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ABSTRACT

We consider Covid-19 financial support measures in the Netherlands, and relate it to the productivity of firms, their investment behavior and expectations, as well as to turnover, and firm exits. This analysis sheds light on both the short and potential longer term effects, by assessing the pre-pandemic, pandemic, and post-pandemic period. Using Unconditional Quantile Regression (UQR), we exploit the full distribution of TFP and investment. Our results suggest that the financial support has increased the chance of survival for firms, but arguably has reduced aggregate productivity by keeping alive the less viable firms, and supporting lower productive firms. Investments have been scaled back, regardless of receiving support, and investment expectations are also lower for those firms with support. Nevertheless, firms that are more productive and have invested more, are better able to survive a crisis independently. This is a strong message to policy makers and the business environment to remain focusing on improving firm productivity, so as to make our economy more resilient in the face of future crises.

1. INTRODUCTION

Pandemics are anything but new, and they have had severe, adverse economic impacts in the past. Given the rapid spread of Covid-19, countries across the world have adopted several public health measures intended to prevent its spread. As part of social distancing measures, businesses, schools and community centers were required to close down, mass gatherings have been prohibited, and lockdown measures have been imposed in many countries, allowing travel only for essential needs. There is a rapidly growing literature on the economic impact of Covid-19 (and the associated restrictions); many of which are discussed in Brodeur et al. (2020).

The Covid-19 crisis has confronted firms with unforeseen economic challenges and restructuring, and pushing most economies into recessions. Its impact on firms' productivity is more complex because one salient feature of this epidemic crisis is its heterogeneous impact. In comparison to other financial crises, evidence shows that corporate profits and investments did not decline compared to the latest financial crisis (EIB, 2021) and bank lending spreads did not increase across countries (Andersson et al., 2021). Thus, it seems that a pandemic crisis unfolds itself differently from other economic (financial) crises endured, though, it can be regarded as a textbook example of an ex-ante financial shock (Fernández-Cerezo et al., 2021).

The resilience of firms plays a role in how they have gone through the coronavirus pandemic (so far). Some firms are better able to absorb the negative consequences of a crisis than others. Some firms had a better starting position than their competitors beforehand, for example in terms of productivity or in terms of investments in digital facilities. Firms are not affected to the same extent by the pandemic. For example, smaller firms seem to be hit harder than larger firms (Fernández-Cerezo et al., 2021). The negative impact of the crisis was stronger for less productive firms (Bloom et al., 2020; Fernández-Cerezo et al., 2021). In addition, the effect of varies between industries (Bloom et al., 2020). This can be explained by a number of reasons, all related to the nature of the sector and the goods and services it produces, for example via the possibility of remote production, the dependence of the production process on personal interactions and via the heterogeneity in the corona rules in different sectors (Bloom et al., 2020).

The effects of Covid-19 on productivity are still largely ambiguous. Because Covid-19 may also force firms to become more efficient (through more innovation, adoption of digitalization), Bénassy-Quéré et al. (2021) find for French firms that the overall level of productivity may increase due to a "cleansing effect". Bloom et al. (2020), on the other hand, show that firms have seen their intermediates costs increased in an effort to deal with the pandemic, and that productivity may have reduced. Brynjolfsson and Petropoulos (2021) show that most OECD countries are not at the lower point in the productivity J-curve. The authors are optimistic that the combination of accelerated take up in digital technologies during the pandemic as well as massive macroeconomic support will boost their productivity. Finally, according to Demertzis and Vieg (2021), Covid-19 led to higher market concentration (sectors like IT and digital services) and this itself is a fact that works against "innovation and productivity".

Government financial support schemes were regarded as an important stimulus for firms to dampen the negative economic shock across countries. What makes the impact different may depend partially on the several types of financial support intervention by governments which may differ across sectors and pre-pandemic performance of firms. This is because micro-economic adjustments to large and temporary shocks may depend on firm performance. Based on their size and lack of credit access, smaller and less productive firms may be more affected by demand shocks and credit guarantees (Greenaway et al., 2007; Muûls, 2008). Besley and Reenan (2018) suggest that credit constraints lowered productivity more through reducing investment, rather than through credit misallocation to unproductive firms, which could also be the case for the situation during the Covid-19 crisis.

From the international literature, the empirical evidence confirms that when (pre-pandemic) firm performance is low, the probability for a firm to receive government support is high. This might imply that the deadweight loss, which refers to the aid allocated to firms that would have survived the crisis without financial support, is minimized. In addition, Aghion et al. (2021) claims that lowering the cost of credit and improving access to finance, increase competitive pressures which in turn imply that less efficient firms are forced to exit markets. In that sense, the risk that firms that would be able to survive while performing below normal profitability thresholds ("zombie" firms), is reduced. Nevertheless, studies for the Netherlands (discussed below) highlight that there is a risk that support schemes may have disturbed the process of creative destruction by making it possible for less viable firms to survive.

