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Abstract

The COVID-19 shock hit firms hard, on average, but how did it hit in the distribution of firms, differently between the high-growth superstars and the firms that were already struggling to survive? This paper implements graphical techniques and quantile regression to analyse the effect of the COVID-19 shock across the distribution of firms. It impacted negatively the growth of sales and value added all across the growth rate distribution with an effect that was slightly larger at the lower quantiles. For employment growth, while the effect was null for most firms, it was not at the lower tail. Analysis of subsamples, as well as quantile regressions with interaction terms, emphasize that firms that received policy support and those from the service sector were relatively more strongly affected by the COVID-19 shock, especially those that were fast decreasing ones. The results confirm the view that the COVID-19 policy support reached the intended recipients.

KEYWORDS: Firm growth, growth rates distribution, COVID-19 shock, quantile regression, hanging rootogram

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Contents

1 Introduction

The COVID-19 shock had a clear adverse effect on the overall economy. It was associated with a spike in uncertainty (Altig et al., 2021) and triggered a sharp economic recession across Europe, threatening employment. At the disaggregated level, however, the impact differed substantially across firms: some grasped the opportunities and thrived amid the chaos that dragged others down. Indeed, research has highlighted that the operating sector was a key factor in explaining the impact, with social intensive ones, such as transportation, accommodation, and food and beverage service activities, being more affected than others, such as information and communication technology (Benedetti Fasil et al., 2021; Coad et al., 2022a). Moreover, firms with online digital business models generally fared better than those with offline business models (Bloom et al., 2021).

A wide range of COVID-19 support packages was put in place to provide assistance to vulnerable firms (Cirera et al., 2021). A common assumption regarding negative macroeconomic shocks is that poor performing firms would be hit especially hard, while high-performing firms are more viable and hence better protected from the threat of exit (Kozeniauskas et al., 2022).

There were fears that the COVID-19 shock would be particularly lethal for vulnerable firms at the lower end of the performance distribution. The exit of poorly performing firms can potentially stimulate the economy if the freed resources are reallocated to better performing firms. This is the classical view on the "cleansing" effect of the recession. However, an abrupt shock that suddenly pushes a large share of relatively underperforming firms into failure could flood the market with resources that are difficult to quickly reallocate towards better-performing survivors. The COVID-19 support was given to firms without a detailed examination of the viability of the recipient firms, prioritizing speed of intervention over concerns over the merit of the recipients. As a result, there are concerns that it may have propped up some unviable firms, putting them on artificial life support (Gourinchas et al., 2021), only to exit *en masse* once the support packages are phased out.

There are also concerns that an adverse macroeconomic shock could hit high-potential firms at the upper end of the performance distribution. The COVID-19 shock would be particularly damaging, for example, for firms that made high-risk investments in additional capacity only to be greeted with a depressed demand. It could be particularly damaging for high-growth firms (HGFs) considering that seed and early finance (compared to late-stage deals) were disproportionately severely hit (Benedetti Fasil et al., 2021), and HGFs may rely on such sources of finance to reach their potential. The COVID-19 shock could be particularly damaging if the uncertainty that accompanies it (Altig et al., 2021) leads to a collapse in demand for the types of speculative emerging markets in which HGFs usually thrive. Finally, it may also disproportionately affect high-performing firms if R&D investors are met with unexpectedly chilly receptions from risk-averse investors and cautious consumers. Coad et al (2022b) observe that HGFs and R&D investors were particularly strongly hit by the COVID-19 shock, in terms of expectations surrounding investment, availability of internal finance, but also availability of external finance.

This paper is not only interested in how the COVID-19 shock hit the "average" firm, but also investigates whether the COVID-19 shock hit firms disproportionately hard at the lower quantiles (low-performance) and the upper quantiles (high performance or HGFs) of the distribution. While standard regression techniques (such as Ordinary Least Squares (OLS) linear regression and many of its variations) focus implicitly on the "average effect for the average firm", it is also much interesting to explore heterogeneous outcomes across quantiles of the distribution (Koenker and Hallock, 2001). We use other statistical techniques such as quantile regression to provide insights into how the COVID-19 shock affected firms differently at both extremes of the performance distribution. We investigate also in more details how are these COVID-19 effects linked to heterogeneity in firms according to policy support received and industrial sectors while controlling for other firm characteristics like age, digitalisation and financial constraints.

Our main contribution to the literature therefore relates to the heterogeneous effects of the COVID-19 shock across the firm growth rates distribution. As it takes years for high-quality data on firm-level performance to become available, which is holding back research into how COVID-19 affected firm-level performance (Haltiwanger, 2022), we provide evidence regarding how the COVID-19 shock affected the distribution of firm growth rates using EIBIS/ORBIS data.

Our main results can be summarized thus. Similar results are observed for growth of sales and growth of value added, with COVID-19 having a negative effect on growth all across the growth rates distribution. The negative COVID-19 effect is slightly larger at the lower quantiles. Hence COVID-19 hit declining firms harder than it hit growing firms. For employment growth, there is no detectable COVID-19 effect for a large share of firms that have zero employment growth, but at the extremes we can observe that declining firms as well as rapid-growth firms were adversely affected by COVID. For labour productivity growth, the COVID-19 effect is relatively small, compared to what we observed for growth of sales and growth of value added. The results for labour productivity are also fairly flat across the quantiles.

Analysis of subsamples shows that firms receiving policy support and those in the service sector were more strongly negatively affected by the COVID-19 shock, in particular firms at the lower quantiles of the growth rates distribution (i.e. firms experiencing rapid decline). Subsamples analysis also shows that fully-digitalized firms appear to have been somewhat shielded from the COVID-19 shock. Multivariate quantile regressions also show that the strongest results are observed for the group of firms receiving policy support. For these firms, the COVID-19 shock had noticeably strong negative effects and these were strongest at the lower quantiles. For other groups of firms (i.e. digitalized firms, financially constrained firms, young firms), it is less clear whether they were affected differently by COVID-19 that what would be observed in a normal year. In sum, our quantile regressions therefore emphasize that firms that were in the subsample that received policy support and those in the service sector were relatively more strongly affected by the COVID-19 shock. This can be taken as suggesting that COVID-19 support was allocated to firms that were hit particularly hard, in line with the policy goals.

The paper unfolds as follows. Section 2 presents our methodology and the dataset used. Section 3 presents the analysis, and Section 4 concludes.

2 Methodology and data

This paper focuses on firm heterogeneity in terms of variation along the quantiles of the dependent variable. Analysis of distributions can help to move beyond a focus on the average, to see whether distortions in the shape of the growth rates distribution have specific implications for high-growth or fast-decline firms (Bottazzi et al., 2014). Analysis of quantiles is done using graphical techniques (growth rate distributions, cumulative distribution functions, and hanging rootograms) as well as quantile regression analysis. We first detail the database before explaining how we control for heterogeneity.

2.1 Database and calculations

Our analysis focuses on a panel database that is built by merging together the European Investment Bank Investment Survey (EIBIS) with the ORBIS dataset maintained by Bureau van Dijk (e.g. Teruel et al., 2021). EIBIS contains information on approximately 12,500 firms in each annual survey wave for the period 2016-2020. EIBIS contains qualitative and quantitative information on the characteristics and performance of non-financial corporates, which includes both SMEs (5–250 employees) as well as larger corporates (250+ employees). EIBIS applies stratified sampling techniques, with the aim of being a representative data source for the included countries (the 27 Member States of the EU, as well as the UK and USA), within countries, within four firm size classes (*i.e.*, micro, small, medium and large) and within four sector groups (*i.e.*, manufacturing, construction, services, and infrastructure). This paper focuses exclusively on the 27 EU Member States. EIBIS is carried out via computer-assisted telephone interviews (CATI) that are undertaken in the local language. The sample of interviewed firms is drawn from Bureau van Dijk's ORBIS database, which allows EIBIS survey answers to be linked to firms' financial variables and other administrative information, although the anonymity of firms' information is maintained. Some details on the EIBIS database creation methodology are available from IPSOS.[1]

Overall, we have about 75,000 observations, that are approximately evenly distributed across the 6 EIBIS survey waves. Our analysis focuses on an unbalanced panel of firms across the survey waves.[2] Table A1 (Appendix 1) contains a description of the main variables and how they are defined. Table A2 presents some summary statistics on the main variables.

Inflation is a year-specific and country-specific phenomenon that affects some of our variables (sales and value-added). We deflate the variables sales and value-added using year-specific and country-specific deflators

1 EIBIS is carried out via computer-assisted telephone interviews (CATI) that are undertaken in the local language. The sample of interviewed firms is drawn from Bureau van Dijk's ORBIS database, which allows EIBIS survey answers to be linked to firms' financial variables and other administrative information, although the anonymity of firms' information is maintained. Some details on the EIBIS database creation methodology are available from IPSOS. Please see https://www.eib.org/attachments/eibis-methodology-report-2019-en.pdf. Brutscher et al., (2020) show evidence that the EIBIS has no systematic sampling bias.

2 When we repeated our quantile regression analysis on a subsample of firms that formed a balanced panel, our sample size was severely reduced.

(harmonized indices of consumer prices, HICPs) from Eurostat.[3] Employment does not need to be deflated given that headcount data is not directly affected by inflation. Labour productivity is deflated indirectly, given that the value-added data that is used to calculate labour productivity has already been deflated.

Growth rates are expressed in terms of log-differences (Tornqvist et al., 1985). In other words, for variable *x*, the annual growth rates for firm *i* over the period *t-1:t* are $gr\_x_{i,t} = \log(x_{i,t}) - \log(x_{i,t-1})$. Hence, the procedure is as follows: some of our variables (i.e. sales and value-added) are deflated, then natural logarithms are taken for our 4 dependent variables (sales, value-added, employment, and labour productivity), and then growth rates for these 4 variables are calculated using log-differences.

These 4 growth rates variables, taken as dependent variables in our estimations, reflect different aspects of "firm performance" (Miller et al., 2013). For example, growth in sales can potentially be achieved without growth in value added or growth in employment. Hence, these four variables are not expected to be perfectly correlated. Table 1 below shows that these four variables have pairwise correlations that are statistically significant at the 5% level, although they are generally far from the benchmark of perfect correlation (in which the correlation statistic would equal 100%). The strongest correlation is between growth of value added and growth of labour productivity (ρ = 0.9 in each case) driven also by the calculation of the productivity using the value added as nominator. We observe a negative correlation coefficient for the pairwise correlation between employment growth and labour productivity growth (ρ ≈ -0.2 in each case), which makes sense considering that labour productivity is calculated with employment as the denominator. The correlations do not seem to change too drastically when comparing non-COVID-19 waves with the COVID-19 wave. The largest change due to COVID, perhaps, is that the correlation between growth of sales and growth of employment moves up from 17.4% to 29.9%.

