	[0.221]		[0.224]	[0.223]
$R\&D_{t-1}$	0.118	0.118	0.118	0.120	-0.030	-0.031	-0.032	-0.028	-0.303	-0.330	-0.330	-0.302
	[0.140]	[0.140]	[0.140]	[0.140]	[0.132]	[0.132]	[0.132]	[0.132]	[0.238]	[0.237]	[0.236]	[0.237]
$Software_{t-1}$	-0.074	-0.074	-0.069	-0.063	0.273***	0.273***	0.271***	0.266***	0.102	0.102	0.091	0.088
	[0.095]	[0.095]	[0.095]	[0.095]	[0.093]	[0.093]	[0.093]	[0.0930	[0.224]	[0.226]	[0.228]	[0.226]
$Training_{t-1}$	0.071	0.071	0.067	0.071	-0.002	-0.002	0.002	0.001	0.498*	0.480*	0.478*	0.497*
	[0.110]	[0.11]	[0.110]	[0.111]	[0.105]	[0.105]	[0.104]	[0.104]	[0.262]	[0.262]	[0.264]	[0.263]
Constant	1.349*	1.339*	1.421*	1.416*	-0.190	-0.213	-0.178	-0.191	-1.492	-0.988	0.658	-1.251
	[0.731]	[0.745]	[0.735]	[0.732]	[0.624]	[0.633]	[0.628]	[0.627]	[1.085]	[1.106]	[0.984]	[1.073]
Pseudo-R^2	0.144	0.144	0.1439	0.12	0.093	0.093	0.093	0.077	0.173	0.176	0.174	0.132
Observations	4,210				5,215				3,088			

*Notes: *** p<0.01, ** p<0.05, * p<0.1 Robust standard errors. Age, Size, country, sector and expectation dummies are included.*

Finally, firms in more digitalised sectors were less likely to remain in the same employment size during the first months of the COVID-19 pandemic, as they had a higher probability to increase or decrease their size slightly (columns 11 and 7, respectively). Hence, we partially confirm hypothesis 1c. Conversely, we are not able to confirm hypothesis 1d, since the estimated coefficient of being more digitalised (in terms of NDT, i.e. full/partial digitalisation) is not significantly correlated with the probability to reduce the number of employees in the short term at conventional levels of statistical significance. Therefore, our results show that the adjustment to the COVID-19 shock has varied according to the degree of sectoral digitalisation.

5.2. The long-term response to COVID-19

The following subsection describes the results regarding the expected long-term response in terms of employment adjustment and digitalisation efforts due to COVID-19 (hypotheses 1a-1d and 2a-2c). Table 3 displays the main results for the expected long-term employment reduction due to the COVID-19 crisis. Clearly, we confirm hypothesis 1a, since the estimated coefficient for productivity is significant and negative. Therefore, more productive firms 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 more productive firms regard themselves as being more resilient to the COVID-19 crisis in terms of avoiding negative employment effects.

Table 3. Determinants of the probability of the long-term expected negative employment decrease. Matched sample. Wave 2020.

	(1)	(2)	(3)	(4)	(5)
HGE_{t-1}	-0.065 [0.062]	-0.384 [0.727]	-0.066 [0.062]	-0.053 [0.061]	-0.065 [0.062]
$LabProd_{t-1}$	-0.055* [0.029]	-0.058* [0.030]	-0.055* [0.029]	-0.087*** [0.028]	-0.056* [0.029]
$HGE_{t-1} \times LabProd_{t-1}$		0.031 [0.070]			
$CovidNeg_{t-1}$			-0.018 [0.060]		
$CovidPos_{t-1}$			-0.042 [0.058]		
$DigitSector_{t-1}$				-0.121** [0.048]	
Full digital $adoption_{t-1}$					0.037 [0.062]
Partial digital $adoption_{t-1}$					0.009 [0.039]

