

# From rapid decline to high growth: Where in the distribution did COVID hit hardest?

Alex Coad,<sup>a</sup> Peter Bauer,<sup>b</sup> Clemens Domnick,<sup>b</sup> Peter Harasztosi,<sup>c</sup> Rozalia Pal,<sup>c</sup> and Mercedes Teruel<sup>d</sup>

a Waseda University, Tokyo, Japan

b Joint Research Centre - European Commission

c European Investment Bank

d Universitat Rovira i Virgili, Department of Economics, GRIT & ECO-SOS

## **ABSTRACT:**

### Purpose

This study aims to explore how did the COVID shock hit European firms at the upper quantiles (the high-growth superstars) or at the lower quantiles (already-struggling firms that may be fighting for their lives)

### Design/methodology/approach

This research uses the European Investment Bank Investment Survey (EIBIS) over the period from 2016 to 2020 merged with the ORBIS dataset from Bureau van Dijk. At methodological level, this exploratory paper applies graphical techniques and quantile regression to analyse the effect of the COVID shock on the full growth rates distribution.

### Findings

Regarding growth of sales and growth of value added, COVID had a negative effect on growth all across the growth rates distribution. The negative COVID effect is slightly larger at the lower quantiles. For employment growth we see no effect for many firms that have zero employment growth, but at the extreme quantiles we can observe that some declining firms were adversely affected by COVID. For labour productivity growth, the COVID effect is relatively small. Analysis of subsamples, as well as quantile regressions with interaction terms, emphasize that firms that received policy support were relatively more strongly affected by the COVID shock, consistent with the interpretation that COVID policy support was reaching the intended recipients. Finally, fully digitalised firms do not seem to have been affected by COVID-19.

### Originality/value

This article makes different contributions. First, the majority of previous studies have focused on the average effect of COVID on the growth performance. Our research contributes to know the incidence of COVID-19 to high-growth firms and declining firms. Second, during the pandemic governments devoted financial support to firms. Our analysis explores if policy support was given

to the companies more affected by this shock. Finally, we analyse if previous digitalization was a relevant strategy on the growth during the COVID-19.

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

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## 1. Introduction

The COVID pandemic had disastrous effects on public health and also led to a sudden economic crisis across Europe, leading to a sharp spike in uncertainty (Altig et al., 2021) and threatening to increase unemployment while negatively affecting indicators of economic activity such as GDP. At the aggregate level, the COVID shock clearly had an adverse effect on the economy. At the disaggregated level, however, there was considerable heterogeneity in the outcomes of firms, such that beneath the average lies a turbulent environment in which some firms grasped opportunities and thrived amid the chaos that dragged others down. Some research has highlighted the role of sector for the COVID shock, with some sectors (such as travel agencies, accommodation, and food and beverage service activities) being more strongly affected than others (such as information and communication technology (ICT)) (Benedetti Fasil et al., 2021; Coad et al., 2022a). Firms with online digital business models generally fared better than those with offline business models (Bloom et al., 2021).

A wide range of COVID support packages were 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 shock would be particularly lethal for vulnerable firms at the lower end of the performance distribution, who would be badly positioned to survive such an adverse shock. While the exit of poorly performing firms can potentially stimulate the economy if these resources are reallocated to better performing firms, nevertheless an abrupt shock that suddenly pushes an excessively large share of relatively underperforming firms into failure could flood the market with resources that are difficult to quickly reallocate towards better-performing survivors. As a result, COVID 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 COVID support may have propped up some unviable firms, putting them on artificial life support (Gourinchas et al., 2021), only to exit *en masse* once the COVID support packages would be withdrawn.

In addition to the classical view on the “cleansing” effect of the recession, that removes unviable firms while allowing viable firms to continue, there are also concerns that an adverse macroeconomic shock could hit high-potential firms at the upper end of the performance distribution. The COVID 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. The COVID shock could be particularly damaging for high-growth

firms (HGFs) considering that seed and early finance (compared to late-stage deals) were disproportionately severely hit by the COVID shock (Benedetti Fasil et al., 2021), and HGFs may rely on such sources of finance to reach their potential. The COVID 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. The COVID shock may also disproportionately affect high-performing firms if R&D investors are met with unexpectedly chilly receptions from risk-averse investors and cautious consumers. As a result, there is interest in whether the COVID shock had a disproportionately large effect on the upper end of the performance distribution. Coad et al. (2022b) observe that HGFs and R&D investors were particularly strongly hit by the COVID shock, in terms of expectations surrounding investment, availability of internal finance, and availability of external finance.

As a consequence, this paper is not only interested in how the COVID shock hit the “average” firm, but also investigates whether the COVID shock hit firms disproportionately hard at the lower quantiles and the upper quantiles of the performance distribution. 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,” whereas it might be more interesting to explore heterogeneous outcomes at the lower and upper quantiles of the distribution (Koenker and Hallock, 2001). Therefore, using other statistical techniques such as quantile regression could give valuable insights into how the COVID shock affected firms at the lower and upper quantiles of the performance distribution.

Our research questions can therefore be stated as follows: i) How did the COVID shock affect the distribution of firm performance?; ii) Did the COVID shock have uneven effects across the distribution, such as disproportionately large effects for low-performing firms (at the lower quantiles) or top-performing firms (at the upper quantiles)?

These research questions are investigated using an exploratory and descriptive research approach that relies on an unconditional graphical analysis of distributions as well as quantile regressions. Our econometric approach does not focus primarily on tracking the performance of individual firms over time, but instead focuses on how the COVID shock distorted the shape of the “population-level” distribution.

Our main contribution to the literature therefore relates to the heterogeneous effects of the COVID shock across the firm growth rates distribution. On the one hand, firm-level analysis usually focuses on the ‘average effect for the average firm’ obtained through OLS-based conditional-mean regression methods, and therefore do not investigate whether there may be heterogeneous outcomes across the growth rates

distribution. On the other hand, it takes years for high-quality data on firm-level performance to become available, which is holding back research into how COVID affected firm-level performance (Haltiwanger, 2022). Therefore, we contribute valuable evidence regarding how the COVID shock affected the distribution of firm growth rates, using recent 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 having a negative effect on growth all across the growth rates distribution. The negative COVID effect is slightly larger at the lower quantiles. Hence COVID hits declining firms harder than it hits growing firms. For employment growth, there is no detectable COVID 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 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 were more strongly negatively affected by the COVID 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 shock, given that the negative coefficient for the COVID shock is generally non-significant across the quantiles for our four indicators.

Multivariate quantile regressions also show that the strongest results are observed for the group of firms receiving policy support. For these firms, the COVID shock had noticeably strong negative effects, that 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 than 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 were relatively more strongly affected by the COVID shock. This can be taken as suggesting that COVID support was allocated to firms that were hit particularly hard, in line with the policy goals.

The paper unfolds as follows. Section 2 describes our dataset and provides some initial summary statistics. Section 3 presents our methodology. Section 4 presents the analysis, and Section 5 concludes.

## 2. Data

### 2.1 Database

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. In our case, 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.<sup>1</sup> Brutscher et al. (2020) show that EIBIS seems to be a reliable data source that has no systematic sampling bias.

### 2.2 Descriptive statistics

Table 1 shows the number of observations in each wave. 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.<sup>2</sup> Table 2 contains a description of the main variables and how they are defined. Table 3 presents some summary statistics on the main variables.

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<sup>1</sup> Please see <https://www.eib.org/attachments/eibis-methodology-report-2019-en.pdf> (last accessed 14th March 2022).

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

Table 1: Observations per wave.

Survey year	Frequency	Percent	Cumulative percentage
2016	12,483	16.66	16.66
2017	12,338	16.46	33.12
2018	12,355	16.49	49.6
2019	12,672	16.91	66.51
2020	12,572	16.77	83.29
2021	12,525	16.71	100
Total	74,945	100	

Table 2: Descriptions and definitions of the main variables.