Table 1: Correlation matrices between the 4 growth rate variables

	NON COVID-19 WAVES Growth of ..				**COVID-19 WAVE** Growth of ..			
	sales	**employment**	**value added**	**productivity**	**sales**	**employment**	**value added**	**productivity**
sales		**18.4%** (15,203)	**36.3%** (15,203)	**25.3%** (15,203)		**24.4%** (4,210)	**44.4%** (4,210)	**31.8%** (4,210)
employment	**17.7%** (18,488)		**14.5%** (15,203)	**-25.3%** (15,203)	**0.2987** (5,009)		**0.2113** (4,210)	**-0.1786** (4,210)
value added	**46.4%** (15,203)	**17.4%** (15,203)		**0.8562** (15,203)	**0.4441** (4,210)	**0.2709** (4,210)		**0.8575** (4,210)
productivity	**39.4%** (15,203)	**-24.5%** (15,203)	**91.2%** (15,203)		**0.2885** (4,210)	**-0.2278** (4,210)	**0.8756** (4,210)	

Note: Correlation matrices between the 4 growth rate variables (i.e. our dependent variables) in years that correspond to either non-COVID-19 waves (pooled together) or the COVID-19 wave. The usual Pearson correlation statistics (as well as number of observations) are shown in the bottom-left lower triangle, while Spearman's rank correlations (and numbers of observations) are shown in the upper-right triangle (in italics and shaded in grey). All correlations are statistically significant at the 5% level.

2.2 Methodology-addressing heterogeneity

Ideally, we would avoid any omitted variable bias (OVB) by controlling for all possible confounding influences that simultaneously have a causal effect on exposure to the COVID-19 shock and firm-level outcomes. However, such an approach is problematic in this case for several reasons. First, while our data is rich, we cannot be sure that the variables in our data would allow us to escape OVB even if these variables were included as control variables. Second, including as many control variables as possible is a problematic empirical strategy, because it could actually introduce new problems of endogeneity that did not previously exist, for example if we control for financial performance which would be a consequence rather than a background factor for some of our

[3] Harmonised Indices of Consumer Prices (HICPs) are designed for international comparisons of consumer price inflation. HICP is used for example by the European Central Bank for monitoring of inflation in the Economic and Monetary Union and for the assessment of inflation convergence as required under Article 121 of the Treaty of Amsterdam. To be precise, we focus on HICP inflation rate TEC00118. Details here: https://ec.europa.eu/eurostat/databrowser/view/tec00118/default/table?lang=en [last accessed 23 April 2022].

dependent variables (the problem of collider bias: Elwert and Winship, 2014). Third, quantile regression estimations may not converge to a solution, which may be particularly problematic in large samples, and may be particularly problematic if a large number of control variables are included. Problems of convergence, even if they affect only a small number of our estimations, will prevent us from getting a complete set of results. In our analyses, we actually experienced a large number of convergence problems, pushing us to rethink our empirical approach. We therefore estimate quantile regressions with a relatively small set of explanatory variables, that will hopefully alleviate OVB, although we do not claim to have completely removed the problem of OVB, and as a result we do not recommend any causal interpretation of our results (instead, they should be seen as conditional associations). Relatedly, another problem linked to the limited computational power is the estimation of quantile regression standard errors via bootstrap replications. As such, we focus on the regular standard errors for quantile regression.[4]

To begin with, we do not attempt to include control variables, and we estimate how the COVID-19 shock relates to firm-level outcomes without controlling for other influences, i.e.

$$GR_i = \alpha_\theta + \beta_\theta COVID_i + \varepsilon_{\theta i} \qquad (1)$$

Where the quantile regression coefficient β_θ varies over the conditional quantiles θ (i.e. over the quantiles of $\varepsilon_{\theta i}$). GR_i corresponds to our four dependent variables (growth of sales, employment, value-added or labour productivity). While OLS finds the regression solution by minimizing the sum of squared residuals, quantile regression minimizes the sum of absolute residuals, which is computationally more complex and convergence of the algorithm to a regression solution is not always guaranteed. This paper applies quantile regression to investigate how the COVID-19 shock is associated with growth outcomes across the distribution of growth outcomes.

A commonly used control variable corresponds to year dummies. In this paper, year dummies would wash away any possible role for our main explanatory variable of interest, i.e. the COVID-19 wave. Therefore, we do not include year dummies as control variables. Year-specific common shocks in the form of inflation have already been taken into account as a consequence of deflating the sales and value-added data at the beginning of our analysis.

Another common technique used in regressions on panel data is to control for time-invariant unobserved heterogeneity by including in the regression model firm-specific fixed effects. In our present context, our variables are growth rates (i.e. log-differences), and as a consequence any time-invariant individual-specific components that may affect outcomes in levels have already been differenced-out. There remains the question whether time-invariant individual-specific components may have an effect on differences (i.e. growth rates), but the available empirical evidence does not support this view, especially in short panels such as ours. Firms have volatile growth paths over time, such that the within-firm variation in growth rates is actually higher than the between-firm variation in growth rates (e.g. Geroski and Gugler, 2004). The approach often taken in previous econometric analyses on panel data of firm growth rates is that there are no firm-specific components in growth rates (e.g. Moneta et al, 2013, Coad et al, 2017).

One approach that we apply to explore the role of heterogeneity, in terms of some key variables (policy support, sectors and digitalization), does not involve the inclusion of these variables as explanatory variables, but by a systematic analysis of equation (1) on subsamples. Note that if the analysis is performed on a subsample of firms receiving policy support, for example, then there would no need to include a dummy variable for policy support, because all firms in the subsample received policy support. In this way, an analysis of subsamples relieves the need to include control variables.

A second approach that we apply to explore the role of heterogeneity involves including a restricted set of control variables in our regressions. Following on from the basic regression equation in (1), we perform multivariate regressions (OLS, panel Fixed-Effects "within" regressions, and quantile regressions) with control variables, as follows:

$$GR_i = a_\theta + b_\theta COVID_i + \gamma_\theta \boldsymbol{X}_i + \vartheta_\theta COVID_i \boldsymbol{X}_i + \varepsilon_{\theta i} \qquad (2)$$

The vector $\boldsymbol{X}_i$ contains a limited set of control variables: the lagged logarithm of sales, dummies for sectors, dummies for broad country groups, a dummy for young firms (younger than 20 years), a dummy for whether the firm benefited from any policy initiative during the COVID-19 wave, a dummy for financially constrained firms, and dummies for whether the firm was either partially digitalized or fully digitalized. The coefficient γ_θ, which

[4] To be precise, the standard errors of the command “qreg” in Stata 17.

varies over the quantiles θ, shows how these explanatory variables are related to growth rates at various quantiles θ of the growth rates distribution.

Equation (2) also contains the interaction terms, represented by the vector of coefficients ϑ_θ, which estimates the relationship between the explanatory variables and the growth rate, specifically at the time of the COVID-19 shock. Were ϑ_θ to be never significantly different from zero, this would mean that the explanatory variables were not differently related to growth rates than what we would find in a 'normal' year. If however ϑ_θ should be significantly different from zero, this would suggest that these explanatory variables had a different association with growth in the COVID-19 year compared to what we would expect in 'normal' years. For example, if the group of firms receiving policy support (variable 'policy_any') were no different in the years before COVID, but had lower growth in the COVID-19 wave, this would be visible in terms of a non-significant coefficient for 'policy_any' but a significant negative coefficient for the interaction term 'policy_any'×COVID.

3 Analysis and results

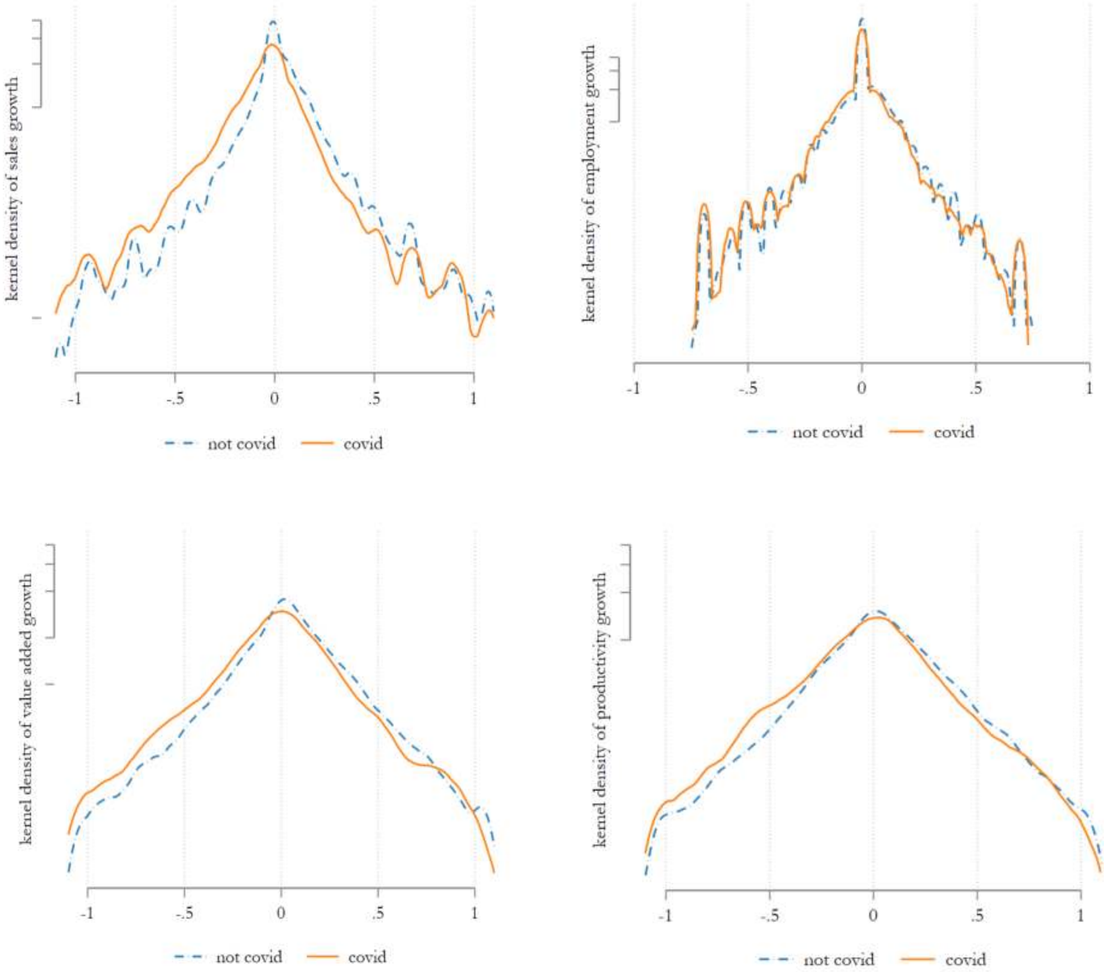
3.1 Graphical analysis

Figure 1 shows the growth rate distributions for growth of sales, employment, value-added, and labour productivity, using kernel density plots plotted on semi-logarithmic axes (note the log scale on the y axis). In each case, we get the familiar Laplace shape (i.e. the 'tent-shaped' growth rates distribution, Bottazzi and Secchi, 2006), which is shifted left for the COVID-19 wave (dash-dot line) because slower growth seems to be observed all across the distribution.[5]

The leftward shift that is observed in the COVID-19 wave is probably the clearest for sales growth, but less obvious for employment growth. In the case of employment growth, the distribution is more jagged, no doubt due to the integer constraints that affect the data on employment headcounts and their changes. In the COVID-19 wave, like for the other years, the peak of the distribution corresponds to a large number of firms that stay inert (i.e. these firms have zero employment change from one year to the next).