Innovation company$_{t-1}$	-0.020 [0.042]	-0.019 [0.042]	-0.019 [0.042]	-0.022 [0.041]	-0.020 [0.042]
Innovation country$_{t-1}$	0.057 [0.087]	0.056 [0.087]	0.058 [0.087]	0.042 [0.085]	0.052 [0.087]
Global Innovation$_{t-1}$	-0.069 [0.084]	-0.069 [0.084]	-0.070 [0.084]	-0.100 [0.082]	-0.072 [0.084]
R&D$_{t-1}$	-0.013 [0.126]	-0.014 [0.126]	-0.013 [0.126]	-0.078 [0.122]	-0.016 [0.126]
Software$_{t-1}$	0.028 [0.084]	0.027 [0.084]	0.027 [0.084]	-0.030 [0.083]	0.030 [0.084]
Training$_{t-1}$	0.228** [0.091]	0.228** [0.091]	0.229** [0.091]	0.242*** [0.088]	0.229** [0.091]
Constant$_t$	-0.976 [0.657]	-0.949 [0.661]	-0.984 [0.657]	0.051 [0.307]	-0.964 [0.656]
Pseudo-R^2	0.1602	0.143	0.160	0.142	0.160
Observations	7,660				

*Notes: *** p<0.01, ** p<0.05, * p<0.1 Robust standard errors. Country and sector dummies included. The estimation with the DigitSector does not include sector dummies (column 4). 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 expecting to reduce the workforce in the long term. The estimated coefficient is negative but not significant. However, in an extension of our analysis which does not control for the R&D and innovation efforts (Table 4) our coefficient of HGEs becomes significant and negative. This suggests that it is mainly innovative HGEs that do not expect negative long-term employment adjustments. Overall, hypothesis 1b is partially confirmed, highlighting the role innovativeness plays for this specific group of firms.

Table 4. Determinants of the probability of the long-term expected employment reduction without controlling for firms' innovativeness. Matched sample. Wave 2020. Robust standard errors.

	LTimpact		
	(1)	(2)	(3)
HGE$_{t-1}$	-0.096* [0.052]	-0.112** [0.055]	-0.112** [0.056]
LabProd$_{t-1}$		-0.073*** [0.025]	-0.074*** [0.025]
Full digital adoption$_{t-1}$			0.012 [0.051]
Partial digital adoption$_{t-1}$			0.034 [0.033]
Constant$_t$	0.016 [0.716]	-0.088 [0.593]	0.985*** [0.254]
Pseudo-R^2	0.0852	0.0874	0.0871
Observations	10,894	9,474	9,457

*Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in brackets. Age, size, country, sector and expectation dummies are included.*

In the following, we turn our attention to sectoral differences (Table 3). We observe that firms belonging to a sector with a sales drop larger than 10% between 2019 and 2020 are not more likely to reduce their workforce permanently (column 3). These results highlight the sectoral nature of the COVID-19 shock, as already observed in the section on the short-term firm adjustment. Firms in sectors with a higher share of digitalisation are in a better position to maintain or even increase the number of employees in the future (column 4). Hence, hypothesis 1c is confirmed with respect to the long-term perspective, i.e. sectoral digitalisation levels play a role in employment adjustments at the firm level in the short and long term.[8]

However, we do not detect a significant effect regarding the level of digitalisation at the firm level and the long-term employment adjustment. Hence, we do not confirm hypothesis 1d. Therefore, the sectoral level of digitalisation matters for the long-term employment outlook. Additionally, in the case of our sectoral-level digitalisation results (Table 3, column 4), we cannot use sectoral dummies to control for sectoral characteristics. Consequently, digitalisation might capture a sector-specific COVID impact (e.g. more impacted sectors are not so digitalised, such as the hospitality sector).

Lastly, we turn our attention to the probability of increasing the digitalisation level in the long term as a reaction to COVID-19 (Table 5). Particularly, we are interested in whether HGEs and more productive firms are more likely to increase their digitalisation level as a crisis response (hypothesis 2a). However, as Table 5 shows, our results do not indicate that HGEs or high-productivity firms before the COVID-19 pandemic are statistically

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

significantly related to long-term digitalisation levels. Nevertheless, it seems that the degree of innovation is positively linked with long-term digitalisation efforts.