Variable	Description
<i>Main dependent variables</i>	
Employees	Number of employees (headcount). Often expressed in terms of logarithms ( <i>log_employees</i> ) or logarithmic growth rate ( <i>gr_employees</i> ).
Sales	Total sales of the firm, based on EIBIS. Often expressed in terms of logarithms ( <i>log_sales</i> ) or logarithmic growth rate ( <i>gr_sales</i> ).
Value added	Total value added of the firm. Often expressed in terms of logarithms ( <i>log_value_added</i> ) or logarithmic growth rate ( <i>gr_value_added</i> ).
Labour productivity	Labour productivity, variable generated by us on the basis of the EIBIS/ORBIS data, measured as value added per employee. Often expressed in terms of logarithms ( <i>log_labprod</i> ) or logarithmic growth rate ( <i>gr_labprod</i> ).
<i>Main explanatory variables for subsample analysis</i>	
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". <ul style="list-style-type: none"> <li>"Center and East": Bulgaria, Czech Republic, Croatia, Hungary, Lithuania, Latvia, Poland, Romania, Slovenia, Slovakia.</li> <li>"South": Cyprus, Spain, France, Greece, Italy, Malta, Portugal.</li> <li>"North-West": Austria, Belgium, Germany, Denmark, Estonia, Finland, Ireland, Luxembourg, Netherlands, Sweden.</li> </ul>
Policy support	Dummy identifying whether the firm received any kind of policy support during the COVID 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	Dummy identifying 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)	Dummy identifying whether the firm is partially digitalized (dummy variable), i.e. firms that reported that they partially implemented digital technology.

Digitalization (total)	Dummy identifying whether the firm is fully digitalized (dummy variable), i.e. firms that reported implemented digital technology by organizing their entire business around it.
Source: own elaboration from EIBIS data.	

Table 3: Summary statistics, 2021 wave.

Variable	Mean	Std. Dev.	10%	25%	median	75%	90%	Min.	Max.	Obs.
Employees	262.52	5997.278	6	10	30	110	350	1	600000	12525
log_employees	3.66	1.576	1.792	2.303	3.401	4.700	5.858	0	13.305	12525
gr_employees	-0.017	0.267	-0.122	0.000	0.000	0.000	0.095	-6.209	5.177	12525
Sales	$4.5 \times 10^7$	$3.6 \times 10^8$	271163.9	755214.8	3264518	$1.7 \times 10^7$	$6.0 \times 10^7$	-2.006	$1.6 \times 10^{10}$	11833
log_sales	15.156	2.118	12.533	13.629	15.061	16.677	17.937	0.923	23.518	11590
gr_sales	-0.078	0.695	-0.515	-0.198	-0.029	0.080	0.301	-9.248	6.974	4968
Value added	$1.0 \times 10^7$	$9.6 \times 10^7$	82797.95	257909.1	904558.8	3964300	$1.4 \times 10^7$	$-8.4 \times 10^8$	$3.6 \times 10^9$	10219
log_value_added	13.88	1.959	11.435	12.512	13.744	15.209	16.487	5.398	21.994	10097
gr_value_added	-0.044	0.702	-0.657	-0.257	-0.011	0.201	0.526	-7.033	9.426	4210
Labour productivity	49578.75	504363.1	7126.16	13563.85	26702.3	48645.37	77306.8	-4290683	$3.4 \times 10^7$	10219
log_labprod	10.14	0.976	8.947	9.540	10.205	10.797	11.258	3.095	17.348	10097
gr_labprod	-0.009	0.694	-0.605	-0.252	-0.004	0.222	0.579	-7.000	9.320	4210
Policy support	0.576	0.494	0	0	1	1	1	0	1	12525
Financial constraints	0.090	0.286	0	0	0	0	0	0	1	12074
Digitalization (partial)	0.474	0.499	0	0	0	1	1	0	1	12496
Digitalization (total)	0.091	0.288	0	0	0	0	0	0	1	12496

## 3. Methodology

### 3.1 Deflating the series

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 (harmonized indices of consumer prices, HICPs) from Eurostat.<sup>3</sup> 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.

### 3.2 Calculating growth rates

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

<sup>3</sup> 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].

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, that we take as dependent variables, reflect the broad overall concept of “firm performance” (Miller et al., 2013) although they certainly capture different aspects of firm performance. For example, growth in sales can potentially be achieved without growth in value added or growth in employment. In statistical terms, these four variables are not expected to be perfectly correlated, even though they represent the same basic concept of “firm performance”. Table 4 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 1.00). The strongest correlation is between growth of value added and growth of labour productivity ( $\rho = 0.9$  in each case). We even observe a negative correlation coefficient for the pairwise correlation between employment growth and labour productivity growth ( $\rho \approx -0.2$  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 waves with the COVID wave. The largest change due to COVID, perhaps, is that the correlation between growth of sales and growth of employment moves up from 0.1743 to 0.2993.

Table 4: Correlation matrices between the 4 growth rate variables (i.e. our dependent variables) in years that correspond to either non-COVID waves (pooled together) or the COVID 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.

NON COVID WAVES					COVID WAVE				
	gr sales	gr_employees	gr value added	gr labprod		gr sales	gr_employees	gr value added	gr labprod
gr sales	1	<i>0.1849</i>	<i>0.3634</i>	<i>0.2533</i>	gr sales	1	<i>0.2443</i>	<i>0.4447</i>	<i>0.3183</i>
	18488	<i>15203</i>	<i>15203</i>	<i>15203</i>		5009	<i>4210</i>	<i>4210</i>	<i>4210</i>
gr_employees	0.1769	1	<i>0.1452</i>	<i>-0.2535</i>	gr_employees	0.2987	1	<i>0.2113</i>	<i>-0.1786</i>
	18488	20264	<i>15203</i>	<i>15203</i>		5009	5328	<i>4210</i>	<i>4210</i>
gr value added	0.4639	0.1738	1	<i>0.8562</i>	gr value added	0.4441	0.2709	1	<i>0.8575</i>
	15203	15203	15203	<i>15203</i>		4210	4210	4210	<i>4210</i>
gr labprod	0.3936	-0.2450	0.9122	1	gr labprod	0.2885	-0.2278	0.8756	1
	15203	15203	15203	15203		4210	4210	4210	4210

### 3.3 Analysis of quantiles

This paper focuses on firm heterogeneity in terms of variation along the quantiles of the dependent variable. Analysis of distributions can help 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.

### 3.4 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 shock and firm-level outcomes. 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 the inclusion of some control variables 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 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. Fourth, our analysis was undertaken on a remote desktop connection to a secure data server at the European Investment Bank (EIB). While this gives us access to rich data, it also places limits on the computational power, and as a consequence our attempts at quantile regressions with control variables took an impractical amount of time. 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.<sup>4</sup>

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

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

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<sup>4</sup> To be precise, the standard errors of the command “qreg” in Stata 17.

Where the quantile regression coefficient  $\beta_\theta$  varies over the conditional quantiles  $\theta$  (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 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 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 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:

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

The vector  $\mathbf{X}_i$  contains a limited set of control variables: the lagged logarithm of sales, 3 dummies for macrosectors, 2 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 wave, a dummy for financially constrained firms, and dummies for whether the firm was either partially digitalized or fully digitalized. The coefficient  $\gamma_\theta$ , which varies over the quantiles  $\theta$ , shows how these explanatory variables are related to growth rates at various quantiles  $\theta$  of the growth rates distribution.

Equation (2) also contains the interaction terms, represented by the vector of coefficients  $\vartheta_\theta$ , which estimates the relationship between the explanatory variables and the growth rate, specifically at the time of the COVID shock. Were  $\vartheta_\theta$  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  $\vartheta_\theta$  should be significantly different from zero, this would suggest that these explanatory variables had a different association with growth in the COVID year compared to what we would expect in 'normal' years. For example, if the group of firms receiving policy support (variable '*Policy\_support*') were no different in the years before COVID, but had lower growth in the COVID wave, this would be visible in terms of a non-significant coefficient for '*Policy\_support*' but a significant negative coefficient for the interaction term '*COVID*  $\times$  *Policy\_support*'.

## 4. Analysis

### 4.1 Nonparametric graphical analysis

#### 4.1.1 Growth rate distributions

Figure 1: Growth rates distributions. 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 wave.