5 Cumulative distribution function plots confirm these findings. Results are available at request.

Figure 1: growth rates distributions

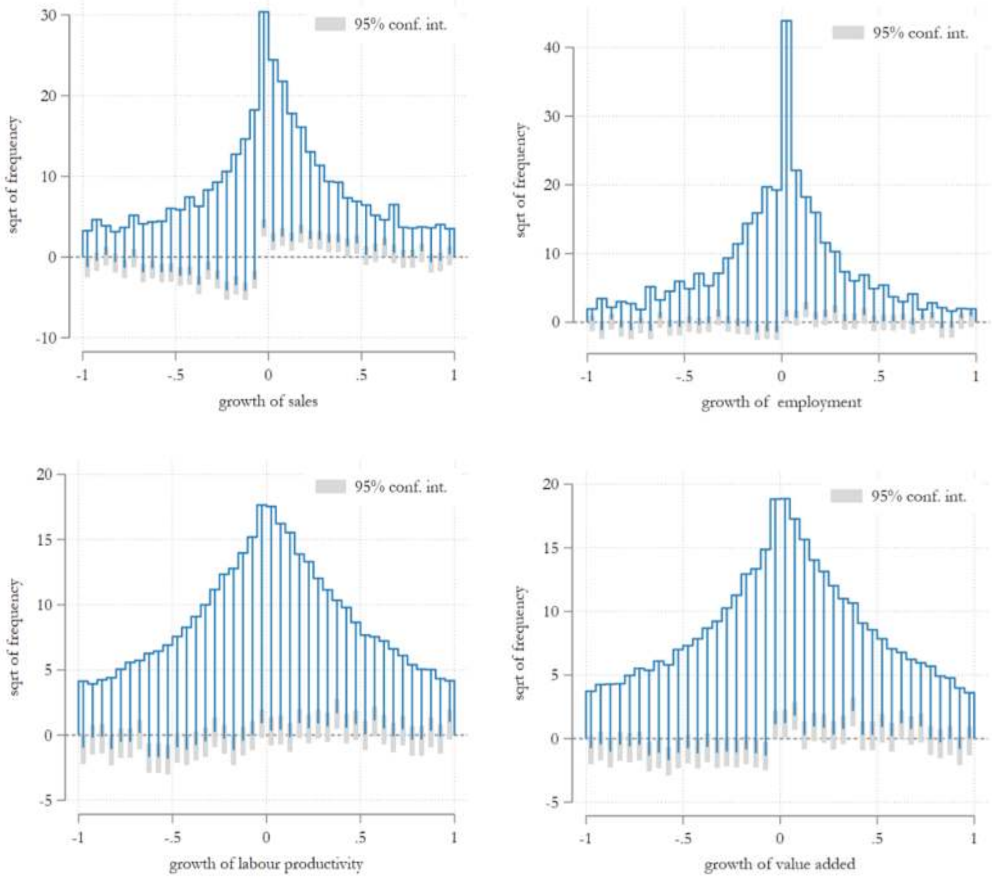


Note: Top left: sales growth. Top right: employment growth. Bottom left: value added growth. Bottom right: growth of labour productivity. Solid line: all years. Dash-dot line: COVID-19 wave.

Hanging rootograms are another useful graphical tool for comparing firm-level distributions (e.g. Barba Navaretti et al., 2019), that can be implemented in Stata.[6] While the kernel density plots in Figure 1 are locally smoothed, the approach taken by hanging rootograms is to split the data into a series of distinct bins. Another difference is that the kernel plots have a logarithmic y axis, while the y axis for hanging rootograms corresponds to a different transformation (i.e. the square root of the frequency). The hanging rootograms highlight the differences between the distribution for previous waves, and for the COVID-19 wave. For sales growth (top left), there is a gap in the distribution for moderate positive growth, and excess weight in the distribution for moderate negative growth. This pattern is most visible for sales growth, but also seems to be detectable (to a lesser extent) for the three other growth rate variables (growth of value added, employment, and labour productivity). Overall, the results in Figure 2 are consistent with our findings in Figure 1. COVID-19 seems to have lowered the overall average sales growth rate by reducing the numbers of moderate-growth firms and increasing the numbers of moderate-decline firms.

6 See http://www.maartenbuis.nl/software/hangroot.html (last accessed 29th April 2022).

Figure 2: hanging rootograms for growth of sales, employment, value-added, and labour productivity.



Note: Top left: sales growth. Top right: employment growth. Bottom left: growth of value added. Bottom right: growth of labour productivity growth (value added per employee). Solid blue line: pooling together all years except the COVID-19 wave. 40 bins. The hanging bars, with 95% confidence intervals (grey shaded boxes) highlight the differences between the non-COVID-19 waves (the blue line from which the lines are hanging) and the COVID-19 wave.

3.2 Quantile regression analysis

We start with a relatively straightforward quantile analysis of the COVID-19 dummy on performance (as shown in equation (1)).

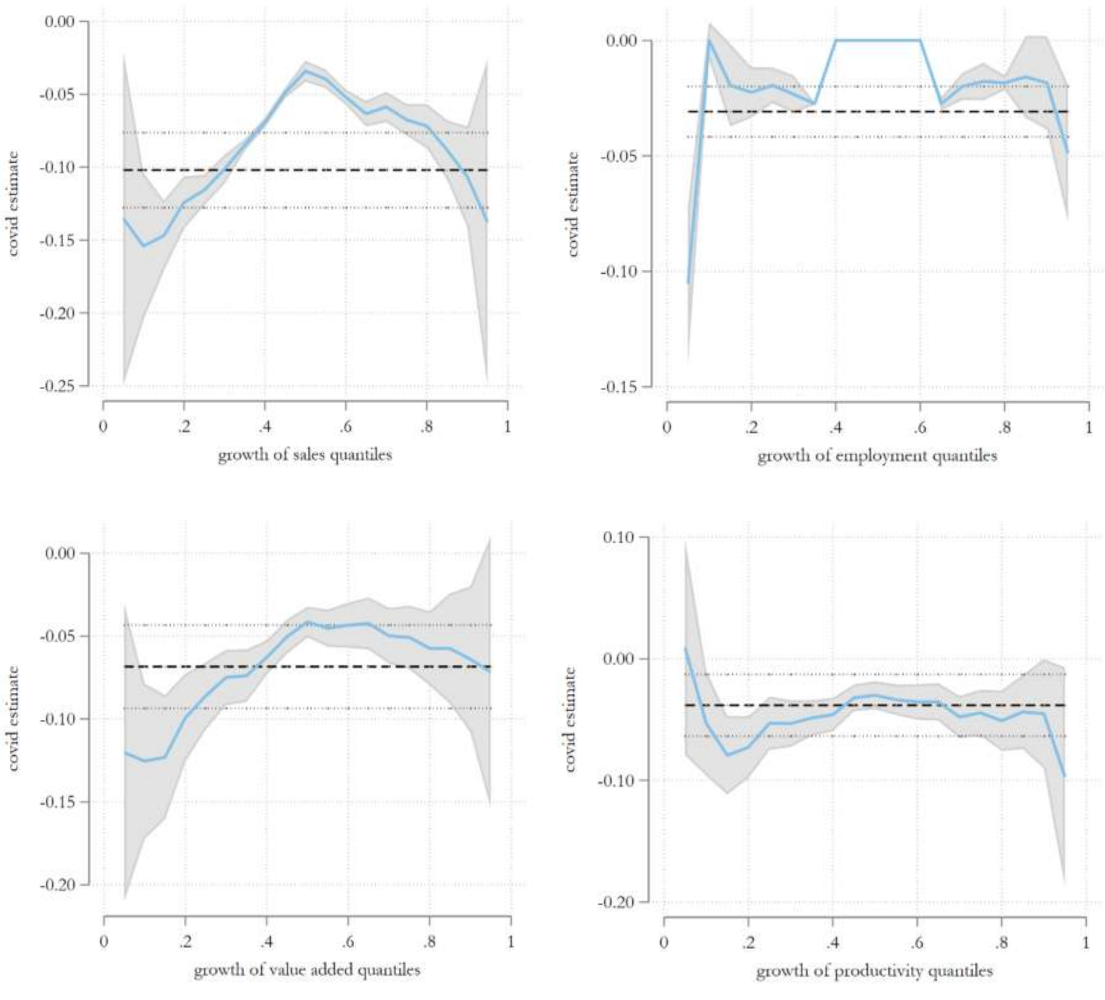
$$GR_i = \alpha_\theta + \beta_\theta COVID_i + \varepsilon_{\theta i} \qquad (1)$$

Where the quantile regression coefficient β_θ varies over the conditional quantiles θ (i.e. over the quantiles of $\varepsilon_{\theta i}$). GR_i corresponds to our four dependent variables (growth of sales, employment, value-added or labour productivity). The quantile regression is applied to investigate how the COVID-19 shock is associated with growth outcomes across the distribution of growth outcomes.

Our quantile regression results are presented in graphical form (Azevedo, 2011). The horizontal axis corresponds to the quantiles, from 0% (minimum) to 50% (the median) to 100% (the maximum), although for computational reasons (Koenker and Hallock, 2001) quantile regression estimates usually only cover the range from 5% to 95%. On the horizontal axis, the 50% quantile (i.e. the median) would correspond to the midpoint or "peak" in the centre of the growth rate distributions in Figure 1. In other words, the median (50% quantile) corresponds to the relatively large share of firms that neither grow nor decline. Below the 50% quantile we see the coefficients for declining firms, with the lowest quantiles (e.g. to name an arbitrary threshold, we could say below 10%) corresponding to the fastest-declining firms. Above the 50% quantile are the coefficients for the positive growth firms, with the fastest-growing firms at the extreme upper quantiles (e.g. 90% and above).