In this paper, we focus on Covid-19 policy support and productivity in the Netherlands. Given the conjecture that financial support was taken up predominantly by less productive firms and less by more productive firms, the effect of the financial support will depend on the productivity level of the firm. To take this heterogeneity into account, we therefore need to look at various levels of the productivity distribution when analysing the impact of support on productivity, and opted for the method of unconditional quantile regression (UQR). We use the most recent pre-pandemic Dutch firm-level data on productivity variables combined with data on Covid-19 financial support.

This study contributes to the debate on the empirical relation between Covid-19 financial support and productivity in several ways. First, we assess the relationship between Covid-19 financial support and productivity at three different stages: (i) pre-pandemic (2019), (ii) during the pandemic (2020), (iii) and after the pandemic (investment expectations for 2021). Second, unlike previous studies, we use Total Factor Productivity (TFP) as our firm performance measure. TFP is invariant to the intensity of the use of observable factor inputs and can be used to measure production efficiency since it can explain labour productivity and output contributions of non-labour inputs at the same time (Syverson, 2011). A change in labour productivity confounds changes in technology and factor accumulation, but TFP measures a firm's abilities that are not accounted for by observed inputs, such as managerial talent, quality of inputs, information technology and R&D. It is thus independent of capital accumulation or other observable input changes and should be considered different from labour productivity as a productivity measure (Bernard & Jones, 1996).

We proceed as follows. First, we quantify at various levels of the productive deciles, the probability of the firm to receive financial Covid-19 support. It is expected that when firm performance is low, the probability of the firm to receive government support is high. On the other hand, for the more productive deciles (where it is expected that firms have invested more), it is expected that the proportion of firms that received financial support is lower. Second, along similar lines, using the UQR method, we exploit (exogenous) pre-crisis variation in productivity levels in order to assess the productivity effects on firms using government support schemes. That is, we verify which firms in the productivity distribution benefited the most from these support measures. This allows us to trace the strength of the reallocation effect as a result of financial support. The UQR method allows us to reveal differences of the impact of financial support on TFP between low- and high-productive firms. Such important differences would have remained unnoticed in conventional mean regressions. Third, we provide descriptive distributional analyses for the crisis 2020 data on productivity related variables (turnover and investment realizations), linking to data on financial support measures. We also look at the support to any potentially non-viable firms. Fourth and lastly, we look at the medium to long-term impact of financial support. For this, we look at information on the expectation on the direction of investments (up, down, or equal) from the Dutch survey on producer confidence (in Dutch: Conjunctuurenquête, COEN). Whereas the analyses described above as most other related studies, focus more on temporary and short-term aspects, looking at investment allows to postulate any potential longer-term effects.

The remainder of the paper is organized as follows. Section 2 provides an explanation of the Dutch financial support schemes. Section 3 provides an overview of related literature incorporating distributional elements with the productivity effects of financial support. Section 4 describes the data. Section 5 presents the main findings. Finally, in Section 6 we conclude.

2. SUPPORT SCHEMES

2.1. DUTCH CONTEXT

Exogenous shocks, such as the coronavirus pandemic or the financial crisis, are characterized by the fact that they can affect the economy on the demand and/or supply side, arise in a certain sector or affect a certain sector, have mainly financial consequences or also affect the real economy (Karpavicius, 2012; IMF, 2003). Due to the emergency measures imposed to contain the spread of the coronavirus, many economies contracted at an unprecedented rate in 2020. The economic impact of the Covid-19 pandemic has been severe and persistent. According to IMF figures, the global economy shrank by 3.1% in 2020 and Europe recorded an economic contraction of 5.6% (IMF, 2022). When a shock occurs, as in the case of a pandemic, it not only affects the traders who are directly involved but also everyone who is connected through production chains. This also applies to Dutch firms; they too have increasingly become part of global production processes and more dependent on foreign suppliers and buyers (CBS, 2021a; CBS, 2021b).

In many ways, the coronavirus crisis has had a different effect than the credit crisis. In 2020, the Covid-19 crisis caused Dutch GDP to contract by 3.8%. The economic recovery took on a powerful V-shape. The Dutch economy bounced back relatively quickly. The economic recovery from the financial crisis, which started in 2008 for the Netherlands, took longer and with the Eurozone crisis, the economy experienced yet another downturn. It took until the end of 2014 – more than six years after the financial crisis broke out – before Dutch GDP was higher than before the credit crisis (CBS, 2021c).

Governments around the world have implemented a wide range of policy measures in response to the crisis to support firms and households. Due to the contact-limiting measures introduced by the Dutch government as a result of the coronavirus pandemic, firms in various sectors were unable to carry out their activities or to a limited extent. To limit direct economic damage and prevent these firms from having to be closed as a result, the Dutch cabinet has introduced various financial support measures since the outbreak of the coronavirus pandemic in March 2020. The crisis situation also led to exceptional financial measures, which have had an impact on the resilience of the business community. Research shows that support measures in several countries have helped firms address liquidity constraints, while receiving wage subsidies seems to be associated with lower probability of firing workers (Cirera et al., 2021; Pál & Lalinsky, 2021).