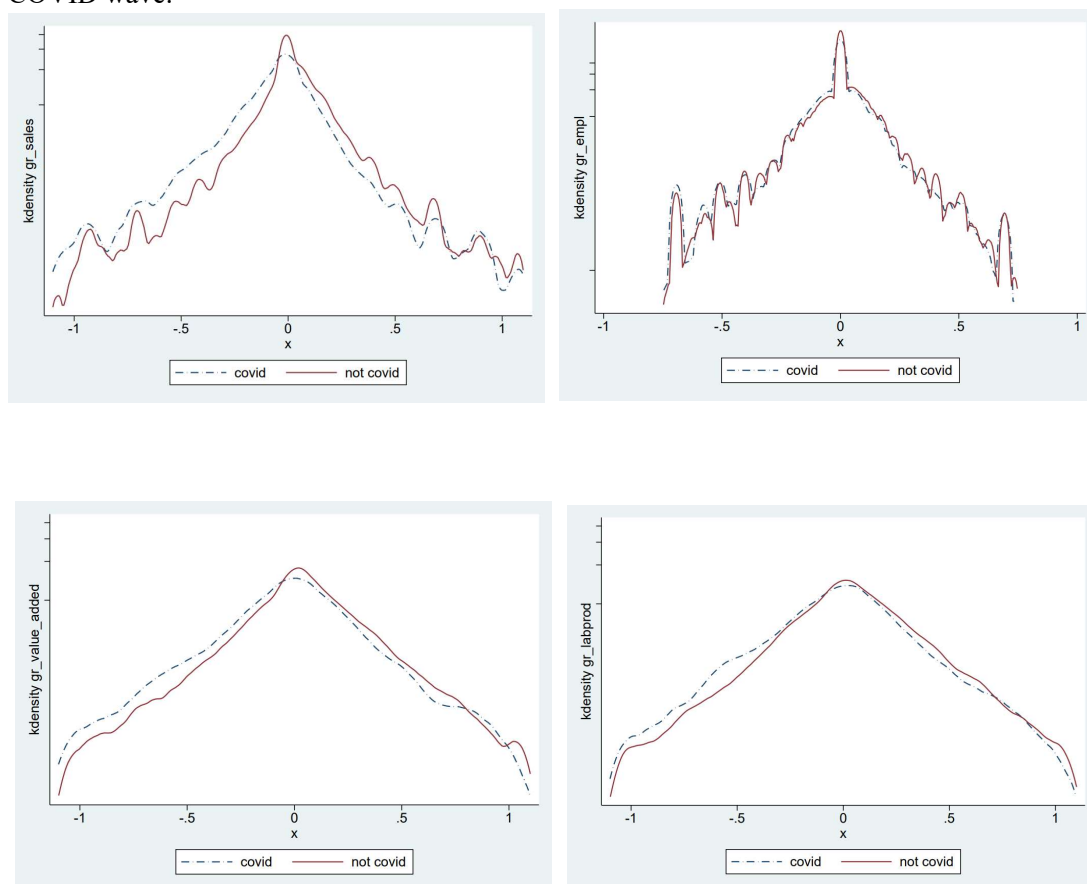


Figure 1 shows the growth rate distributions for growth of sales, employment, value-added, and labour productivity, using kernel density plots plotted on semi-logarithmic axes (note the log scale on the y axis). Kernel density plots are like smoothed histograms that provide a useful first look at the shape of a distribution. For each of our four growth rate variables, kernel plots show the familiar Laplace shape (i.e. the ‘tent-shaped’ growth rates distribution, Bottazzi and Secchi, 2006), which is shifted left for the COVID wave (dash-dot line) because slower growth seems to be observed all across the distribution.

The leftward shift that is observed in the COVID 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 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).

Appendix 1 shows cumulative distribution function (CDF) plots for these variables. These CDF plots largely confirm the results from the growth rate distributions, and also show that there is a mass point at which about a quarter of firms that have an employment growth rate of exactly 0.00 employees in each year.

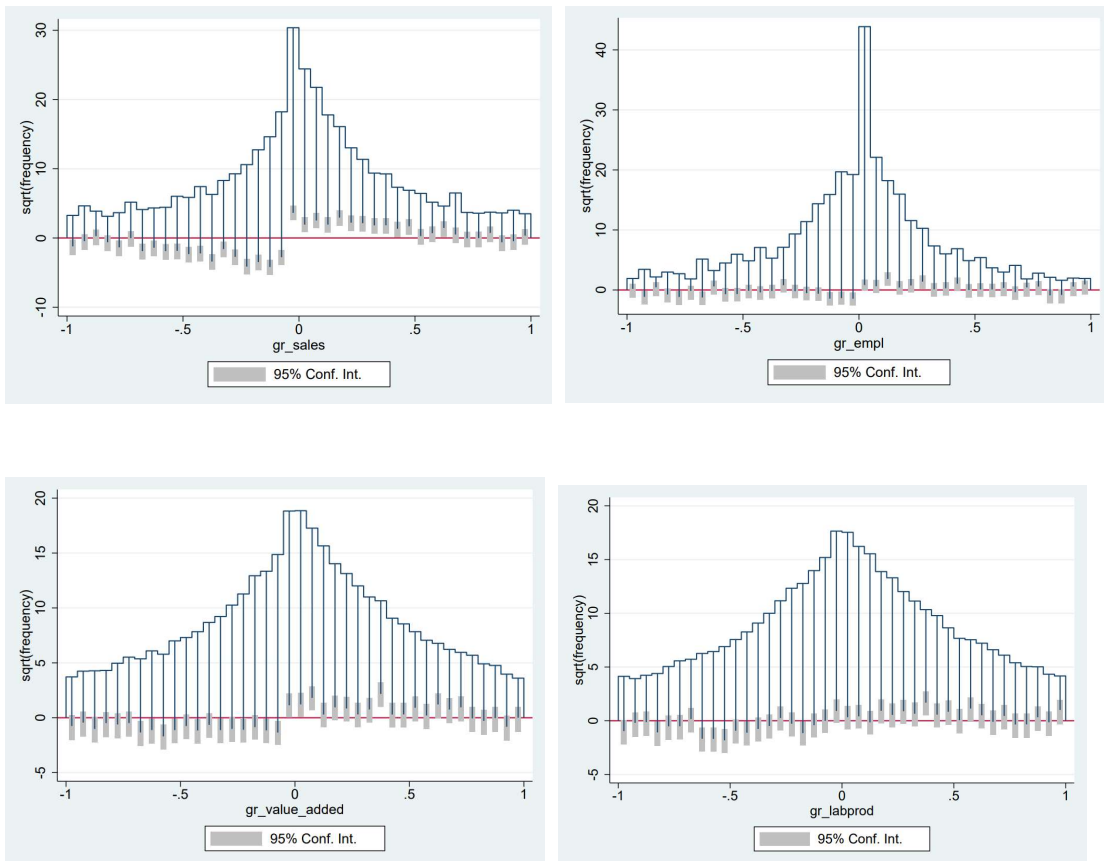
#### 4.1.2 Hanging rootograms

Hanging rootograms are a useful tool for comparing firm-level distributions (e.g. Barba Navaretti et al., 2022), that can be implemented in Stata.<sup>5</sup> 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 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 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.

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<sup>5</sup> 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. 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 wave. The hanging bars, with 95% confidence intervals (grey shaded boxes) highlight the differences between the non-COVID waves (the blue line from which the lines are hanging) and the COVID wave.



## 4.2 Quantile regression analysis

### 4.2.1 Basic analysis

We start with a relatively straightforward quantile analysis of the COVID dummy on performance (as shown in equation (1)). 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 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 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 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: Estimated coefficient of *COVID*. Quantile regression results for equation (1). Top left: sales growth (23,497 observations). Top right: employment growth (25,592 observations). Bottom left: value added growth (19,413 observations). Bottom right: labour productivity growth (19,413 observations).