The vertical axis plots the quantile regression coefficient, which may be positive, negative, or indistinguishable from zero. Given that we expect that the COVID-19 shock negatively affected firm performance, we generally expect the quantile regression coefficients to be negative. The quantile regression coefficients of interest, corresponding to how the COVID-19 wave predicts growth outcomes, are plotted to show how they vary across the quantiles of the (conditional) growth rates distribution. Indeed, it may be the case that COVID-19 hit some groups of firms (e.g. declining firms that are at the lower quantiles of the growth rates distribution) without necessarily affecting other groups located at other parts of the distribution (e.g. in the middle of the growth rates distribution, which would correspond to stasis). Therefore, we are interested in seeing whether coefficients vary along the quantiles of the growth rates distribution. The shaded area around the quantile regression coefficient estimates corresponds to the 95% confidence interval. The thick dashed horizontal line corresponds to the Ordinary Least Squares (OLS) regression coefficient (with error bars on either side corresponding to the 95% confidence interval).

Figure 3: quantile regression results for equation (1)



Top left: sales growth (23,497 obs). Top right: employment growth (25,592 obs). Bottom left: value added growth (19,413 obs). Bottom right: labour productivity growth (19,413 obs).

Figure 3 begins with results for the full sample. Two important reference points are the horizontal line across from 0.0 (i.e. corresponding to no COVID-19 effect) as well as the horizontal line corresponding to the OLS regression estimate (the thick dashed line). In each of the four cases in Figure 3, the thick dashed line is below 0.00, indicating that the average effect (as estimated by OLS) is that the COVID-19 shock had a negative effect on firm growth, on average. As before (for Figures 1 and 2), growth of sales and growth of value added have similar patterns, with COVID-19 having a negative effect on growth all across the growth rates distribution (because the quantile regression coefficients are always below the value of 0.00 on the vertical axis). For both variables, the negative COVID-19 effect is slightly larger at the lower quantiles. Hence COVID-19 seems to hit declining firms harder than it hits growing firms.

For employment growth (Figure 3 top right), these results also mirror what we observed previously in Figures 1 and 2. In the middle quantiles, there is a subset of firms that have zero employment growth, and whose employment growth does not seem to be related to the COVID-19 shock. At the upper and lower quantiles, however, the coefficient appears to be negative, with the strongest negative coefficient observed at the very lowest observed quantile.

For labour productivity growth, the COVID-19 effect is relatively small, compared to what we observed for growth of sales and growth of value added. The results for labour productivity are also fairly flat across the quantiles, generally being not statistically significantly different from the OLS estimate.[7]

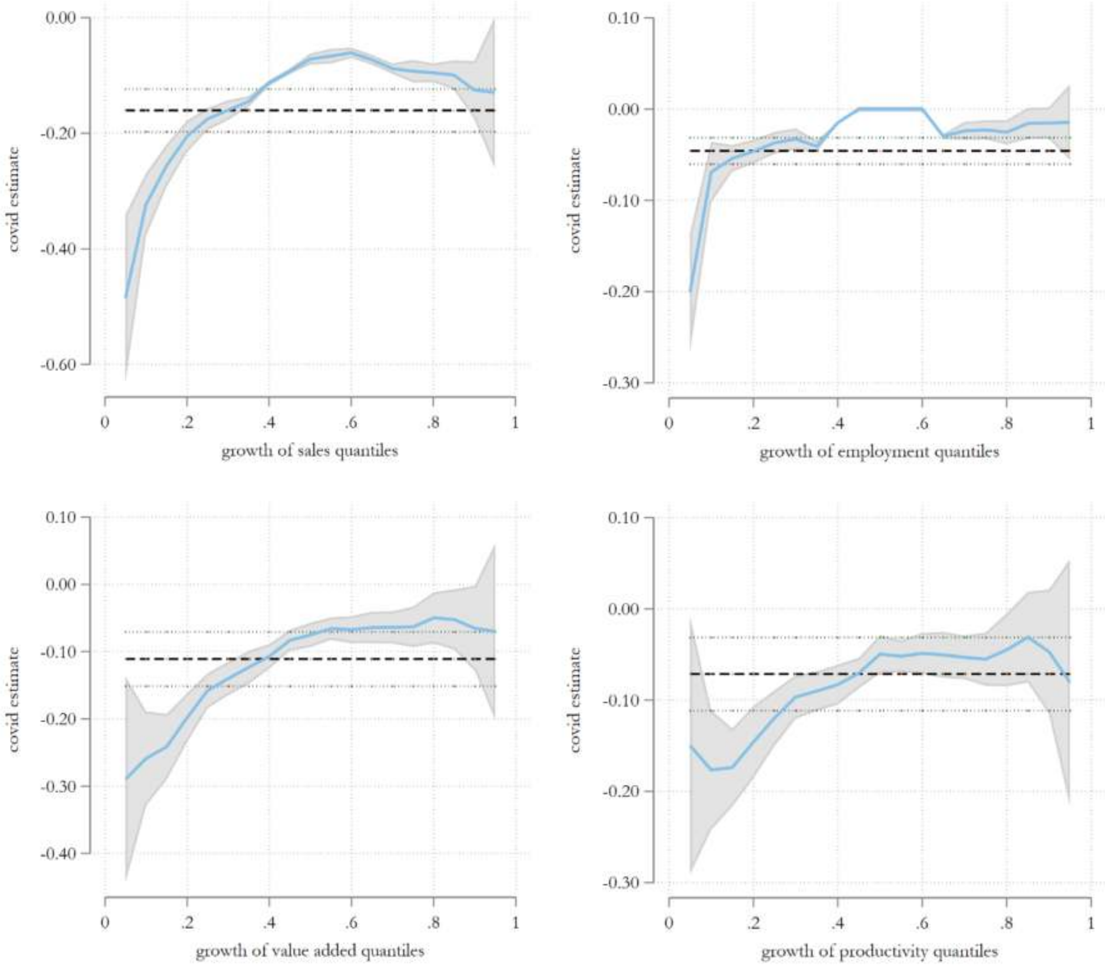
3.2.1 Subsample analysis -firms receiving policy support

Figure 4 shows similar patterns as Figure 3 regarding growth of sales and value added: i.e. that declining firms are hit harder by the COVID-19 shock. However, the coefficient magnitudes are larger in Figure 4 than in Figure 3, with magnitudes about twice as large for declining firms (e.g. coefficients of about -0.40 at the lower quantiles of Figure 4 top left, compared to coefficients of about -0.15 at the lower quantiles of Figure 3 top left). This suggests that those firms receiving some policy support have been harder hit than the full sample of firms in general.

Regarding growth of employment (Figure 4, top right), the coefficients are also more negative here than in the full sample. For growth of labour productivity (Figure 4, bottom right), the negative effect here is clearer than in the full sample (which appeared to generally be not different from zero). In particular, the COVID-19 shock had a negative effect on productivity growth for those firms at the lower quantiles, while the COVID-19 effect seems much milder at the middle and upper quantiles. To the extent that policy support is associated with firms that are hit harder, Figure 4 seems to support the idea that policy support was going to those in most need (Harasztosi et al, 2022).

7 The quantile regression coefficients' confidence intervals (shaded in grey) generally overlap with the OLS coefficient estimate (thick dashed line) in Figure 3 bottom right, at all quantiles except for 0.15%-0.2%. At the very lowest quantile, the coefficient appears to increase, although the error bars show that this coefficient is not precisely estimated and should therefore not receive undue emphasis.

Figure 4: Estimated coefficient of COVID-19 - quantile regression results for firms receiving support

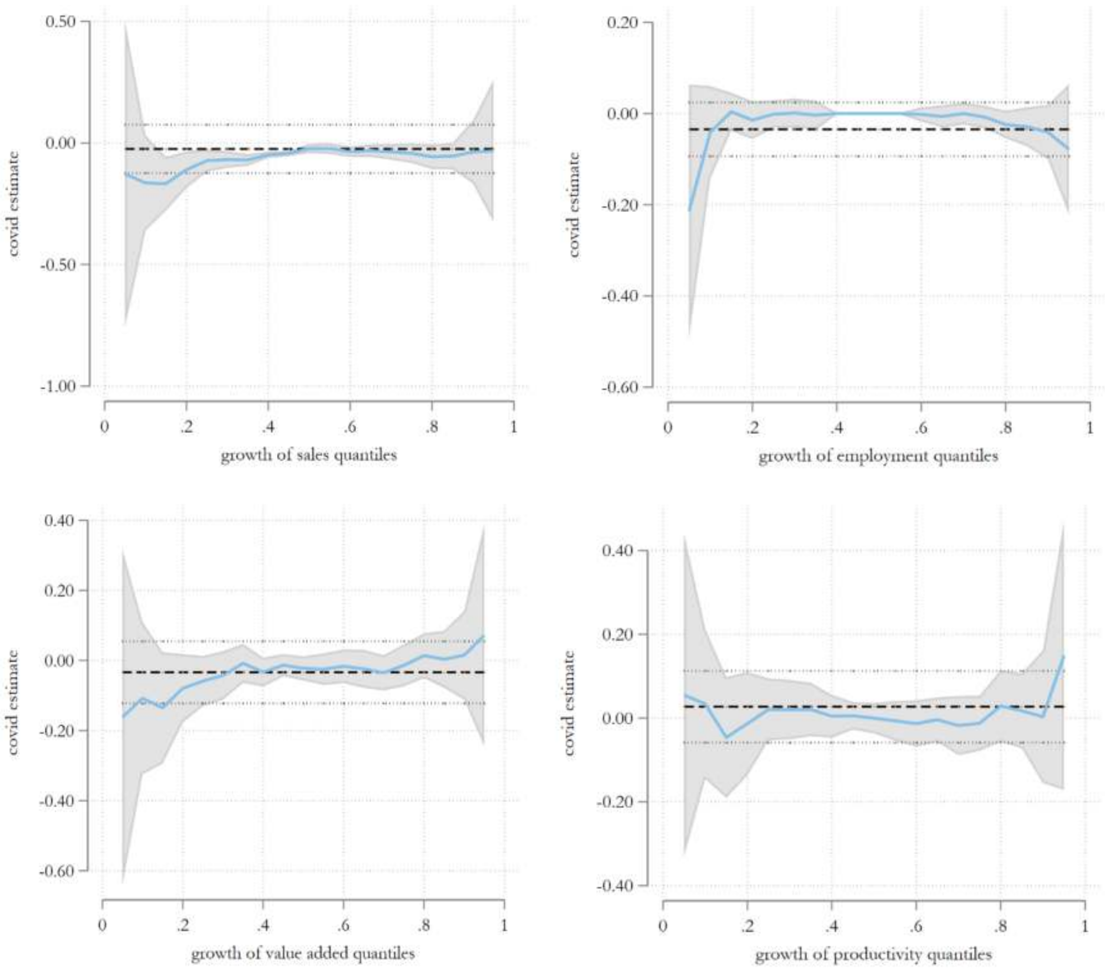


Note: Subsample of firms receiving any kind of policy support regarding COVID-19 (variable "policy_any"), Top left: sales growth (6,276 obs). Top right: employment growth (6,727 obs). Bottom left: value added growth (5,351 obs). Bottom right: labour productivity growth (5,351 obs).