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

	(1)	(2)	(3)	(4)
HGE_{t-1}	0.017 [0.055]	0.582 [0.691]	0.017 [0.055]	0.007 [0.055]
$LabProd_{t-1}$	0.022 [0.026]	0.027 [0.027]	0.022 [0.026]	0.021 [0.025]
$HGE_{t-1} \times LabProd_{t-1}$		-0.055 [0.066]		
$CovidNeg_{t-1}$			-0.054 [0.058]	
$CovidPos_{t-1}$			-0.021 [0.050]	
$DigitSector_{t-1}$				0.105** [0.044]
Full digital adoption $_{t-1}$	0.151*** [0.056]	0.150*** [0.056]	0.151*** [0.056]	0.162*** [0.055]
Partial digital adoption $_{t-1}$	0.241*** [0.035]	0.241*** [0.035]	0.241*** [0.035]	0.234*** [0.035]
Innovation $company_{t-1}$	0.140*** [0.038]	0.139*** [0.038]	0.140*** [0.038]	0.136*** [0.038]
Innovation $countryy_{t-1}$	0.122 [0.078]	0.123 [0.078]	0.122 [0.078]	0.119 [0.077]
Global $Innovation_{t-1}$	0.305*** [0.078]	0.305*** [0.078]	0.305*** [0.078]	0.284*** [0.077]
$R\&D_{t-1}$	0.051 [0.111]	0.053 [0.111]	0.050 [0.111]	0.069 [0.106]
$Software_{t-1}$	0.278*** [0.076]	0.279*** [0.076]	0.277*** [0.076]	0.296*** [0.074]
$Training_{t-1}$	0.162* [0.084]	0.162* [0.084]	0.163* [0.084]	0.151* [0.083]
Constant	-1.342* [0.772]	-1.383* [0.768]	-1.353* [0.772]	-1.117*** [0.281]
Pseudo-R^2	0.088	0.089	0.099	0.088
Observations	7,714			

*Notes: *** p<0.01, ** p<0.05, * p<0.1 Robust standard errors. Age, size, country, sector and expectation dummies included. The estimation with the DigitSector does not include sector dummies.*

We now focus on the relationship between the degree to which a sector has been affected by the pandemic, the digitalisation level of the sector (hypothesis 2b) and the digitalisation level of the firm (hypothesis 2c), on the probability of digitalising due to the COVID-19 pandemic. First, firms in sectors negatively affected by COVID-19 are not significantly more likely to continue their digitalisation process in comparison with those in intermediate sectors (Table 5, column 3). A plausible explanation is that firms in sectors particularly affected by the pandemic might have a lower capability to introduce NDTs because they are contact-intensive sectors (accommodation, leisure, among others).

Second, firms operating in digitalised sectors are significantly more prone to continue their digitalisation process (Table 5, column 4). 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 further widen the digital gap with respect to 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 NDTs and investments in the internal capabilities to exploit these technologies. Both types of investment foster the probability of continuing investment in digitalisation.

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

6. Conclusions

COVID-19 led to massive economic disruptions. First, the pandemic has generally pushed firms to increase their digitalisation efforts in order to adjust to the new circumstances. Second, the crisis might have also had a more detrimental impact on less productive firms, due to their lower skill level, lower liquidity and profitability or worst managerial organization, in line with the general view of the existence of cleansing effects of recessions. In order to shed light on the potential heterogeneous firm-level response to the pandemic, this paper analyses how firms adjusted their employment levels and digital activities in the short and long term as a response to the COVID-19 shock, both depending on their productivity levels and on their previous growth performance. This paper uses the EIBIS database from waves 2019 and 2020 merged with Bureau van Dijk's ORBIS database.

Our results can be summarized as follows. First, the impact of the COVID-19 pandemic has been especially negative for less productive firms, since they have been more likely to decrease their workforce than more productive firms. This result highlights that the least efficient firms can increase their resilience by boosting their productivity levels. Our results also show that COVID-19 has affected (positively or negatively) a significant share of firms in the short term, regardless of their productivity levels. However, productivity levels are important for the expectations on the long-term consequences of the COVID-19 crisis, as firms with higher productivity levels are less likely to reduce the number of employees in the long run.