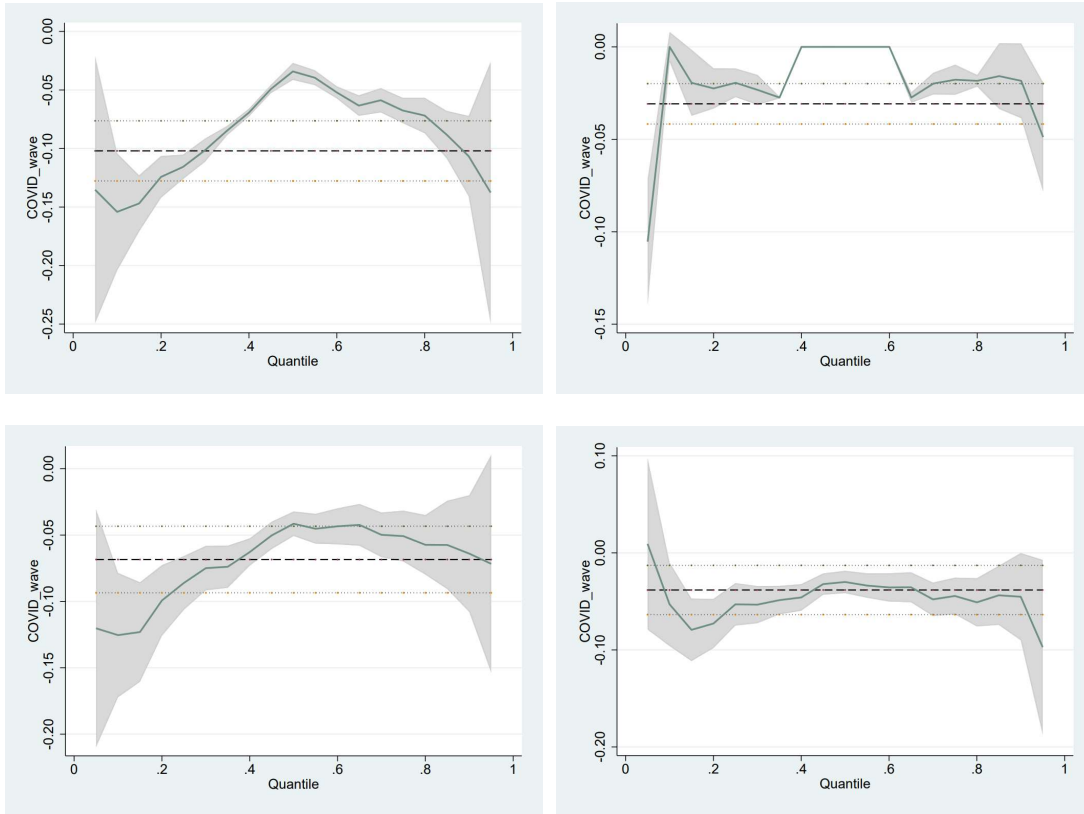


Figure 3 begins with results for the full sample. Two important reference points are the horizontal line across from 0.00 (i.e. corresponding to no COVID effect) as well as the horizontal line corresponding to the OLS regression estimate (the thick dashed line). In each of the four cases in Figure 3, the thick dashed line is below 0.00, indicating that the average effect (as estimated by OLS) is that the COVID 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 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). The case of value added growth (bottom left), in particular, shows that the negative COVID effect is slightly larger at the lower quantiles. Hence COVID 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 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 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.<sup>6</sup>

#### 4.2.2 Subsample analysis

The following subsection presents the results of our two subsamples. First, we present the results related to the subsample of firms receiving policy support. Second, we consider firms that were already digitalized before COVID-19 pandemic. This analysis allows us to analyse the allocation efficiency of the policy support and also the importance of digitalization during the pandemic.

Concerning the group of firms that were recipients of 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 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 here than in the full sample (which appeared to generally be not different from zero). In particular, the COVID shock

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<sup>6</sup> 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.

had a negative effect on productivity growth for those firms at the lower quantiles, while the COVID 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).

Figure 4: Estimated coefficient of *COVID*. Quantile regression results for equation (1). Subsample of firms receiving any kind of policy support regarding COVID (variable “*Policy\_support*”), Top left: sales growth (6,276 observations). Top right: employment growth (6,727 observations). Bottom left: value added growth (5,351 observations). Bottom right: labour productivity growth (5,351 observations).

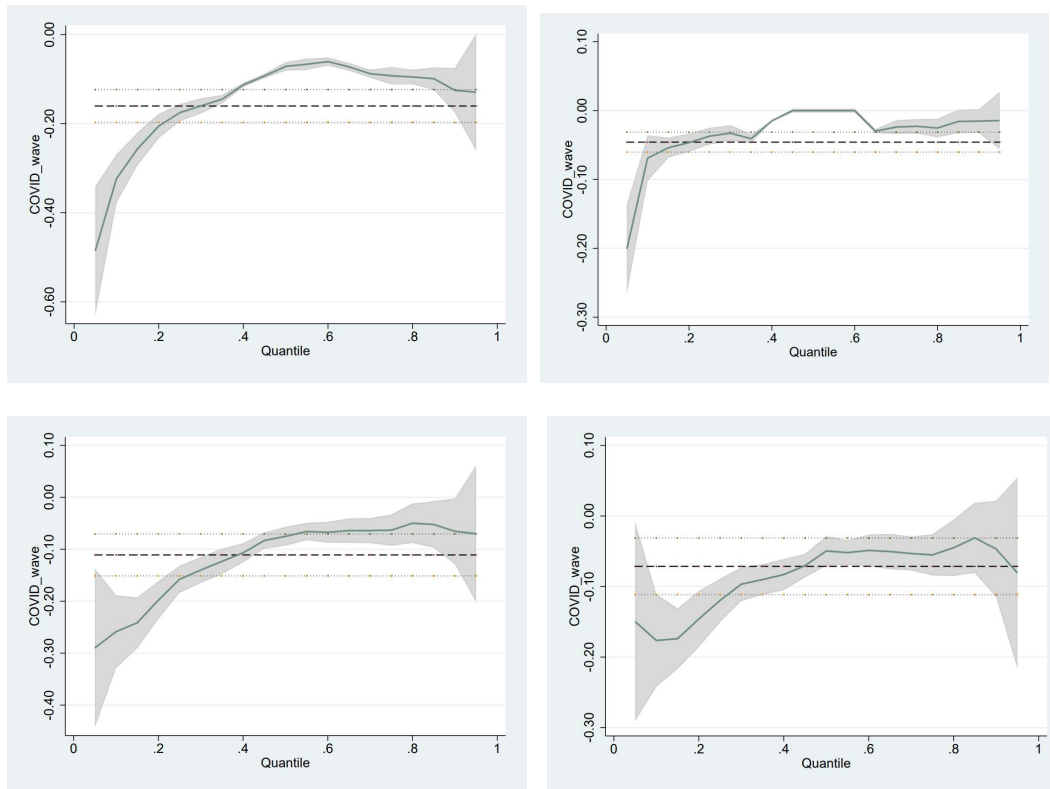


Figure 5: Estimated coefficient of *COVID*. Quantile regression results for equation (1), for the subsample of firms that reported implemented digital technology by organising their entire business around it. Top left: sales growth (1,365 observations). Top right: employment growth (1,456 observations). Bottom left: value added growth (1,172 observations). Bottom right: labour productivity growth (1,172 observations).

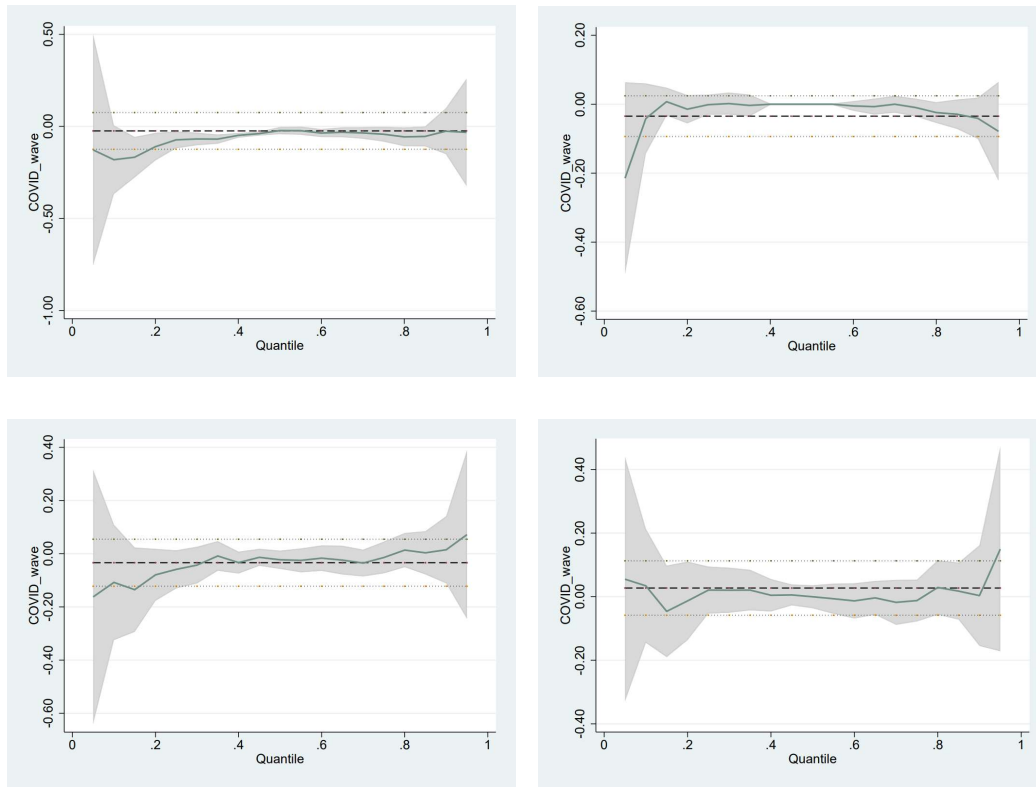


Figure 5 shows the results for the subsample of fully digitalized firms, i.e. a subsample of firms that reported implementing digital technology by organizing their entire business around it. For each of the growth rate variables (growth of sales, employment, value added and labour productivity) we essentially no longer observe a significantly negative coefficient of the COVID shock at the lower quantiles. This contrasts with the results in Figure 4 for firms receiving policy support, where the COVID 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 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 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 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).