2.2. OVERVIEW DUTCH SUPPORT MEASURES

Due to the coronavirus outbreak, the Dutch government has decided to implement a series of unprecedented economic measures. The measures are designed not only to protect our health, but also to protect people's jobs and livelihoods and to minimize the impact on self-employed people, small and medium-sized enterprises and major firms. These measures are aimed at mitigating economic damage due to efforts controlling the current pandemic. The measures will ensure that firms are able to pay their employees' wages, grant a bridging arrangement for self-employed people and allow firms to hang on to their money through relaxed tax provisions, allowances and supplemental lines of credit. The various support measures are described in Box 1.

Box 1. Description of Dutch Covid support measures

(More information: https://www.rijksoverheid.nl/onderwerpen/coronavirus-financiele-regelingen/overzicht-financiele-regelingen.)

Temporary Emergency Bridging Measure for Sustained Employment
The Temporary Emergency Bridging Measure for Sustained Employment (in Dutch: Noodfonds Overbrugging Werkgelegenheid, NOW) has been created for employers who, as a result of the coronavirus pandemic, are faced with an (expected) loss of turnover of at least 20% in various application periods. The NOW provides financial help for employers to pay their employees' wages in regard to the Covid-19 crisis (CBS, 2022a; Government of the Netherlands, 2020). NOW data is obtained from the Netherlands Employees Insurance Agency (UWV).

The Reimbursement Fixed Costs Scheme
The Reimbursement Fixed Costs Scheme (in Dutch: Tegemoetkoming Vaste Lasten, TVL) for SMEs aims to compensate SMEs in selected sectors for fixed costs other than wage costs. Entrepreneurs with loss of turnover as a result of the Covid-19 measures were able to make use of the TVL under certain conditions. Entrepreneurs can apply for TVL at the Netherlands Enterprise Agency (RVO) (CBS, 2022a; Government of the Netherlands, 2020). TVL data is obtained from Netherlands Enterprise Agency (RVO).

Direct compensation for entrepreneurs in affected sectors
The Direct compensation for entrepreneurs in affected sectors (in Dutch: Tegemoetkoming ondernemers getroffen sectoren, TOGS) is an arrangement for entrepreneurs who are affected by Dutch government measures taken to reduce the spread of the coronavirus pandemic. Under this arrangement entrepreneurs can receive a one-off compensation (CBS, 2022a; Government of the Netherlands, 2020). TOGS data is also obtained from RVO.

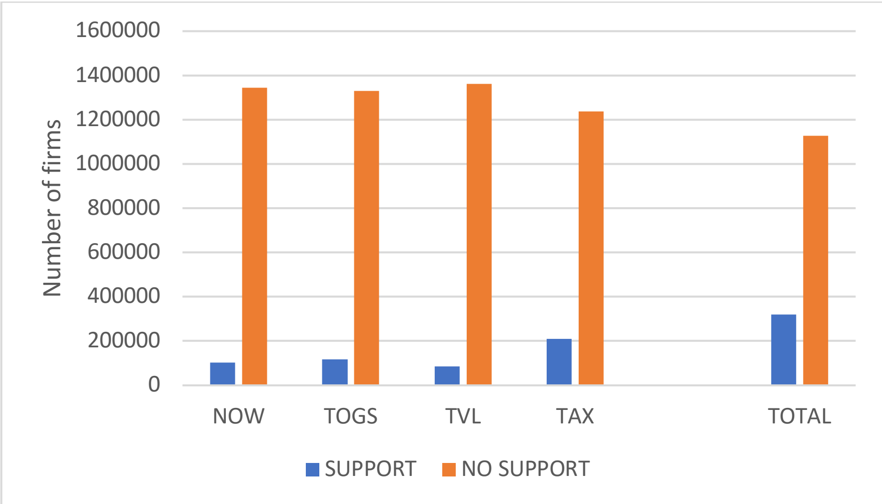
Relaxed rules with respect to the payment of taxes and reduced fines
Until the end of 2021, the Dutch Tax and Customs Administration offers a number of measures and possibilities for payment extensions to help businesses and employers during the coronavirus pandemic. The deferment of payment applies to income tax, corporation tax, payroll tax and value-added tax (VAT). Any fines that may be imposed for the late payment of taxes do not need to be paid (CBS, 2022a; Government of the Netherlands, 2020). These data are obtained from the tax authorities.

Our indicator of financial support comprises more support measures, but the above are the main ones and the use of the other types of support is relatively small.

Almost 22% of the firms in the Netherlands have applied for financial Covid-19 support (see figure 2.2.1). The vast majority of these firms applied for support in the form of wage support for their staff (NOW), followed by deferral of tax payments and an allowance for fixed costs (TVL and TOGS). Most firms used a combination of these financial support measures. The number of firms that made use of the other types of support measures, which are not shown in figure 2.2.1, are negligibly small.