Second, firms belonging to a highly digitalised sector have a higher probability to continue to digitalise in the future. Third, firms that had already implemented NDTs are more likely to invest in digitalisation than non-digitalised firms. These results suggest a widening gap in terms of the degree of digitalisation across firms, and emphasises the importance of core internal abilities at the firm level that are necessary for adopting digital technologies with a view to increasing firms' competitiveness and resilience.

Fourth, our results highlight the innovative dimension of HGEs. When we do not control for firms' innovative characteristics of firms, HGEs present 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 probability 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 firms develop their internal capabilities to increase competitiveness.

The main message arising from this paper 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 adjusted their labour force, at least in the short term. This means that less productive firms decreased their employment more due to the COVID-19 crisis, thus contributing positively to aggregate productivity growth. This finding is consistent with recent research by Bloom et al. (2021) and Andrews et al. (2021a). Our results indicate that innovative activity as well as productivity levels are correlated with shock-resilience at the firm-level. Finally, we document a certain degree of persistence in digitalisation efforts during the COVID-19 crisis, which might also be related to region- or firm-size-specific digitalisation obstacles. 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 across European economies.

We must highlight some limitations of our analysis. 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 response 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 but should be interpreted as conditional correlations. Third, we must be cautious with our results, since the medium-term effect of the COVID-19 crisis on labour reallocation is uncertain, as governmental support tended to be given to lower productivity firms (Harasztosi et al., 2021). This governmental support may cause an upward bias (i.e. without this support firms' response to COVID-19 shock would have been worse). For instance, low-productivity firms seem to have adjusted better than they would have done without this support (Harasztosi et al., 2021). However, country dummies may mitigate the bias of cross-country variation of the policy support, as they capture the average effect of the policy support at the country level.

Our research contributes to discussions about how firms responded to the crisis in terms of their employment levels and their digitalisation efforts, taking their initial productivity levels into account. Hence, we can capture how firms reacted in terms of employment and digitalization in the presence of an unexpected shock. Future research should analyse the capability of firms to recover from COVID-19 by analysing their post-2020 performance in terms of both employment adjustment and productivity. Finally, independently of the COVID-19 crisis, an analysis of the persistence of the technological digital gap, its underlying factors and its effect on firm's performance is also a worthwhile research extension.

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APPENDIX 1. Main statistics

Table A-1. Description of variables

Name	Description
impactHL	Dummy equal to 1 if the firm reduced its staff during the pandemic more than 50% in comparison with a moderate reduction (they have reduced less than 50% or they were going to start in the next three months).
impactLN	Dummy equal to 1 if the firm reduced its staff during the pandemic less than 50% or they are going to start in the next three months and 0 if they did not decrease the number of employees.
impactNG	Dummy equal to 1 if the firm did not decrease the number of employees and 0 if they increased.
LTimpact	Dummy if the firm expects that COVID-19 pandemic will cause a decrease of their staff in the long term
impact	Dummy equal to 1 if the firm had a high or a moderate reduction of their staff during the pandemic (the reduction of the staff was up to a quarter or they were going to start in the next three months) and 0 otherwise.
LTdigit	Dummy equal to 1 if the firm expects that 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 company, 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
Full digital adoption *Partial digital adoption*	Dummy if the firm has adopted fully or partially digital technologies
SECTORS	
CovidNeg, CovidPos	Dummy identifying sectors at country level that decreased their turnover more than 10% or had a positive growth between 2019 and 2020.
DigitSector	Dummy identifying sectors with a mean expenditure per worker in software, data, web and IT 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 *ExtFundsIMP, ExtFundsDET* *BussProspectsIMP, BussProspectsDET* *EconClimateIMP, EconClimateDET*	Dummy if the firm perceives improvement or deterioration of: Availability of internal funds Availability of external funds Business prospects Overall economic climate

COUNTRY DUMMIES are included (UK = reference)
SECTOR DUMMIES AT 2-DIGIT NACE LEVEL are included

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
Fulll_digital adoption	0.106	0.307	0	1
Partial digital adoption	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
Innovation company	0.294	0.456	0	1
Innovation country	0.070	0.255	0	1
Innovation 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
Subsidary	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_digitzalizator	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