### 4.2.3 Multivariate analysis

Our basic quantile regression analysis in subsection 4.2.1 is followed by a more detailed multivariate analysis, involving quantile regression estimates of equation (2). 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 shock, by looking at their respective interaction terms with the COVID shock.

The strongest results in Appendix 2 regarding the COVID shock seem to be that firms receiving any kind of policy support (variable ‘*Policy\_support*’) were hit especially hard (at all quantiles, but especially at the lower quantiles) during the COVID shock, in a way that was different from their outcomes in previous years. Strong negative coefficients for the interaction of *COVID* and *Policy\_support* 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 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 wave compared to their performance in previous years.<sup>7</sup> While we observed in the previous subsection (4.2.2) that digitalized firms were not significantly negatively affected by the COVID 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.

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<sup>7</sup> 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 wave. The coefficients on the interaction terms for financially constrained firms during the COVID 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 wave to do better-than-expected with regards to labour productivity.

## 5. Conclusion

The COVID shock had a strong negative effect on aggregate economic performance, with the average firm taking a hit on sales 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 shock disproportionately deter tomorrow's superstars at the upper end of the distribution, thus sacrificing future growth potential? This paper investigates where the COVID shock hit the firm growth distribution, using graphical techniques and quantile regressions to analyse the full distribution of firm growth rates in terms of sales, value added, employment, and labour productivity.

Growth of sales and growth of value added were observed to have similar patterns, with COVID having a negative effect on growth all across the growth rates distribution. The negative COVID effect is generally slightly larger at the lower quantiles. Hence COVID hits declining firms harder than it hits growing firms.

For employment growth we see no effect for many firms that have zero employment growth, but at the extremes we can observe that some fast-declining and fast-growing firms were adversely affected by COVID.

For labour productivity growth, the COVID 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 that were in the subsample that received policy support were relatively more strongly affected by the COVID shock. This can be taken as suggesting that COVID 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 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, reveal that the strongest results are observed for the group of firms receiving policy support. For these firms, the COVID 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 than what would be observed in a normal year. Overall, therefore, multivariate quantile regressions confirm the subsample analysis and emphasize that firms that were in the subsample that received policy support were relatively more strongly affected by the COVID shock. This can be taken as suggesting that COVID support was allocated to firms that were hit particularly hard, in line with the policy goals.

Like all research, this paper is not without its limitations. 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. 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). In particular, given that COVID 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 in future work. 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 shock, to complement the current paper's focus on growth rates of continuing firms. Further analysis of how the COVID 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 shock.

## Appendix 1: Cumulative Distribution Function (CDF) plots

CDF (Cumulative distribution function) plots to compare distributions in a way that the differences jump out at the eye.

Figure A1.1: CDF plots for growth of sales, employment, value added, and labour productivity. Top left: sales growth. Top right: employment growth. Bottom left: value added growth. Bottom right: growth of labour productivity. Blue line: all non-COVID years pooled together. Red line: COVID wave.

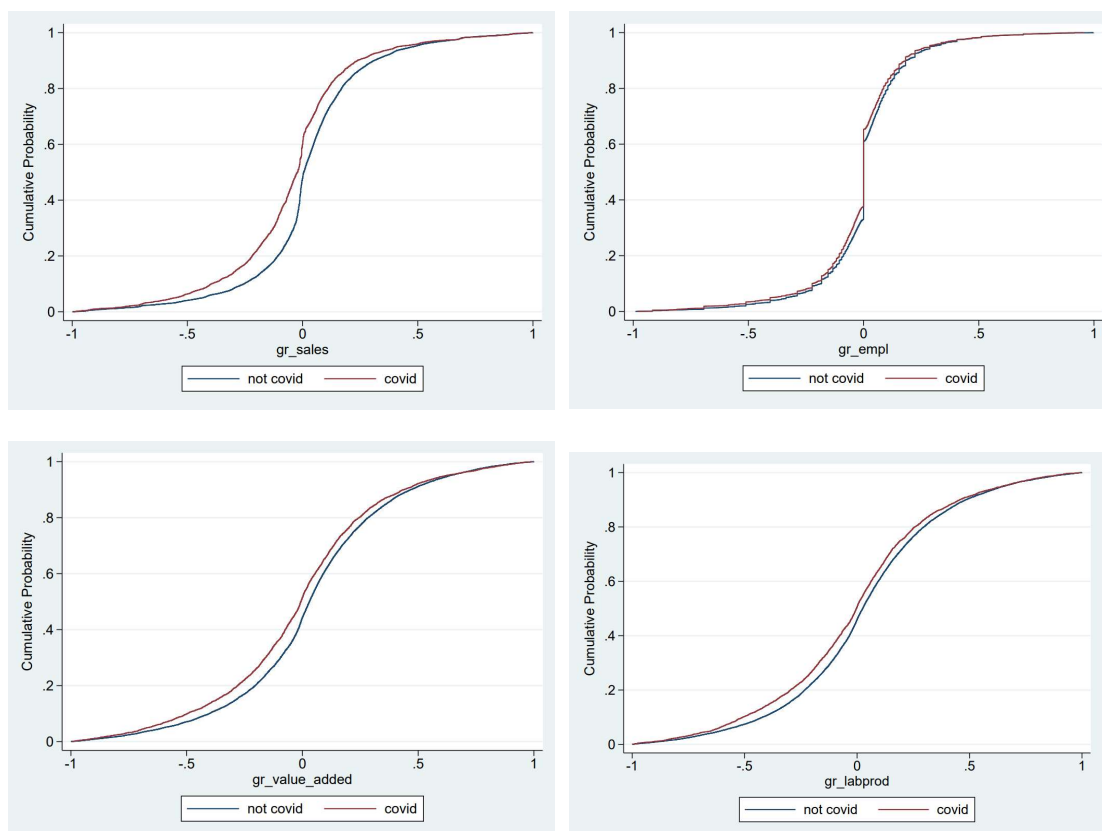


Figure A1.1 shows CDF plots for several variables. The best-looking graphs are for growth of sales, and growth of labour productivity, where growth rates were lower in the COVID wave all across the distribution. For growth of employment, there is granularity, with for example a mass-point at exactly 0.000, which is presumably because of integer constraints affecting employee headcounts.