3.2.2 Subsample analysis -fully digitalized firms

Figure 5 shows the results for the subsample of fully digitalized firms, i.e. a subsample of firms that reported implementing digital technology by organizing their entire business around it. For each of the growth rate variables (growth of sales, employment, value added and labour productivity) we essentially no longer observe a significantly negative coefficient of the COVID-19 shock at the lower quantiles. This contrasts with the results in Figure 4 for firms receiving policy support, where the COVID-19 shock had relatively large and significant negative coefficients. The confidence intervals always include the value 0.00 at the lowest quantiles, indicating that the coefficient is not significantly different from zero at these quantiles. This is consistent with the explanation that fully digitalized firms were immune to the COVID-19 shock and did not experience the strong and significantly negative coefficients that were observed for most other firms. Overall, therefore, digitalized firms seem to have suffered less as a consequence of the COVID-19 shock. The implications for business strategy and for economic policy could be that boosting the digital capabilities of firms may be able to shield them from adverse shocks such as the COVID-19 shock. A caveat of these results, however, is that the number of observations for this subsample of fully-digitalized firms is rather low (or, relatedly, the confidence intervals for the coefficient estimates are rather large).

Figure 5: Estimated coefficient of COVID-19 - quantile regression results for digital firms



Note: for the subsample of firms that reported implemented digital technology by organising their entire business around it. Top left: sales growth (1365 obs). Top right: employment growth (1456 obs). Bottom left: value added growth (1172 obs). Bottom right: labour productivity growth (1172 obs).

3.2.3 Subsample analysis -sectoral analysis

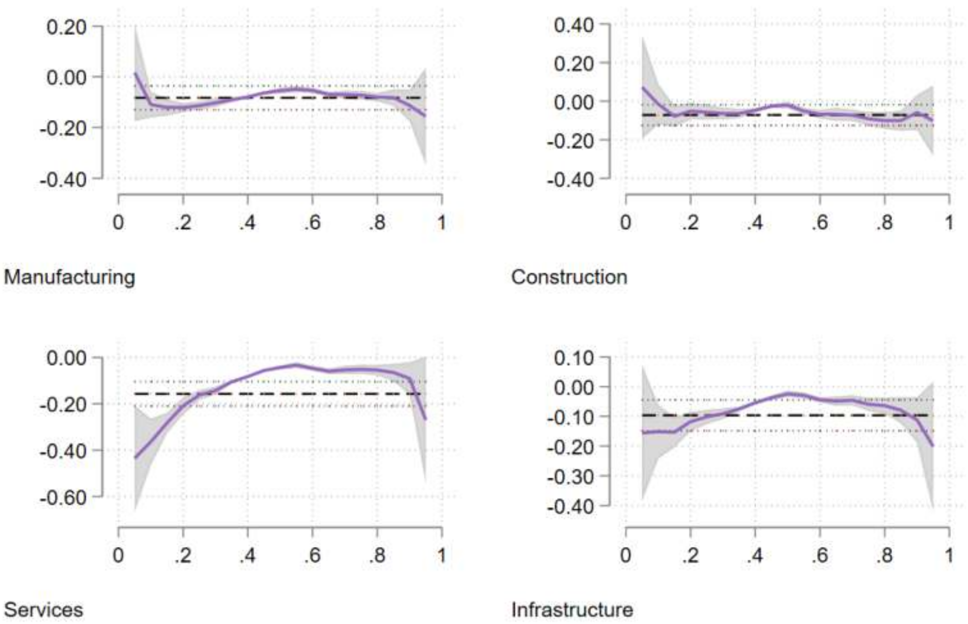
Sectors were affected differently by the COVID-19 shock. In this subsection we present details of the graphical representation of the quantile analysis by each sector.

Figure 6 shows a clearly stronger impact regarding growth of sales on the lower end of distribution only for the service sector: i.e. that declining service firms are hit harder by the COVID-19 shock. The coefficient magnitudes are larger for service sector than for whole sample (presented in Figure 3), with magnitudes more than twice as large for declining firms (e.g. coefficients of about -0.40 at the lower quantiles of Figure 6 bottom left, compared to coefficients of about -0.15 at the lower quantiles of Figure 1 (top left) and lower quantile of any other sectors).

Regarding growth of value added and employment (Figure A3.1 and A3.2, Appendix 3), the coefficients are also more negative for declining service firms than in the full sample and other sectors. For growth of labour productivity (Figure A3.3, Appendix 3), the negative effect is not different from zero.

Our results suggest that firms in the service sectors were hit on average harder in terms of sales, value added, and employment compared to other sectors, and the discrepancy is even stronger among declining service firms compared to declining non-service firms.

Figure 6: quantile regression results for equation (1) by sectors: growth in sales



3.2.4 Multivariate analysis

As an extension to the previous analysis, we apply to explore the role of heterogeneity involves including a restricted set of control variables in our regressions. Still, we should highlight that including even a minimum set of control variables in our quantile regression context encountered computational problems (high computational burden, and in many cases a lack of convergence to a regression solution).

Following on from the basic regression equation in (1), we perform multivariate regressions (OLS, panel Fixed-Effects "within" regressions, and quantile regressions) with control variables, as follows:

$$GR_i = a_\theta + b_\theta COVID_i + \gamma_\theta \boldsymbol{X}_i + \vartheta_\theta COVID_i \boldsymbol{X}_i + \varepsilon_{\theta i} \quad (2)$$

The vector $\boldsymbol{X}_i$ contains a limited set of control variables: the lagged logarithm of sales, dummies for sectors, dummies for broad country groups, a dummy for young firms (younger than 20 years), a dummy for whether the firm benefited from any policy initiative during the COVID-19 wave, a dummy for financially constrained firms, and dummies for whether the firm was either partially digitalized or fully digitalized. Equation (2) also contains the interaction terms, represented by the vector of coefficients ϑ_θ, which estimates the relationship between the explanatory variables and the growth rate, specifically at the time of the COVID-19 shock.

The quantile regression results tables are shown in Appendix 2. There is evidence, in some cases, that sectors and country groups were affected differently by the COVID-19 shock, by looking at their respective interaction terms with the COVID-19 shock (in line with subsection 3.3.3 on sectoral analysis). The strongest results regarding the COVID-19 shock seem to be that firms receiving any kind of policy support (variable 'policy_any') were hit especially hard (at all quantiles, but especially at the lower quantiles) during the COVID-19 shock, in a way that was different from their outcomes in previous years. Strong negative coefficients for the interaction of COVID_wave and policy_any are observed for growth of sales, value-added, and labour productivity (although not for employment growth). While we are cautious regarding any causal interpretations of our results, nevertheless these results are consistent with the COVID-19 shock hitting vulnerable firms hard (in terms of sales, value added and labour productivity), although the employment outcomes of these vulnerable firms were not negatively affected.

Results for other groups of firms that have received policy interest (digitalized firms, young firms, financially-constrained firms) are generally not statistically significant from zero, suggesting that these firms were not affected differently by the COVID-19 wave compared to their performance in previous years.[8] While we observed

[8] The most noteworthy result for other groups of firms could be the results observed for labour productivity growth of financially constrained firms in the COVID-19 wave. The coefficients on the interaction terms for financially constrained firms during the COVID-19

in the previous subsection (3.3.2) that digitalized firms were not significantly negatively affected by the COVID-19 shock, the regressions in Appendix 2 suggest that this lack of a significant negative coefficient could simply be due to a small sample size that yields imprecise estimates. Therefore, we remain cautious about this result.

4 Conclusion

The COVID-19 shock had a strong negative effect on aggregate economic performance, with the average firm taking a hit on sales revenues and financial performance. However, how do the effects vary if we go beyond a focus on the average? Were already-struggling firms hit hardest, threatening their very survival? Or did the COVID-19 shock disproportionately deter tomorrow's superstars at the upper end of the distribution, thus sacrificing future growth potential? This paper investigates where the COVID-19 shock hit the firm growth distribution, using graphical techniques and quantile regressions to analyse the full distribuiton of firm growth rates. We investigate how the COVID-19 shock relates to growth outcomes for four dependent variables: growth of sales, value added, employment, and labour productivity.

Growth of sales and growth of value added were observed to have similar patterns, with COVID-19 having a negative effect on growth all across the distribution. The negative COVID-19 effect is generally slightly larger at the lower quantiles. Hence COVID-19 hit declining firms harder than it hit growing firms. For employment growth, we don't find effect for many firms that have zero employment growth, but at the extremes, observe that some fast-declining and fast-growing firms were adversely affected by COVID-19. For labour productivity growth, the COVID-19 effect is relatively small, compared to what we observed for growth of sales and growth of value added. The results for labour productivity are also fairly flat across the quantiles.

Subsample analysis observes that firms in the service sector and those that were in the subsample that received policy support were relatively more strongly affected by the COVID-19 shock. This suggests that COVID-19 support was allocated to firms that were hit particularly hard, in line with the policy goals. For a subsample of digitalized firms, these firms seem to have suffered less as a consequence of the COVID-19 shock, presumably because online business models can better adapt to the sudden shift to social distancing and lockdown measures. However, the number of observations for fully digitalized firms is low, and these coefficients for digitalization are not precisely estimated.

Multivariate quantile regressions, likewise, confirm the results obtained from the subsample analysis. The strongest results are observed for the service sector and the group of firms receiving policy support (variable 'policy_any'). For these firms, the COVID-19 shock had particularly strong negative effects, that were strongest at the lower quantiles. For other groups of firms that have received policy interest (i.e. digitalized firms, financially constrained firms, young firms; results in Appendix 2), it is less clear whether they were affected differently by COVID-19 that what would be observed in a normal year. Overall, therefore, multivariate quantile regressions emphasize that firms that were in the subsample that received policy support were relatively more strongly affected by the COVID-19 shock. Overall, this suggests that COVID-19 support was allocated to firms that were hit particularly hard, in line with the policy goals.

Our research has several limitations left for further work. A first area for extending the current analysis is to go deeper in the direction of the usual multivariate regression framework, and have a larger number of control variables. In particular, given that COVID-19 had remarkably uneven effects across different sectors (e.g. Benedetti Fasil et al., 2021), a more finely-disaggregated set of industry controls could be investigated. Future work could also take an alternative dependent variable to investigate how survival chances varied for different types of firms as a consequence of the COVID-19 shock, to complement the current paper's focus on growth rates of continuing firms. Finally, further analysis of how the COVID-19 shock affected firm performance could therefore help us to better understand firm resilience and performance during adverse shocks and recessions, as well as contributing to improving our understanding of the optimal design of policy support during hard times such as the COVID-19 shock.

wave shows positive and significant coefficients (at quantiles 25% and 50%, and also for OLS and FE; although positive but not significant at other quantiles) in the case of labour productivity (Table A2.4). This is consistent with the explanation that financially constrained firms may have benefitted from the supportive policy environment on offer during the COVID-19 wave to do better-than-expected with regards to labour productivity.