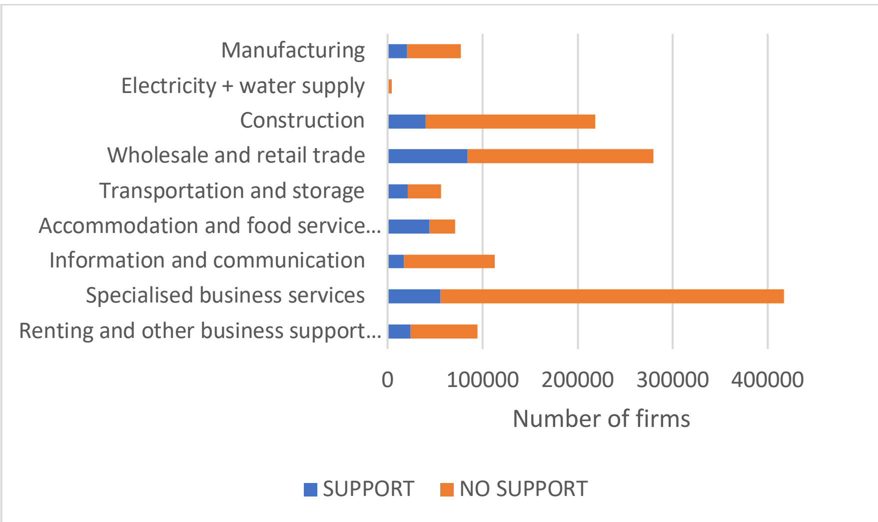
In absolute numbers, most of the financial support went to the specialized business services, as well as to the wholesale and retail trade industry (see figure 2.2.2). In relative terms, the accommodation and food service activities stand out: 62% of the firms in this sector have applied for a financial corona allowance.

Figure 2.2.1 Number of firms with vs. without support measures in the Netherlands, by type[1)]



[1)] The sum of the total number of firms with Covid-19 financial support is not equal to the sum of the different types of support measures. Firms with support are defined as firms that have applied for at least 1 support measure in 2020 and/or 2021.

Figure 2.2.2 Number of firms with vs. without support measures in the Netherlands, by sector



Previous CBS (2021d) research shows that between April 2020 and the end of March 2021, more than 13,000 firms closed down that made use of at least 1 government support measure related to Covid-19. 10% of all closed firms used a support measure. For firms that (partially) went bankrupt, this was more than 53%. Bankruptcies are only a small part of firm closures and the number of bankruptcies is historically low, but increased somewhat during the first quarter of 2022. Based on further analyses, CBS (2022b) reports that of the 488 bankruptcies in the first quarter of 2022, almost 44% were at a firm that made use of corona support in the second half of 2021.

3. LITERATURE

3.1. SUPPORT MEASURES

The study of Bos et al. (2021) provides more insight into which type of business has made use of the (different) Covid-19 financial support measures supplied by the Dutch government. For example, it is interesting to know whether these firms were already less productive before the start of the coronavirus crisis. In addition, they investigate whether the characteristics of users between different types of support measures correspond or differ. Their descriptive statistics show a lower (labour) productivity level (in 2019) for users compared to non-users of financial support measures. This difference is visible for each type of support measure. To test which characteristics influence the probability of a firm using a particular support measure, the researchers performed logistic regression analyses, controlling for sector, size class, firm age and family business. The chance that firms will apply for a support measure increases if firms have a lower productivity level. This result applies to NOW, TOGS and tax deferral, but not to TVL.

Adema et al. (2021) link the received Covid-19 support to the initial solvency and labour productivity of firms (in 2019). A large part of the financial support has gone to relatively low productive firms and to firms with low solvency. These are firms that may have been less viable already before the coronavirus crisis. It is therefore likely that such firms have now only been kept afloat by financial support. Highly solvent firms have also made use of the support measures, while they needed less support because they could absorb the shock themselves. Adema et al. (2021) show that the probability of receiving financial support and the amount of financial support decrease the higher the initial productivity is. Firms with the lowest productivity have received the most and the highest value of support.

Bighelli et al. (2022) use data on firm performance (during 2019) together with firm-level information on employment subsidies[1] (during 2020) for Croatia, Finland, Slovakia, the Netherlands and Slovenia. It is generally found that around one third of the subsidies to

[1] They include for Finland and the Netherlands a broader set of subsidies.

firms in Croatia, Slovakia and Slovenia was allocated to productive firms in the middle of the labour productivity distribution in 2019. However, for the Netherlands it is found that only firms in the 2nd and 3rd productivity deciles tend to be supported with a high probability and then the probability steeply declines. Overall, for the Netherlands and Slovenia, the authors report an overall negative relationship between both the probability to receive subsidies and firm's productivity, which was mainly driven by the upper part of their productivity distribution. Similar results were found when looking at the size of the support. In a next step when quantifying the effect of support on productivity, the results suggest that the distribution of the productivity after receiving government subsidies lies somewhere between the pre-pandemic productivity and pandemic productivity without support. The pandemic led to a significant short-term decline in productivity. The impact of subsidies on productivity has only partially offset the large negative shock to productivity. For the Netherlands, it is seen that the mitigation effect of the support decreases with firm productivity deciles suggesting the strongest effect for low productive firms.