## Appendix 2: Quantile regressions with basic control variables

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

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	FE	Qreg 10%	Qreg 25% <sup>d</sup>	Qreg 50% <sup>d</sup>	Qreg 75%	Qreg 90%
COVID	-0.010 [0.047]	-0.005 [0.033]	0.006 [0.088]	-0.041 [0.026]	-0.027** [0.014]	-0.032 [0.021]	0.027 [0.064]
log_sales (1 lag)	-0.080*** [0.010]	-1.187*** [0.039]	0.001 [0.008]	0.004 [0.002]	-0.002* [0.001]	-0.019*** [0.002]	-0.056*** [0.006]
Construction	-0.030 [0.033]	-0.100 [0.090]	-0.130** [0.065]	-0.029 [0.019]	0.024** [0.010]	0.072*** [0.015]	0.152*** [0.047]
Services	-0.030 [0.033]	-0.053 [0.090]	-0.046 [0.061]	0.015 [0.018]	-0.004 [0.009]	-0.021 [0.014]	-0.013 [0.044]
Infrastructure	-0.042 [0.033]	0.031 [0.069]	-0.013 [0.061]	0.026 [0.018]	0.002 [0.009]	-0.017 [0.014]	-0.011 [0.044]
COVID × Construction	-0.044 [0.042]	0.091*** [0.032]	0.018 [0.087]	0.011 [0.025]	-0.008 [0.013]	-0.034* [0.020]	-0.089 [0.063]
COVID × Services	-0.079* [0.043]	-0.009 [0.036]	-0.184** [0.082]	-0.051** [0.024]	-0.001 [0.013]	0.016 [0.019]	0.014 [0.060]
COVID × Infrastructure	-0.034 [0.043]	0.033 [0.038]	-0.143* [0.081]	-0.027 [0.024]	-0.002 [0.013]	-0.002 [0.019]	-0.012 [0.059]
South countries	0.024 [0.033]		0.057 [0.057]	0.023 [0.017]	-0.001 [0.009]	-0.016 [0.014]	-0.016 [0.042]
North-West countries	0.043 [0.033]		0.058 [0.054]	-0.016 [0.016]	-0.014* [0.008]	-0.034*** [0.013]	-0.017 [0.040]
COVID × South countries	0.057 [0.041]	0.011 [0.032]	-0.030 [0.077]	-0.009 [0.022]	0.016 [0.012]	0.030* [0.018]	0.008 [0.056]
COVID × North-West countries	0.021 [0.039]	-0.013 [0.031]	0.027 [0.072]	0.058*** [0.021]	0.040*** [0.011]	0.053*** [0.017]	0.008 [0.052]
Young	-0.051* [0.027]	-0.026 [0.054]	-0.034 [0.049]	-0.003 [0.014]	0.004 [0.008]	0.021* [0.012]	0.037 [0.036]
COVID × Young	-0.025 [0.034]	-0.001 [0.027]	-0.063 [0.065]	-0.001 [0.019]	0.015 [0.010]	0.025* [0.015]	0.054 [0.047]
Policy support	-0.006 [0.026]		0.060 [0.045]	-0.015 [0.013]	-0.007 [0.007]	-0.005 [0.011]	-0.034 [0.033]
COVID × Policy support	-0.150*** [0.033]	-0.130*** [0.026]	-0.278*** [0.061]	-0.130*** [0.018]	-0.055*** [0.010]	-0.072*** [0.014]	-0.083* [0.044]
Financial constraints	-0.072 [0.067]	-0.017 [0.039]	-0.069 [0.085]	-0.040 [0.025]	-0.002 [0.013]	-0.011 [0.020]	0.113* [0.062]
COVID × Financial constraints	-0.051 [0.074]	-0.029 [0.056]	-0.129 [0.112]	-0.060* [0.032]	-0.021 [0.017]	-0.004 [0.026]	-0.174** [0.081]
Digitalization(partial)	0.055** [0.024]	0.013 [0.023]	0.006 [0.045]	-0.000 [0.013]	0.011 [0.007]	0.019* [0.011]	0.061* [0.033]
COVID × Digitalization(partial)	0.016 [0.031]	-0.023 [0.028]	0.061 [0.060]	0.008 [0.018]	-0.014 [0.009]	-0.022 [0.014]	-0.060 [0.044]
Digitalization(total)	-0.055 [0.039]	-0.030 [0.033]	-0.110 [0.073]	-0.022 [0.021]	-0.001 [0.011]	-0.001 [0.017]	-0.043 [0.053]
COVID × Digitalization(total)	0.073 [0.062]	-0.002 [0.070]	0.040 [0.104]	0.017 [0.030]	0.013 [0.016]	0.014 [0.025]	0.076 [0.076]
Constant	1.260*** [0.147]	18.308*** [0.606]	-0.327** [0.140]	-0.136*** [0.041]	0.042* [0.022]	0.430*** [0.033]	1.186*** [0.102]
Observations	8,909	8,909	8,909	8,909	8,909	8,909	8,909
Pseudo-R <sup>2</sup>	0.051	0.688	0.0353	0.0263	0.0092	0.0255	0.0561
Number of respondentid		5,103					

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

VARIABLES	(1) OLS	(2) FE	(3) Qreg 10%	(4) Qreg 25% <sup>d</sup>	(5) Qreg 50% <sup>d</sup>	(6) Qreg 75%	(7) Qreg 90%
COVID	0.004 [0.020]	0.025 [0.022]	0.067 [0.044]	0.018 [0.015]	0.000 [0.000]	0.012 [0.015]	0.031 [0.029]
log_sales (1 lag)	-0.001 [0.003]	-0.058** [0.023]	0.019*** [0.004]	0.012*** [0.001]	0.000 [0.000]	-0.003** [0.001]	-0.012*** [0.003]
Construction	-0.004 [0.014]	-0.019 [0.152]	-0.049 [0.033]	-0.018 [0.011]	0.000 [0.000]	0.032*** [0.011]	0.085*** [0.021]
Services	-0.008 [0.013]	-0.075 [0.096]	0.025 [0.031]	-0.007 [0.010]	0.000 [0.000]	0.016 [0.010]	0.032 [0.020]
Infrastructure	0.006 [0.013]	0.016 [0.076]	0.027 [0.031]	0.009 [0.010]	0.000 [0.000]	0.009 [0.010]	0.051** [0.020]
COVID × Construction	-0.010 [0.019]	0.024 [0.023]	-0.111** [0.044]	-0.008 [0.014]	0.000 [0.000]	0.013 [0.014]	0.008 [0.028]
COVID × Services	-0.040** [0.018]	-0.028 [0.020]	-0.127*** [0.041]	-0.031** [0.014]	0.000 [0.000]	-0.022 [0.014]	-0.027 [0.027]
COVID × Infrastructure	-0.021 [0.019]	-0.010 [0.021]	-0.059 [0.041]	-0.012 [0.014]	0.000 [0.000]	0.002 [0.014]	-0.041 [0.027]
South countries	0.023* [0.012]		0.006 [0.029]	0.007 [0.010]	0.000 [0.000]	0.027*** [0.010]	0.047** [0.019]
North-West countries	0.002 [0.011]		-0.029 [0.027]	-0.007 [0.009]	0.000 [0.000]	0.022** [0.009]	0.041** [0.018]
COVID × South countries	-0.008 [0.018]	-0.007 [0.018]	-0.009 [0.039]	-0.013 [0.013]	0.000 [0.000]	-0.014 [0.013]	-0.015 [0.025]
COVID × North-West countries	-0.012 [0.016]	-0.018 [0.020]	-0.026 [0.036]	-0.017 [0.012]	0.000 [0.000]	-0.017 [0.012]	-0.010 [0.023]
Young	-0.003 [0.011]	0.036 [0.039]	-0.032 [0.025]	-0.006 [0.008]	0.000 [0.000]	0.030*** [0.008]	0.043*** [0.016]
COVID × Young	-0.013 [0.016]	-0.013 [0.019]	-0.034 [0.033]	-0.004 [0.011]	0.000 [0.000]	0.010 [0.011]	0.018 [0.021]
Policy support	-0.003 [0.010]		-0.017 [0.023]	-0.011 [0.008]	0.000 [0.000]	0.001 [0.008]	0.002 [0.015]
COVID × Policy support	-0.004 [0.015]	-0.014 [0.016]	-0.034 [0.031]	-0.012 [0.010]	0.000 [0.000]	-0.013 [0.010]	-0.016 [0.020]
Financial constraints	0.027 [0.027]	0.020 [0.030]	-0.049 [0.043]	-0.002 [0.014]	0.000 [0.000]	0.009 [0.014]	-0.013 [0.028]
COVID × Financial constraints	-0.049 [0.032]	-0.010 [0.034]	-0.046 [0.056]	-0.032* [0.019]	0.000 [0.000]	-0.013 [0.019]	0.028 [0.036]
Digitalization(partial)	0.013 [0.009]	0.035** [0.015]	0.012 [0.023]	0.006 [0.008]	0.000 [0.000]	0.007 [0.008]	0.035** [0.015]
COVID × Digitalization(partial)	-0.009 [0.014]	-0.024 [0.017]	-0.022 [0.030]	-0.010 [0.010]	0.000 [0.000]	-0.003 [0.010]	-0.034* [0.020]
Digitalization(total)	-0.010 [0.024]	0.007 [0.033]	-0.063* [0.037]	-0.018 [0.012]	0.000 [0.000]	0.007 [0.012]	0.010 [0.024]
COVID × Digitalization(total)	-0.006 [0.039]	-0.006 [0.058]	-0.003 [0.053]	0.006 [0.017]	0.000 [0.000]	-0.003 [0.017]	0.018 [0.034]
Constant	0.002 [0.049]	0.866** [0.357]	-0.449*** [0.071]	-0.238*** [0.023]	0.000 [0.000]	0.079*** [0.023]	0.266*** [0.046]
Observations	8,960	8,960	8,960	8,960	8,960	8,960	8,960
Pseudo-R <sup>2</sup>	0.006	0.016	0.0315	0.0175	0.0000	0.0125	0.0256
Number of respondentid		5,141					