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Appendix 1: Complementary information

Table A1: Descriptions and definitions of the main variables.

Variable	Description
Main **dependent variables**	
Employees	Number of employees (headcount). Often expressed in terms of logarithms.
Sales	Total sales of the firm, based on EIBIS. Often expressed in terms of logarithms.
Value_added	Total value added of the firm. Often expressed in terms of logarithms.
Labour productivity	Labour productivity, variable generated by us on the basis of the EIBIS/ORBIS data, measured as value added per employee.
Main **explanatory variables** for subsample analysis	
Firm size	4 size classes, micro (23% of observations), small (34% of obs), medium (29% of obs) and large (15% of obs).
Young	Age of the firm (categorical variable, ranging from 1 to 5). 5 categories: less than 2 years (0.39% of observations); 2 years to less than 5 years (3.89% of obs); 5 years to less than 10 years (10.71% of obs); 10 years to less than 20 years (24.99% of obs); 20 years or more (60.02% of obs). These are grouped into two approximately equi-populated groups of firms younger than 20, and firms aged 20+.
Sector	Broad sector groups (dummy variables): Manufacturing (28% of observations); Construction (22% of obs); Services (26% of obs); and Infrastructure (23% of obs).
Country group	Countries are grouped together into three groups: "Center and East"; "South"; and "North-West". "Center and East": BG, CZ, HR, HU, LT, LV, PL, RO, SI, SK., "South": CY, ES, FR, GR, IT, MT, PT, "North-West": AT, BE, DE, DK, EE, FI, IE, LU, NL, SE.
Policy support	Whether the firm received any kind of policy support during the COVID-19 year. Four types of support are considered: (1) New subsidized or guaranteed credits (e.g. loan, overdraft or credit card from a bank or other finance provider) that will need to be paid back in the future but may have preferential or reduced interest rates and/or an extended repayment plan; (2) Deferral of payments which still leave a liability to be paid by the company in the future (e.g. deferral of tax payments, deferral of rent or mortgage for commercial property, suspension of interest payments); (3) subsidies or any other type of financial support that need no repayment; and, (4) any other type of support.
Financial constraints	Whether the firm is classified as financially constrained. Finance constrained firms include: those dissatisfied with the amount of finance obtained (received less), firms that sought external finance but did not receive it (rejected) and those who did not seek external finance because they thought borrowing costs would be too high (too expensive) or they would be turned down (discouraged).
Digitalization (partial)	Whether the firm is partially digitalized (dummy variable), i.e. firms that reported that they partially implemented digital technology
Digitalization (total)	Whether the firm is fully digitalized (dummy variable), i.e. firms that reported implemented digital technology by organizing their entire business around it

Table A2: Summary statistics, 2021 wave

	Mean	Sd.	p-10%	p-25%	p-50%	p-75%	p-90%	min	max	N
Employees	262.52	5997.2	6.00	10.00	30.00	110.00	350.00	1.00	600000.0	12525
Employees (logs)	3.66	1.58	1.79	2.30	3.40	4.70	5.86	0.00	13.3	12525
Employment growth	-0.04	0.36	-0.22	-0.08	0.00	0.06	0.18	-5.83	5.2	5328
Sales*	45.95	365.03	0.28	0.83	3.46	17.32	61.61	0.00	16356.0	11676
Sales (logs)	15.15	2.12	12.53	13.62	15.06	16.67	17.94	0.92	23.5	11676
Sales growth	-0.08	0.69	-0.51	-0.20	-0.03	0.08	0.30	-9.25	7.0	5009
Value_added (VA)*	10.44	96.07	0.08	0.26	0.90	3.96	14.25	-845.10	3562.1	10219
VA (logs)	13.88	1.96	11.43	12.51	13.74	15.21	16.49	5.40	22.0	10097
VA growth	-0.04	0.70	-0.66	-0.26	-0.01	0.20	0.53	-7.03	9.4	4210
Labour productivity*	0.05	0.50	0.01	0.01	0.03	0.05	0.08	-4.29	34.2	10219
Labour productivity (logs)	10.14	0.98	8.95	9.54	10.21	10.80	11.26	3.10	17.4	10097
Labour productivity (growth)	-0.01	0.69	-0.61	-0.25	0.00	0.22	0.58	-7.00	9.3	4210
Policy support (dummy)	0.58	0.49	0.00	0.00	1.00	1.00	1.00	0.00	1.0	12525
Financial constraint (dummy)	0.09	0.29	0.00	0.00	0.00	0.00	0.00	0.00	1.0	12074
Digitalization (partial)	0.48	0.50	0.00	0.00	0.00	1.00	1.00	0.00	1.0	12478
Digitalization (total)	0.09	0.29	0.00	0.00	0.00	0.00	0.00	0.00	1.0	12478

Appendix 2: Quantile regressions with basic control variables

Table A2.1: Regression results, for OLS, panel fixed-effects and quantile regression: sales growth

	OLS	FE	Qreg 10%	Qreg 25%	Qreg 50%	Qreg 75%	Qreg 90%
COVID	-0.01	-0.005	0.006	-0.041	-0.027**	-0.032	0.027
	[0.047]	[0.033]	[0.088]	[0.026]	[0.014]	[0.021]	[0.064]
sales log (t-1)	-0.080***	-1.187***	0.001	0.004	-0.002*	-0.019***	-0.056***
	[0.010]	[0.039]	[0.008]	[0.002]	[0.001]	[0.002]	[0.006]
construction (dummy)	-0.03	-0.1	-0.130**	-0.029	0.024**	0.072***	0.152***
	[0.033]	[0.090]	[0.065]	[0.019]	[0.010]	[0.015]	[0.047]
services (dummy)	-0.03	-0.053	-0.046	0.015	-0.004	-0.021	-0.013
	[0.033]	[0.090]	[0.061]	[0.018]	[0.009]	[0.014]	[0.044]
manufacturing (dummy)	-0.042	0.031	-0.013	0.026	0.002	-0.017	-0.011
	[0.033]	[0.069]	[0.061]	[0.018]	[0.009]	[0.014]	[0.044]
COVID-19 x construction (dummy)	-0.044	0.091***	0.018	0.011	-0.008	-0.034*	-0.089
	[0.042]	[0.032]	[0.087]	[0.025]	[0.013]	[0.020]	[0.063]
COVID-19 x services (dummy)	-0.079*	-0.009	-0.184**	-0.051**	-0.001	0.016	0.014
	[0.043]	[0.036]	[0.082]	[0.024]	[0.013]	[0.019]	[0.060]
COVID-19 x manufacturing (dummy)	-0.034	0.033	-0.143*	-0.027	-0.002	-0.002	-0.012
	[0.043]	[0.038]	[0.081]	[0.024]	[0.013]	[0.019]	[0.059]
South Europe	0.024		0.057	0.023	-0.001	-0.016	-0.016
	[0.033]		[0.057]	[0.017]	[0.009]	[0.014]	[0.042]
North West Europe	0.043		0.058	-0.016	-0.014*	-0.034***	-0.017
	[0.033]		[0.054]	[0.016]	[0.008]	[0.013]	[0.040]
COVID-19 x South Europe	0.057	0.011	-0.03	-0.009	0.016	0.030*	0.008
	[0.041]	[0.032]	[0.077]	[0.022]	[0.012]	[0.018]	[0.056]
COVID-19 x North West Europe	0.021	-0.013	0.027	0.058***	0.040***	0.053***	0.008
	[0.039]	[0.031]	[0.072]	[0.021]	[0.011]	[0.017]	[0.052]
Young firm (dummy)	-0.051*	-0.026	-0.034	-0.003	0.004	0.021*	0.037
	[0.027]	[0.054]	[0.049]	[0.014]	[0.008]	[0.012]	[0.036]
COVID-19 x Young firm (dummy)	-0.025	-0.001	-0.063	-0.001	0.015	0.025*	0.054
	[0.034]	[0.027]	[0.065]	[0.019]	[0.010]	[0.015]	[0.047]
Policy support	-0.006		0.06	-0.015	-0.007	-0.005	-0.034
	[0.026]		[0.045]	[0.013]	[0.007]	[0.011]	[0.033]
COVID-19 x Policy support	-0.150***	-0.130***	-0.278***	-0.130***	-0.055***	-0.072***	-0.083*
	[0.033]	[0.026]	[0.061]	[0.018]	[0.010]	[0.014]	[0.044]
Financial constraint	-0.072	-0.017	-0.069	-0.04	-0.002	-0.011	0.113*
	[0.067]	[0.039]	[0.085]	[0.025]	[0.013]	[0.020]	[0.062]
COVID-19 x Financial constraint	-0.051	-0.029	-0.129	-0.060*	-0.021	-0.004	-0.174**
	[0.074]	[0.056]	[0.112]	[0.032]	[0.017]	[0.026]	[0.081]
Partially digital	0.055**	0.013	0.006	0	0.011	0.019*	0.061*
	[0.024]	[0.023]	[0.045]	[0.013]	[0.007]	[0.011]	[0.033]
COVID-19 x Partially digital	0.016	-0.023	0.061	0.008	-0.014	-0.022	-0.06
	[0.031]	[0.028]	[0.060]	[0.018]	[0.009]	[0.014]	[0.044]
Totally Digital	-0.055	-0.03	-0.11	-0.022	-0.001	-0.001	-0.043
	[0.039]	[0.033]	[0.073]	[0.021]	[0.011]	[0.017]	[0.053]
COVID-19 x Totally Digital	0.073	-0.002	0.04	0.017	0.013	0.014	0.076
	[0.062]	[0.070]	[0.104]	[0.030]	[0.016]	[0.025]	[0.076]
Constant	1.260***	18.308***	-0.327**	-0.136***	0.042*	0.430***	1.186***
	[0.147]	[0.606]	[0.140]	[0.041]	[0.022]	[0.033]	[0.102]
Observations	8,909	8,909	8,909	8,909	8,909	8,909	8,909
(Pseudo-)R^2	0.051	0.688	0.0353	0.0263	0.0092	0.0255	0.0561

Table A2.2: Regression results, for OLS, panel fixed-effects and quantile regression: employment growth