Although constrained by data availability, early research has provided mixed evidence on the support measure scheme influencing productivity growth. A couple of studies look at firms' pre-pandemic performance to assess the productivity effect of firms using government support schemes. In a recent paper, Morikawa (2021) uses survey data of Japanese firms to calculate and compare the productivity (TFP) of firms that used relief policies relative to those that did not use such policies. A distinction is made between 3 government support schemes: (i) financial assistance, (ii) a sustainability subsidy and (iii) an employment subsidy. For all three policies, it was shown that in 2018 the productivity of firms using the relief policies was between 12 to 19 log points lower than the productivity of those firms that did not use any of these three policies after controlling for firm size and industry effects. Thus, the productivity of firms that used relief policies was lower than the non-users even before the onset of the Covid-19 crisis, suggesting that inefficient firms have been affected seriously.

3.2. BUSINESS EXPECTATIONS

Jibril et al. (2021) uses quarterly SME data collected by a survey of UK firms. The survey incorporated questions related to the impact the pandemic had on their business expectations for the future as well as their use of the government support schemes covering the period (after in the third and fourth quarter of 2020) in which most firms had access to the support. It is estimated that firms that receive government support, relative to firms that did not receive any support, are 35% points more likely to plan to invest in capital equipment than firms with no support. Similar results are found for future intentions in innovation, training and market development, which according to e.g., which according to Aghion et al. (2021) and Demmou at al. (2021) prove to be important determinants of long-term productivity. These results prove to be stronger for smaller firms, which are more financially constrained and hence point to the additionality of the support measures. The authors conclude that this evidence confirms the potential for a positive productivity impact of the support measures.

Similarly, Cirera et al. (2021) utilizes a unique survey dataset conducted by the World Bank, covering more than 120,000 firms across 60 countries. The survey collects some questions on several measures of business performance through the Covid-19 shock and on the effectiveness of policies. The authors provide evidence that firms with low pre-crisis productivity are significantly more likely to get support than firms with high pre-crisis productivity. Harasztosi et al. (2022) use a 2021 EIB Investment Survey which contains a detailed set of questions regarding policy support to firms during the Covid-19 crisis. First, by looking at the distribution of the policy support, the authors found evidence that the support went to firms that were most affected by the crisis in terms of sale losses. In addition, it is also shown that the share of firms planning to invest more in the year 2021 is higher when sale losses were lower. Comparing across groups with similar degrees of losses, the analysis also looks at whether firms that receive support plan to raise investment by more than firms without support. The effects, while positive across estimations, are mostly insignificant.

4. DATA AND VARIABLE DEFINITIONS

4.1. OUR APPROACH

The evidence from the literature (see section 3), suggests that when pre-Covid19 firm performance is low, the probability of the firm to receive government support is high. On the other hand, at the higher productive deciles (where it is expected that firms have invested more in R&D/innovation), it is expected that the proportion of firms receiving government support is lower. This might imply that the deadweight loss, which refers to the support allocated to firms that would have survived the crisis without financial support, is minimized. Although at lower levels of the distribution, financial support to firms that would otherwise exited the market may occur. This remains an empirical question we seek to answer by looking at market related mechanism (R&D, investments, long terms strategies) which we link to varying productivity levels of the distribution. We postulate that for the Netherlands, excessive misallocation of resources remains limited.

As a result, there is a need to understand the distributional tendencies when looking how support shapes the productivity distribution. In the first part of the analysis, the empirical question is as follows: Is the probability of receiving support higher for ex-ante more productive firms? And which other drivers may be important in determining? the probability that firms receive financial support. The evidence, as shown below, supports the conjecture that financial support was taken up predominantly by less productive firms. For high productive firms, there will be less probability to exit markets, and therefore, also less deadweight loss. On the other hand, at lower levels of the productivity distribution, there is a higher probability to exit markets, and thus more deadweight loss. As a follow up, we therefore also compare financial support effects along the productivity distribution. The use of Unconditional Quantile Regression will help to bring out the full productivity differences between supported and non-supported firms. This technique allows us to examine the heterogeneity of the relative productivity differences between supported and non-supported firms across different quantiles of the unconditional distribution of Total Factor Productivity.