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

VARIABLES	(1) OLS	(2) FE	(3) Qreg 10%	(4) Qreg 25% <sup>d</sup>	(5) Qreg 50% <sup>d</sup>	(6) Qreg 75%	(7) Qreg 90%
COVID	0.031 [0.050]	0.032 [0.063]	0.031 [0.088]	-0.003 [0.042]	-0.030 [0.022]	0.023 [0.038]	0.175** [0.077]
log_sales (1 lag)	-0.032*** [0.009]	-0.478*** [0.083]	-0.006 [0.008]	0.005 [0.004]	0.001 [0.002]	-0.016*** [0.004]	-0.036*** [0.007]
Construction	0.009 [0.032]	-0.163 [0.196]	-0.103 [0.065]	0.013 [0.031]	0.016 [0.016]	0.075*** [0.028]	0.167*** [0.056]
Services	-0.000 [0.035]	-0.144 [0.161]	-0.075 [0.061]	-0.032 [0.029]	-0.012 [0.015]	0.001 [0.026]	0.085 [0.053]
Infrastructure	-0.040 [0.033]	0.033 [0.155]	-0.138** [0.061]	0.002 [0.029]	-0.001 [0.015]	-0.004 [0.026]	0.109** [0.053]
COVID × Construction	-0.060 [0.045]	0.009 [0.057]	0.048 [0.087]	-0.004 [0.041]	-0.006 [0.022]	-0.036 [0.038]	-0.196*** [0.076]
COVID × Services	-0.105** [0.045]	-0.075 [0.059]	-0.139* [0.082]	-0.036 [0.039]	-0.004 [0.021]	-0.012 [0.036]	-0.085 [0.072]
COVID × Infrastructure	0.020 [0.044]	0.027 [0.059]	0.085 [0.081]	0.007 [0.038]	-0.001 [0.020]	-0.017 [0.035]	-0.108 [0.071]
South countries	0.033 [0.034]		0.109* [0.057]	0.019 [0.027]	-0.013 [0.014]	-0.030 [0.025]	-0.005 [0.050]
North-West countries	-0.000 [0.034]		0.079 [0.055]	-0.019 [0.026]	-0.033** [0.014]	-0.033 [0.024]	0.015 [0.048]
COVID × South countries	-0.055 [0.045]	-0.084 [0.059]	-0.151** [0.077]	-0.043 [0.036]	0.004 [0.020]	0.017 [0.033]	-0.046 [0.067]
COVID × North-West countries	0.007 [0.041]	0.013 [0.054]	-0.074 [0.072]	0.024 [0.034]	0.040** [0.018]	0.004 [0.031]	-0.103 [0.063]
Young	-0.029 [0.027]	0.027 [0.083]	-0.050 [0.049]	0.000 [0.023]	0.010 [0.012]	0.038* [0.021]	0.073* [0.043]
COVID × Young	0.007 [0.037]	0.022 [0.049]	-0.155** [0.066]	-0.032 [0.031]	0.016 [0.017]	0.023 [0.028]	0.064 [0.057]
Policy support	0.004 [0.026]		0.025 [0.046]	0.011 [0.022]	-0.014 [0.012]	0.001 [0.020]	0.013 [0.040]
COVID × Policy support	-0.104*** [0.034]	-0.114*** [0.044]	-0.167*** [0.061]	-0.127*** [0.029]	-0.055*** [0.016]	-0.076*** [0.027]	-0.112** [0.054]
Financial constraints	-0.131* [0.070]	-0.123 [0.082]	-0.186** [0.087]	-0.106*** [0.041]	-0.030 [0.022]	-0.023 [0.038]	-0.055 [0.076]
COVID × Financial constraints	0.147* [0.080]	0.257** [0.113]	0.116 [0.114]	0.053 [0.054]	0.024 [0.029]	0.057 [0.049]	0.131 [0.099]
Digitalization(partial)	0.044* [0.024]	0.056 [0.036]	0.071 [0.045]	0.040* [0.021]	0.005 [0.011]	0.005 [0.020]	-0.006 [0.040]
COVID × Digitalization(partial)	-0.000 [0.032]	-0.027 [0.048]	0.033 [0.061]	-0.013 [0.029]	-0.001 [0.015]	0.008 [0.026]	0.037 [0.053]
Digitalization(total)	-0.039 [0.041]	0.054 [0.056]	-0.048 [0.073]	-0.030 [0.034]	-0.011 [0.018]	0.022 [0.031]	-0.054 [0.063]
COVID × Digitalization(total)	0.028 [0.058]	0.000 [0.098]	-0.089 [0.103]	0.030 [0.048]	0.019 [0.026]	-0.035 [0.044]	0.041 [0.089]
Constant	0.505*** [0.137]	7.429*** [1.281]	-0.386*** [0.143]	-0.241*** [0.067]	0.027 [0.036]	0.447*** [0.062]	0.969*** [0.124]
Observations	7,562	7,562	7,562	7,562	7,562	7,562	7,562
Pseudo-R <sup>2</sup>	0.015	0.107	0.0267	0.0140	0.0056	0.0089	0.0201
Number of respondentid		4,465					

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

VARIABLES	(1) OLS	(2) FE	(3) Qreg 10%	(4) Qreg 25%d	(5) Qreg 50%d	(6) Qreg 75%	(7) Qreg 90%
COVID	0.018 [0.050]	0.009 [0.065]	-0.044 [0.082]	-0.051 [0.041]	-0.014 [0.025]	0.035 [0.038]	0.163** [0.076]
log_sales (1 lag)	-0.029*** [0.009]	-0.435*** [0.086]	0.000 [0.008]	0.006* [0.004]	-0.005** [0.002]	-0.025*** [0.004]	-0.040*** [0.007]
Construction	0.017 [0.033]	-0.159 [0.203]	-0.074 [0.060]	0.000 [0.030]	0.020 [0.018]	0.061** [0.028]	0.123** [0.056]
Services	0.008 [0.036]	-0.029 [0.158]	-0.102* [0.057]	-0.044 [0.029]	-0.014 [0.017]	0.014 [0.027]	0.062 [0.053]
Infrastructure	-0.041 [0.032]	0.028 [0.163]	-0.116** [0.056]	-0.013 [0.028]	0.010 [0.017]	-0.019 [0.026]	0.042 [0.052]
COVID × Construction	-0.057 [0.045]	-0.041 [0.058]	0.043 [0.081]	-0.030 [0.041]	-0.031 [0.024]	-0.044 [0.038]	-0.033 [0.075]
COVID × Services	-0.072 [0.046]	-0.053 [0.060]	-0.039 [0.077]	0.002 [0.039]	-0.001 [0.023]	0.004 [0.036]	-0.014 [0.071]
COVID × Infrastructure	0.036 [0.044]	0.033 [0.060]	0.066 [0.075]	0.035 [0.038]	-0.015 [0.023]	0.016 [0.035]	0.019 [0.070]
South countries	0.023 [0.035]		0.032 [0.053]	-0.019 [0.027]	-0.031* [0.016]	-0.004 [0.025]	0.005 [0.049]
North-West countries	0.004 [0.034]		0.033 [0.051]	-0.049* [0.026]	-0.040*** [0.015]	-0.012 [0.024]	0.048 [0.047]
COVID × South countries	-0.054 [0.045]	-0.087 [0.060]	-0.057 [0.072]	-0.028 [0.036]	0.009 [0.022]	-0.020 [0.034]	-0.100 [0.067]
COVID × North-West countries	0.022 [0.041]	0.035 [0.054]	0.005 [0.067]	0.063* [0.034]	0.054*** [0.020]	0.016 [0.031]	-0.116* [0.062]
Young	-0.023 [0.027]	-0.000 [0.084]	-0.017 [0.046]	-0.023 [0.023]	0.009 [0.014]	0.028 [0.021]	0.111*** [0.043]
COVID × Young	0.031 [0.037]	0.041 [0.051]	-0.076 [0.061]	-0.008 [0.031]	0.005 [0.018]	0.022 [0.029]	-0.002 [0.057]
Policy support	0.005 [0.026]		0.043 [0.043]	0.027 [0.022]	-0.002 [0.013]	0.005 [0.020]	0.039 [0.040]
COVID × Policy support	-0.099*** [0.034]	-0.103** [0.044]	-0.139** [0.057]	-0.107*** [0.029]	-0.060*** [0.017]	-0.078*** [0.027]	-0.120** [0.053]
Financial constraints	-0.172** [0.067]	-0.167** [0.085]	-0.125 [0.081]	-0.126*** [0.041]	-0.061** [0.024]	-0.023 [0.038]	-0.092 [0.075]
COVID × Financial constraints	0.214*** [0.078]	0.304*** [0.115]	0.083 [0.106]	0.122** [0.054]	0.081** [0.032]	0.072 [0.050]	0.157 [0.099]
Digitalization(partial)	0.026 [0.025]	0.026 [0.037]	0.067 [0.042]	0.012 [0.021]	0.003 [0.013]	0.000 [0.020]	-0.003 [0.039]
COVID × Digitalization(partial)	0.014 [0.033]	-0.004 [0.049]	0.012 [0.056]	0.016 [0.028]	-0.001 [0.017]	0.005 [0.026]	0.018 [0.052]
Digitalization(total)	-0.037 [0.040]	0.036 [0.058]	-0.108 [0.068]	-0.023 [0.034]	-0.002 [0.020]	0.026 [0.032]	-0.035 [0.063]
COVID × Digitalization(total)	0.060 [0.053]	0.031 [0.093]	0.075 [0.095]	0.068 [0.048]	0.011 [0.029]	-0.008 [0.045]	0.048 [0.089]
Constant	0.472*** [0.136]	6.787*** [1.327]	-0.472*** [0.133]	-0.247*** [0.067]	0.117*** [0.040]	0.592*** [0.062]	1.029*** [0.123]
Observations	7,562	7,562	7,562	7,562	7,562	7,562	7,562
Pseudo-R <sup>2</sup>	0.013	0.088	0.0156	0.0105	0.0046	0.0116	0.0216
Number of respondentid		4,465					