	OLS	FE	Qreg 10%	Qreg 25%	Qreg 50%	Qreg 75%	Qreg 90%
COVID	0.004	0.025	0.067	0.018	0.00	0.012	0.031
	[0.020]	[0.022]	[0.044]	[0.015]	[0.000]	[0.015]	[0.029]
sales log (t-1)	-0.001	-0.058**	0.019***	0.012***	0.00	-0.003**	-0.012***
	[0.003]	[0.023]	[0.004]	[0.001]	[0.000]	[0.001]	[0.003]
construction (dummy)	-0.004	-0.019	-0.049	-0.018	0.00	0.032***	0.085***
	[0.014]	[0.152]	[0.033]	[0.011]	[0.000]	[0.011]	[0.021]
services (dummy)	-0.008	-0.075	0.025	-0.007	0.00	0.016	0.032
	[0.013]	[0.096]	[0.031]	[0.010]	[0.000]	[0.010]	[0.020]
manufacturing (dummy)	0.006	0.016	0.027	0.009	0.00	0.009	0.051**
	[0.013]	[0.076]	[0.031]	[0.010]	[0.000]	[0.010]	[0.020]
COVID-19 x construction (dummy)	-0.01	0.024	-0.111**	-0.008	0.00	0.013	0.008
	[0.019]	[0.023]	[0.044]	[0.014]	[0.000]	[0.014]	[0.028]
COVID-19 x services (dummy)	-0.040**	-0.028	-0.127***	-0.031**	0.00	-0.022	-0.027
	[0.018]	[0.020]	[0.041]	[0.014]	[0.000]	[0.014]	[0.027]
COVID-19 x manufacturing (dummy)	-0.021	-0.01	-0.059	-0.012	0.00	0.002	-0.041
	[0.019]	[0.021]	[0.041]	[0.014]	[0.000]	[0.014]	[0.027]
South Europe	0.023*		0.006	0.007	0.00	0.027***	0.047**
	[0.012]		[0.029]	[0.010]	[0.000]	[0.010]	[0.019]
North West Europe	0.002		-0.029	-0.007	0.00	0.022**	0.041**
	[0.011]		[0.027]	[0.009]	[0.000]	[0.009]	[0.018]
COVID-19 x South Europe	-0.008	-0.007	-0.009	-0.013	0.00	-0.014	-0.015
	[0.018]	[0.018]	[0.039]	[0.013]	[0.000]	[0.013]	[0.025]
COVID-19 x North West Europe	-0.012	-0.018	-0.026	-0.017	0.00	-0.017	-0.01
	[0.016]	[0.020]	[0.036]	[0.012]	[0.000]	[0.012]	[0.023]
Young firm (dummy)	-0.003	0.036	-0.032	-0.006	0.00	0.030***	0.043***
	[0.011]	[0.039]	[0.025]	[0.008]	[0.000]	[0.008]	[0.016]
COVID-19 x Young firm (dummy)	-0.013	-0.013	-0.034	-0.004	0.00	0.01	0.018
	[0.016]	[0.019]	[0.033]	[0.011]	[0.000]	[0.011]	[0.021]
Policy support	-0.003		-0.017	-0.011	0.00	0.001	0.002
	[0.010]		[0.023]	[0.008]	[0.000]	[0.008]	[0.015]
COVID-19 x Policy support	-0.004	-0.014	-0.034	-0.012	0.00	-0.013	-0.016
	[0.015]	[0.016]	[0.031]	[0.010]	[0.000]	[0.010]	[0.020]
Financial constraint	0.027	0.02	-0.049	-0.002	0.00	0.009	-0.013
	[0.027]	[0.030]	[0.043]	[0.014]	[0.000]	[0.014]	[0.028]
COVID-19 x Financial constraint	-0.049	-0.01	-0.046	-0.032*	0.00	-0.013	0.028
	[0.032]	[0.034]	[0.056]	[0.019]	[0.000]	[0.019]	[0.036]
Partially digital	0.013	0.035**	0.012	0.006	0.00	0.007	0.035**
	[0.009]	[0.015]	[0.023]	[0.008]	[0.000]	[0.008]	[0.015]
COVID-19 x Partially digital	-0.009	-0.024	-0.022	-0.01	0.00	-0.003	-0.034*
	[0.014]	[0.017]	[0.030]	[0.010]	[0.000]	[0.010]	[0.020]
Totally Digital	-0.01	0.007	-0.063*	-0.018	0.00	0.007	0.01
	[0.024]	[0.033]	[0.037]	[0.012]	[0.000]	[0.012]	[0.024]
COVID-19 x Totally Digital	-0.006	-0.006	-0.003	0.006	0.00	-0.003	0.018
	[0.039]	[0.058]	[0.053]	[0.017]	[0.000]	[0.017]	[0.034]
Constant	0.002	0.866**	-0.449***	-0.238***	0.00	0.079***	0.266***
	[0.049]	[0.357]	[0.071]	[0.023]	[0.000]	[0.023]	[0.046]
Observations	8,960	8,960	8,960	8,960	8,960	8,960	8,960
(Pseudo-)R^2	0.006	0.016	0.0315	0.0175		0.0125	0.0256

Table A2.3: Regression results, for OLS, panel fixed-effects and quantile regression: growth of value added

	OLS	FE	Qreg 10%	Qreg 25%	Qreg 50%	Qreg 75%	Qreg 90%
COVID	0.031	0.032	0.031	-0.003	-0.03	0.023	0.175**
	[0.050]	[0.063]	[0.088]	[0.042]	[0.022]	[0.038]	[0.077]
sales log (t-1)	-0.032***	-0.478***	-0.006	0.005	0.001	-0.016***	-0.036***
	[0.009]	[0.083]	[0.008]	[0.004]	[0.002]	[0.004]	[0.007]
construction (dummy)	0.009	-0.163	-0.103	0.013	0.016	0.075***	0.167***
	[0.032]	[0.196]	[0.065]	[0.031]	[0.016]	[0.028]	[0.056]
services (dummy)	0.00	-0.144	-0.075	-0.032	-0.012	0.001	0.085
	[0.035]	[0.161]	[0.061]	[0.029]	[0.015]	[0.026]	[0.053]
manufacturing (dummy)	-0.04	0.033	-0.138**	0.002	-0.001	-0.004	0.109**
	[0.033]	[0.155]	[0.061]	[0.029]	[0.015]	[0.026]	[0.053]
COVID-19 x construction (dummy)	-0.06	0.009	0.048	-0.004	-0.006	-0.036	-0.196***
	[0.045]	[0.057]	[0.087]	[0.041]	[0.022]	[0.038]	[0.076]
COVID-19 x services (dummy)	-0.105**	-0.075	-0.139*	-0.036	-0.004	-0.012	-0.085
	[0.045]	[0.059]	[0.082]	[0.039]	[0.021]	[0.036]	[0.072]
COVID-19 x manufacturing (dummy)	0.02	0.027	0.085	0.007	-0.001	-0.017	-0.108
	[0.044]	[0.059]	[0.081]	[0.038]	[0.020]	[0.035]	[0.071]
South Europe	0.033		0.109*	0.019	-0.013	-0.03	-0.005
	[0.034]		[0.057]	[0.027]	[0.014]	[0.025]	[0.050]
North West Europe	0.00		0.079	-0.019	-0.033**	-0.033	0.015
	[0.034]		[0.055]	[0.026]	[0.014]	[0.024]	[0.048]
COVID-19 x South Europe	-0.055	-0.084	-0.151**	-0.043	0.004	0.017	-0.046
	[0.045]	[0.059]	[0.077]	[0.036]	[0.020]	[0.033]	[0.067]
COVID-19 x North West Europe	0.007	0.013	-0.074	0.024	0.040**	0.004	-0.103
	[0.041]	[0.054]	[0.072]	[0.034]	[0.018]	[0.031]	[0.063]
Young firm (dummy)	-0.029	0.027	-0.05	0.00	0.01	0.038*	0.073*
	[0.027]	[0.083]	[0.049]	[0.023]	[0.012]	[0.021]	[0.043]
COVID-19 x Young firm (dummy)	0.007	0.022	-0.155**	-0.032	0.016	0.023	0.064
	[0.037]	[0.049]	[0.066]	[0.031]	[0.017]	[0.028]	[0.057]
Policy support	0.004		0.025	0.011	-0.014	0.001	0.013
	[0.026]		[0.046]	[0.022]	[0.012]	[0.020]	[0.040]
COVID-19 x Policy support	-0.104***	-0.114***	-0.167***	-0.127***	-0.055***	-0.076***	-0.112**
	[0.034]	[0.044]	[0.061]	[0.029]	[0.016]	[0.027]	[0.054]
Financial constraint	-0.131*	-0.123	-0.186**	-0.106***	-0.03	-0.023	-0.055
	[0.070]	[0.082]	[0.087]	[0.041]	[0.022]	[0.038]	[0.076]
COVID-19 x Financial constraint	0.147*	0.257**	0.116	0.053	0.024	0.057	0.131
	[0.080]	[0.113]	[0.114]	[0.054]	[0.029]	[0.049]	[0.099]
Partially digital	0.044*	0.056	0.071	0.040*	0.005	0.005	-0.006
	[0.024]	[0.036]	[0.045]	[0.021]	[0.011]	[0.020]	[0.040]
COVID-19 x Partially digital	0.00	-0.027	0.033	-0.013	-0.001	0.008	0.037
	[0.032]	[0.048]	[0.061]	[0.029]	[0.015]	[0.026]	[0.053]
Totally Digital	-0.039	0.054	-0.048	-0.03	-0.011	0.022	-0.054
	[0.041]	[0.056]	[0.073]	[0.034]	[0.018]	[0.031]	[0.063]
COVID-19 x Totally Digital	0.028	0.00	-0.089	0.03	0.019	-0.035	0.041
	[0.058]	[0.098]	[0.103]	[0.048]	[0.026]	[0.044]	[0.089]
Constant	0.505***	7.429***	-0.386***	-0.241***	0.027	0.447***	0.969***
	[0.137]	[1.281]	[0.143]	[0.067]	[0.036]	[0.062]	[0.124]
Observations	7,562	7,562	7,562	7,562	7,562	7,562	7,562
(Pseudo-)R^2	0.015	0.107	0.027	0.014	0.006	0.009	0.020

Table A2.4: Regression results, for OLS, panel fixed-effects and quantile regression: growth of productivity