The pandemic shock also brought an increase in uncertainty for not only current but also future outcomes related to the severity of the pandemic itself, short term measures of business activities, the financial support measure and the policy surrounding it, the speed of the recovery, but also long-term measures of business activities. We look at short-term effects by comparing distributions of turnover for all firms during the pre-pandemic period (2019) and during the pandemic period (2020) where we distinguish between those firms that did and did not receive support. Next, we look at expected investments. We analyse this by viewing average expectations of groups of enterprises that have received support or not, and a binary productivity measure. Lastly, we assess enterprise deaths with respect to support application. Arguably, exits have long-term effects as they affect the composition of the firm population active in the market.

4.2. SAMPLE

This study uses data for 2019 and 2020[2] from the Production Statistics. Annually, Statistics Netherlands compiles the Production Statistics (PS) of various industries. In this PS a level estimate of the operating income and expenses is given. Based on the levels, insight is gained into the structure of the operating income and expenses. The population of the Production Statistics consists of firms in the non-financial business sector. For small businesses (fewer than 10 employees) data for the production statistics are taken from tax registrations as much as possible. In addition, businesses with fewer than 50 employees receive a questionnaire on a sample basis and enterprises with 50 employees or more are all included in the survey.

We selected only the firms operating in the industry classification SBI 10-82, excluding SBI 19 and 68.[3] We require a minimum of 10 persons employed, because the tax data do not cover all variables needed for the productivity calculations, and smaller firms are covered only

[2] To define the zombie firms, we also used the PS data for the years 2017 and 2018.
[3] SBI is the Dutch industry classification ('Standaardbedrijfsindeling'); the first two digits coincide with the NACE Rev. 2 classification. SBI 19 = Manufacture of coke and refined petroleum products; SBI 68 = Renting and buying and selling of real estate. In these industries it is difficult to determine productivity due to respectively, large variation in prices, and the importance of capital income.

incidentally. Taking all these adjustments along with the presence of zero-values into account, we were left with an estimation sample containing 165,526 observations for the period 2019-2020. For the pre-pandemic year 2019 we were left with an estimation sample containing 28,076 observations. For the pandemic year 2020 we were left with an estimation sample containing 29,8222 observations.

In the last part of this study, we utilize COEN data as a proxy for enterprises' longer term expectations in terms of investments. The Netherlands Business Survey (Dutch: Conjunctuurenquête, COEN) monitors quarterly the most important economic developments for the Dutch business sector (i.e., all businesses except financial companies and those in the energy sector.) This is a sample-based survey among active local business establishments with 5 or more persons employed. The statistical unit is the local establishment, rather than the enterprise. We assume that the information at the establishment level is an accurate proxy for the information about the enterprise (by far most enterprises consist of a single establishment). The response is about 5,500 establishments each quarter. We only use observations that are not corrected or imputed, i.e., only plausible response data are used. The survey collects information related to expected developments. We use the information on the expected direction (decrease, increase, or no change) of investments next year, which is gathered every last quarter of the year. Thus, we use the expectations in 2020 about 2021.

4.3. VARIABLES

Below we describe the variables that are used for the analysis, by source.

Production Statistics

Output is measured in terms of value added at factor cost. Capital inputs are proxied by a firm's depreciation cost, assuming these are more or less proportional to the firm's capital stock. Labour inputs are measured in full-time equivalent persons employed. These firm-level data are taken from the Dutch Production Statistics (PS) survey. We restrict the sample to firms with 10 persons employed or more. In principle, the survey only covers firms above this size, but in each year smaller firms are covered for selected sectors, which would then be overrepresented in a particular year (2019 in our case).

The TFP-index uses industry-specific (and time varying) factor shares sourced from the Dutch growth accounts. Nominal output and capital input values are converted to real values using sector-level price deflator from the National Accounts. Firm-level TFP is then calculated as (real) value added divided by the geometric weighted average of capital and labour inputs (i.e., according to a Cobb-Douglas production function), where the factor weights are equal to the industry factor shares.

TFP deciles are determined separately for each industry. This ensures that the distribution across the TFP deciles is proportional across industries. If this would not be done, for instance, if the chemical industry is relatively high productive and the textile industry relatively low productive, the bulk of the firms in the chemical industry would be in the higher TFP deciles, and textile manufacturers in the lower TFP deciles. By looking by industry, the productivity levels across industries are in fact normalized (by that of the median productivity firm in the industry).

Turnover is the revenue from the selling of goods or services to third parties, excluding VAT. This is turnover generated from the enterprise's main economic activity, as well as sideline economic activities, if any.
We define a zombie firm as a firm that reports negative profits for three consecutive years (2017, 2018 and 2019).

Investments in tangible assets
Investment is sourced from the annual investment survey. It concerns monetary investments in means of production that can be used in the production process and last more than a year. The tangible assets need to be acquired in ownership. Main categories for tangible assets are land, buildings, computers, machines, means of transport, installations and a category 'other'.

Covid-19 support schemes data
The Covid-19 support schemes data is aggregated on the business unit level. If an enterprise has made use of any of these support schemes in 2020 or 2021, a dummy variable gets the value 1, otherwise it gets the value 0. This provides a binary yes/no variable to indicate whether an enterprise has made use of Covid-19 support, which is then used in our analyses. In some analyses we only look at specific Covid-19 measures, in which case a dummy variable is obtained in a similar manner.