## References

- Altig, D., Baker, S., Barrero, J.M., Bloom, N., Bunn, P., Chen, S., Davis, S.J., Leather, J., Meyer, B., Mihaylov, E., Mizen, P., Parker N., Renault T., Smietanka P. and Thwaites, G. (2020), “*Economic uncertainty before and during the COVID-19 pandemic*”, *Journal of Public Economics*, Vol. 191, pp. 104274.
- Archibugi, D., Filippetti, A. and Frenz, M. (2013), “*Economic crisis and innovation: is destruction prevailing over accumulation?*”, *Research Policy*, Vol. 42, N.2, pp. 303-314.
- Barba Navaretti, G. B., Castellani, D. and Pieri, F. (2022), “*CEO Age, shareholder monitoring and the organic growth of European firms*”, *Small Business Economics*, Vol. 59, N. 1 pp. 361-382.
- Benedetti Fasil, C, Domnick, C, del Rio, J-C, Fákó, P, Flachenecker, F., Gavigan, J. P., Janiri, M. L., Stamenov, B. and Testa, G., (2021), “*High Growth Enterprises in the COVID-19 Crisis Context demographics, environmental innovations, digitalization, finance and policy measures*”, EUR 30686 EN, Publications Office of the European Union, Luxembourg, 2021, ISBN 978-92-76-37269-1, doi:10.2760/63402, JRC124469
- Bloom, N., Fletcher, R. S. and Yeh, E. (2021), “*The impact of COVID-19 on US firms*”, (No. w28314). National Bureau of Economic Research.
- Bottazzi G. and Secchi A., (2006), “*Explaining the distribution of firm growth rates*”, *Rand Journal of Economics*, Vol. 37, N. 2, pp. 235-256.
- Bottazzi, G., Secchi, A. and Tamagni, F. (2014), “*Financial constraints and firm dynamics*”, *Small Business Economics*, Vol. 42, pp. 99-116.
- Brutscher P.-B., Coali A., Delanote J. and Harasztosi P. (2020), “*EIB Group Survey on Investment and Investment Finance: A technical note on data quality*”, European Investment Bank, working paper 2020/08. DOI 10.2867/772584
- Canay, I.A. (2011), “*A simple approach to quantile regression for panel data*”, *Econometrics Journal*, Vol. 14, pp. 368-386.
- Cirera, X., Cruz, M., Davies, E., Grover, A., Iacovone, L., Cordova, J.E.L., Medvedev, D., Maduko, F.O., Nayyar, G., Reyes Ortega, S. and Torres, J. (2021), “*Policies to Support Businesses through the COVID-19 Shock: A Firm Level Perspective*”, *World Bank Research Observer*, Vol. 36, N. 1, pp. 41-66.
- Coad, A. and Broekel, T. (2012), “*Firm growth and productivity growth: evidence from a panel VAR*”, *Applied Economics*, Vol. 44, pp. 1251–1269.
- Coad, A., Cowling, M. and Siepel, J. (2017), “*Growth processes of high-growth firms as a four-dimensional chicken and egg*”, *Industrial and Corporate Change*, Vol. 26, N. 4, pp. 537–554.
- Coad, A., Amaral-Garcia, S., Bauer, P., Domnick, C., Harasztosi, P., Pál, R. and Teruel, M. (2022a), “*HGEs’ investment plans in times of COVID: an overview*”, Unpublished.

- Coad, A., Amaral-Garcia, S., Bauer, P., Domnick, C., Harasztosi, P., Pál, R. and Teruel, M. (2022b), “*Investment expectations by vulnerable European firms: A difference-in-difference approach*”, EIB Working Paper 2022/04. European Investment Bank.
- Elwert, F. and Winship, C. (2014), “*Endogenous selection bias: The problem of conditioning on a collider variable*”, *Annual Review of Sociology*, Vol. 40, pp. 31-53.
- Frölich, M. and Melly, B. (2010), “*Estimation of quantile treatment effects with Stata*”, *The Stata Journal*, Vol. 10, N. 3, pp. 423-457.
- Geroski, P. and Gugler, K. (2004), “*Corporate growth convergence in Europe*”, *Oxford Economic Papers* Vol. 56, N. 4, pp. 597–620.
- Gourinchas, P. O., Kalemli-Özcan, Ş., Penciakova, V. and Sander, N. (2021), “*COVID-19 and Small-and Medium-Sized Enterprises: A 2021 "Time Bomb"?*”, *American Economic Association Papers and Proceedings*, Vol. 111, pp. 282-86. <https://doi.org/10.1257/pandp.20211109>
- Haltiwanger, J. (2022), “*Spatial and Sectoral Reallocation of Firms, Workers and Jobs in the Pandemic and Recovery*”, Unpublished manuscript.
- Harasztosi, P., Maurin, L., Pál, R., Revoltella, D. and van der Wielen, W. (2022), “*Firm-level policy support during the crisis: So far, so good?*”, European Investment Bank. EIB Working Paper 2022/01.
- Koenker, R. and Hallock, K.F. (2001), “*Quantile Regression*”, *Journal of Economic Perspectives*, Vol. 15 N. 4, pp. 143-156.
- Kozeniauskas, N., Moreira, P. and Santos, C. (2022), “*On the cleansing effect of recessions and government policy: Evidence from Covid-19*”, *European Economic Review*, 104097.
- Miller, C.C., Washburn, N.T. and Glick, W.H. (2013), “*The myth of firm performance*”, *Organization Science*, Vol. 24, N. 3, pp. 948-964.
- Moneta, A., Entner, D., Hoyer, P. O. and Coad, A. (2013), “*Causal inference by independent component analysis: Theory and applications*”, *Oxford Bulletin of Economics and Statistics*, Vol. 75, N. 5, pp. 705–730.
- Teruel, M., Coad, A., Domnick, C., Flachenecker, F., Harasztosi, P., Janiri, M. L. and Pal, R. (2022), “*The birth of new HGEs: internationalization through new digital technologies*”, *Journal of Technology Transfer*, Vol. 47, N. 3, pp. 804-845.
- Tornqvist, L., Vartia, P. and Vartia, Y.O. (1985), “*How Should Relative Changes Be Measured?*”, *American Statistician*, Vol. 39, N. 1, pp. 43-46.