	OLS	FE	Qreg 10%	Qreg 25%	Qreg 50%	Qreg 75%	Qreg 90%
COVID	0.018	0.009	-0.044	-0.051	-0.014	0.035	0.163**
	[0.050]	[0.065]	[0.082]	[0.041]	[0.025]	[0.038]	[0.076]
sales log (t-1)	-0.029***	-0.435***	0.00	0.006*	-0.005**	-0.025***	-0.040***
	[0.009]	[0.086]	[0.008]	[0.004]	[0.002]	[0.004]	[0.007]
construction (dummy)	0.017	-0.159	-0.074	0.00	0.02	0.061**	0.123**
	[0.033]	[0.203]	[0.060]	[0.030]	[0.018]	[0.028]	[0.056]
services (dummy)	0.008	-0.029	-0.102*	-0.044	-0.014	0.014	0.062
	[0.036]	[0.158]	[0.057]	[0.029]	[0.017]	[0.027]	[0.053]
manufacturing (dummy)	-0.041	0.028	-0.116**	-0.013	0.01	-0.019	0.042
	[0.032]	[0.163]	[0.056]	[0.028]	[0.017]	[0.026]	[0.052]
COVID-19 x construction (dummy)	-0.057	-0.041	0.043	-0.03	-0.031	-0.044	-0.033
	[0.045]	[0.058]	[0.081]	[0.041]	[0.024]	[0.038]	[0.075]
COVID-19 x services (dummy)	-0.072	-0.053	-0.039	0.002	-0.001	0.004	-0.014
	[0.046]	[0.060]	[0.077]	[0.039]	[0.023]	[0.036]	[0.071]
COVID-19 x manufacturing (dummy)	0.036	0.033	0.066	0.035	-0.015	0.016	0.019
	[0.044]	[0.060]	[0.075]	[0.038]	[0.023]	[0.035]	[0.070]
South Europe	0.023		0.032	-0.019	-0.031*	-0.004	0.005
	[0.035]		[0.053]	[0.027]	[0.016]	[0.025]	[0.049]
North West Europe	0.004		0.033	-0.049*	-0.040***	-0.012	0.048
	[0.034]		[0.051]	[0.026]	[0.015]	[0.024]	[0.047]
COVID-19 x South Europe	-0.054	-0.087	-0.057	-0.028	0.009	-0.02	-0.1
	[0.045]	[0.060]	[0.072]	[0.036]	[0.022]	[0.034]	[0.067]
COVID-19 x North West Europe	0.022	0.035	0.005	0.063*	0.054***	0.016	-0.116*
	[0.041]	[0.054]	[0.067]	[0.034]	[0.020]	[0.031]	[0.062]
Young firm (dummy)	-0.023	0.00	-0.017	-0.023	0.009	0.028	0.111***
	[0.027]	[0.084]	[0.046]	[0.023]	[0.014]	[0.021]	[0.043]
COVID-19 x Young firm (dummy)	0.031	0.041	-0.076	-0.008	0.005	0.022	-0.002
	[0.037]	[0.051]	[0.061]	[0.031]	[0.018]	[0.029]	[0.057]
Policy support	0.005		0.043	0.027	-0.002	0.005	0.039
	[0.026]		[0.043]	[0.022]	[0.013]	[0.020]	[0.040]
COVID-19 x Policy support	-0.099***	-0.103**	-0.139**	-0.107***	-0.060***	-0.078***	-0.120**
	[0.034]	[0.044]	[0.057]	[0.029]	[0.017]	[0.027]	[0.053]
Financial constraint	-0.172**	-0.167**	-0.125	-0.126***	-0.061**	-0.023	-0.092
	[0.067]	[0.085]	[0.081]	[0.041]	[0.024]	[0.038]	[0.075]
COVID-19 x Financial constraint	0.214***	0.304***	0.083	0.122**	0.081**	0.072	0.157
	[0.078]	[0.115]	[0.106]	[0.054]	[0.032]	[0.050]	[0.099]
Partially digital	0.026	0.026	0.067	0.012	0.003	0	-0.003
	[0.025]	[0.037]	[0.042]	[0.021]	[0.013]	[0.020]	[0.039]
COVID-19 x Partially digital	0.014	-0.004	0.012	0.016	-0.001	0.005	0.018
	[0.033]	[0.049]	[0.056]	[0.028]	[0.017]	[0.026]	[0.052]
Totally Digital	-0.037	0.036	-0.108	-0.023	-0.002	0.026	-0.035
	[0.040]	[0.058]	[0.068]	[0.034]	[0.020]	[0.032]	[0.063]
COVID-19 x Totally Digital	0.06	0.031	0.075	0.068	0.011	-0.008	0.048
	[0.053]	[0.093]	[0.095]	[0.048]	[0.029]	[0.045]	[0.089]
Constant	0.472***	6.787***	-0.472***	-0.247***	0.117***	0.592***	1.029***
	[0.136]	[1.327]	[0.133]	[0.067]	[0.040]	[0.062]	[0.123]
Observations	7,562	7,562	7,562	7,562	7,562	7,562	7,562
(Pseudo-)R^2	0.013	0.088	0.016	0.011	0.005	0.012	0.022

Appendix 3: Sectoral results

Figure A3.1 quantile regression results for equation (1) by sectors: growth in value added

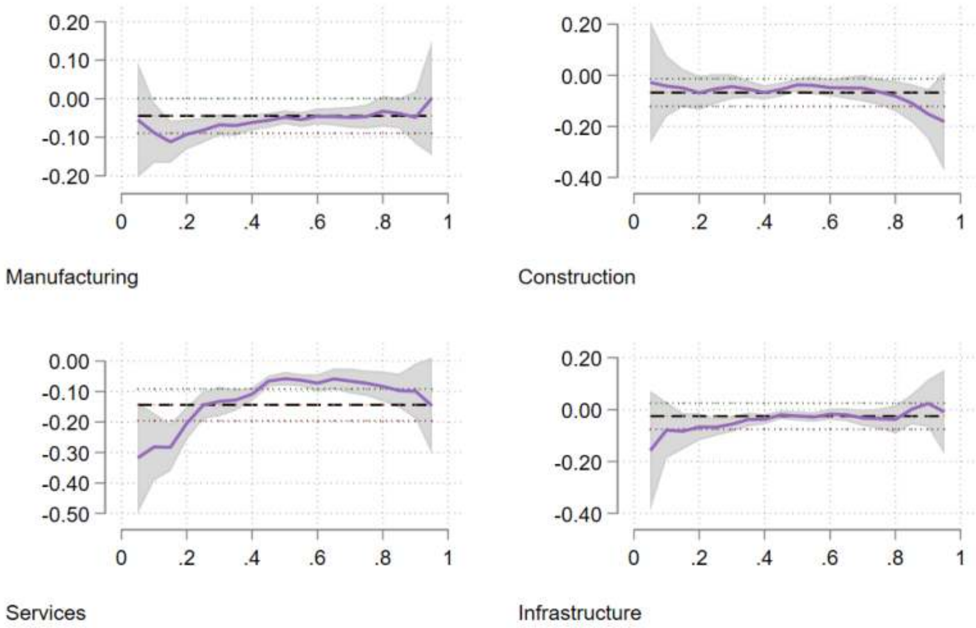


Figure A3.2 quantile regression results for equation (1) by sectors: growth in employment

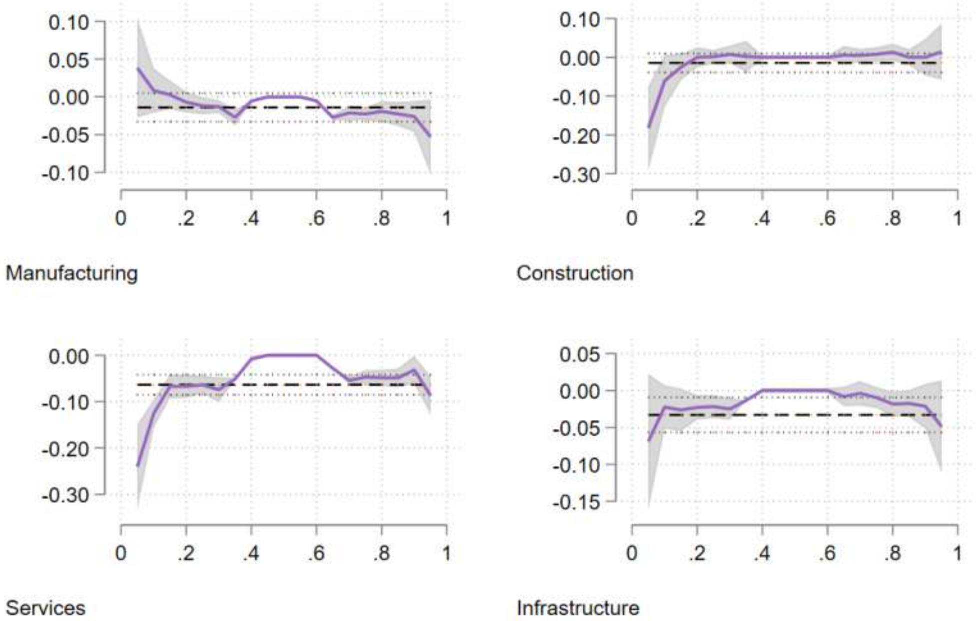
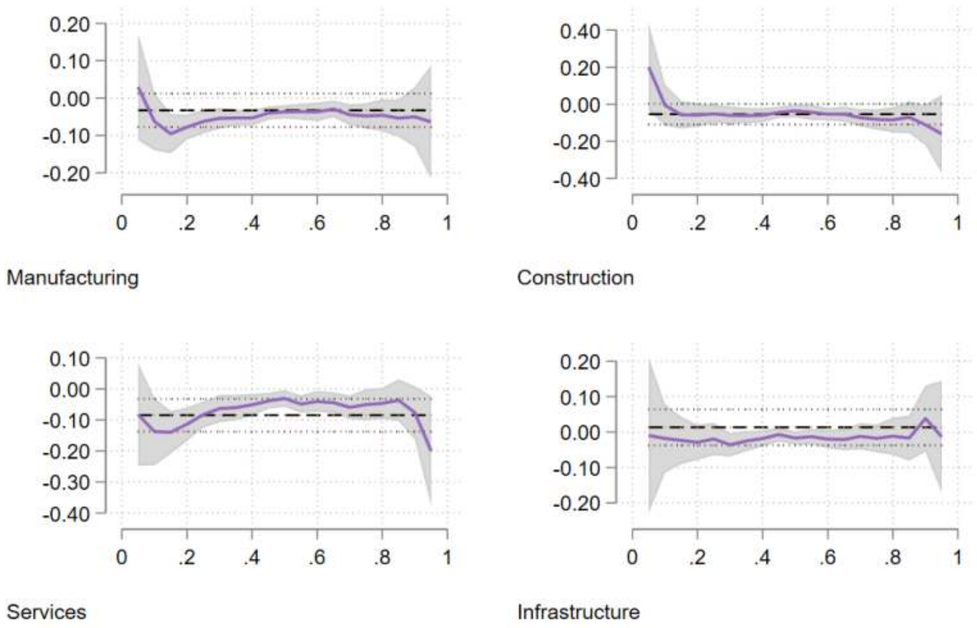


Figure A3.3 quantile regression results for equation (1) by sectors: growth in labour productivity



Which European firms were hardest hit by COVID-19?

September 2023

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