Innovative in 2018
An enterprise that has indicated to be 'innovative' in the Community Innovation Survey of the period 2016-2018. An innovative enterprise has established a novelty in terms of products or in terms of business processes. The novelty may be new or significantly improved to the market or to the enterprise itself.

Enterprise exit
Information on the exit of firms is sourced from the Business Demography statistics. Exit concerns an enterprise that ceases its activities in a year and with that, the enterprise itself is terminated. This excludes cases where there is a merger, acquisition or split off; a change in name, legal form or owner; a gradual change in economic activities; or relocations.

Table 4.3.1 present basic descriptive statistics regarding the observed characteristics of the firms in our sample and for some variables in the entire Dutch population.

Table 4.3.1 Descriptive statistics

Variable	Dataset	Year	N	Mean	Median
TFP	Estimation sample	2019	21,210	60.969	51.402
LP	Estimation sample	2019	26,354	94.941	69.086
Support	Estimation sample	2020	26,354	0.64	
Support	Population	2020	1,447,358	0.22	
Innovative	Estimation sample	2018	5,009	0.60	
Investment (in €1,000)	Estimation sample	2019	26,354	1,646.31	86.999
Investment (in €1,000)	Estimation sample	2020	27,756	1,476.859	93.000
Investment IT (in €1,000)	Estimation sample	2019	26,354	74.180	5.000
Investment IT (in €1,000)	Estimation sample	2020	27,756	99.407	6.000
Investment build., install., machines (in €1,000)	Estimation sample	2019	26,354	932.575	19.767
Investment build., install., machines (in €1,000)	Estimation sample	2020	27,756	878.856	24.412
Turnover (in €1,000)	Estimation sample	2019	26,354	46,221.260	8,371.000
Turnover (in €1,000)	Estimation sample	2020	27,756	42,052.560	7,598.000
Zombie	Estimation sample	2019	10,670	0.04	
Enterprise deaths	Population	2020	1,331,615	0.073	-
Enterprise deaths	Population	2021	1,252,520	0,058	-
Enterprise deaths	Population	2022Q1	1,252,520	0,027	-

The population used for the enterprise deaths refer to the sections B-N, excl. K and L; 2021Q1 uses the same reference population as 2021, because of support linkage and 2022 data only being available for the first quarter. 2021 and 2021Q enterprise deaths have not been corrected for any possible reactivations.

5. EMPIRICAL RESULTS

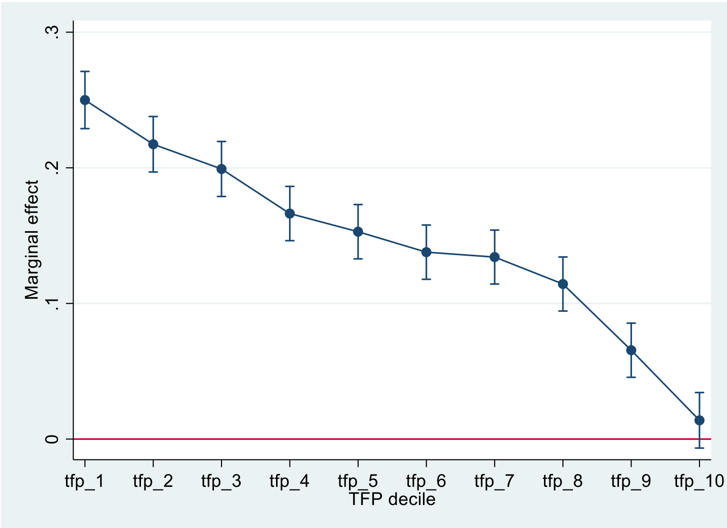
5.1. PROBIT MODELS

Low productivity means that a firm within a sector produces less efficiently, is therefore relatively more expensive or less profitable than its competitor, and may have less market share. In general, firms with higher productivity levels within an industry also show greater adaptability, allowing them to adapt more quickly to new or changing market conditions. Firms with a higher productivity level may also have larger financial buffers due to higher profit margins. Controlling for between-industry differences, we therefore expect that the chance of using a Covid-19 support measure is higher if the productivity level of a firm is lower before the start of the coronavirus pandemic. While this study presents unique evidence on Dutch firms' use of financial support measures during the Covid-19 pandemic, we observe the productivity distribution of firms only before the Covid-19 crisis. In order to understand the distribution of the Covid-19 related support we start with employing probit models to assess the relationship between firm productivity, measured as Total Factor

Productivity (TFP), and corresponding support. Firms are classified into TFP deciles, taking into account the year and industry.

For the Netherlands, we observe a steeply declining relationship between the probability to receive Covid-19 financial support and firm productivity (see Figure 5.1.1). The pattern of the marginal effects is similar if labour productivity deciles are used. Firms in the bottom TFP decile have on average a (significant) chance of 25% to be financially supported. For firms in the top TFP decile, this chance is 1%, but not significantly from 0 at the 5% significance level. In short, firms in the 1st TFP decile (least productive firms) tend to be supported with a significantly higher probability than firms in the 10th TFP decile (most productive firms), in line with the earlier research as discussed in section 3. The plot for innovative firms (not shown here) also displays a same downward trend. This indicates that also for innovative firms, the probability of support decreases significantly as productivity increases.

Figure 5.1.1 Average Marginal Effects with 95% confidence intervals for total support and TFP deciles



We find a similar declining pattern as shown in Figure 5.1.1 for most sectors (see Figure 5.1.2 for the manufacturing sector; the pattern is the same for the other sectors, but is not shown graphically here). Exceptions are the construction sector, accommodation and food service activities and renting and leasing of tangible goods and other business support services. For those latter two sectors we see in Figure 5.1.4 and 5.1.5 a fairly stable line, which means that the difference in the probability of receiving financial support for low and high productive firms is more or less similar. During pandemic, many firms had a hard time, partly because some sectors were even forced to close during lockdowns, and several sectors faced shortages due to supply chain disruptions. The accommodation and food service activities industry, for instance, was hit hard by lockdowns: cafes and restaurants were closed for a long time and travelers no longer came to the Netherlands due to the lockdown. Other business support activities include travel services, employment agencies, and supporting activities such as cleaning and security, which were significantly downscaled during the crisis.

Thus, it is likely that even high productivity enterprises in these sectors needed to file for support (consistent with the relatively high shares of firms that applied for support, in Figure 2.2.2). We observe a declining pattern for the construction industry, though less pronounced and less significant (see Figure 5.1.3).

Figure 5.1.2 Average Marginal Effects with 95% confidence intervals for total support and TFP deciles, sector manufacturing

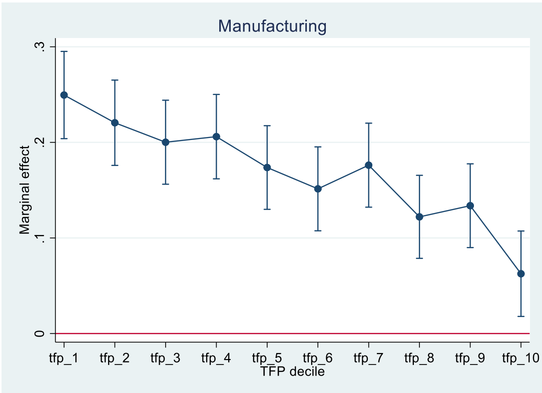


Figure 5.1.3 Average Marginal Effects with 95% confidence intervals for total support and TFP deciles, sector construction

Figure 5.1.4 Average Marginal Effects with 95% confidence intervals for total support and TFP deciles, sector accommodation and food service activities

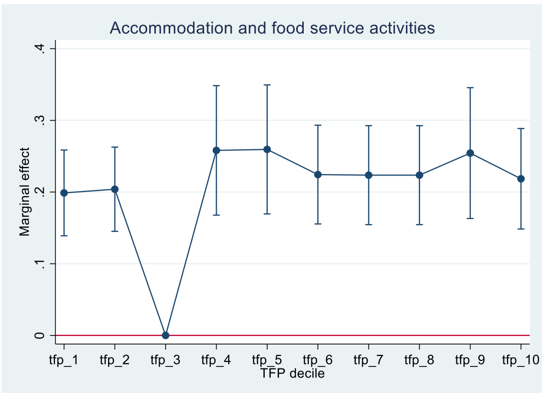
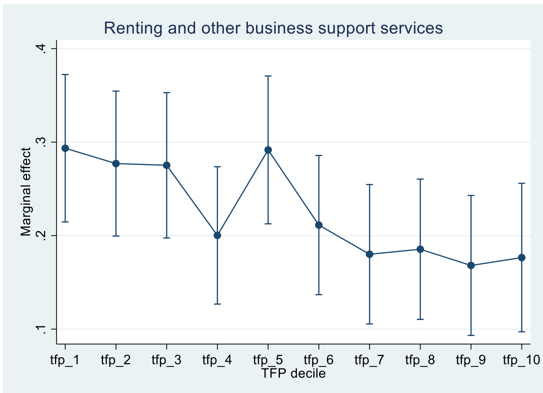


Figure 5.1.5 Average Marginal Effects with 95% confidence intervals for total support and TFP deciles, sector renting and other business support services



A potential issue with a generic support package is that firms that were non-viable before the pandemic are kept alive. Such “zombie” firms are firms that would (or should) typically exit in a competitive market. The negative impacts of surviving inefficient firms on the overall economy are referred to as a problem of zombie firms (e.g., Caballero et al., 2008). McGowan et al. (2018) indicate that the prevalence of zombie firms in nine OECD countries has risen since the mid-2000s, and the increasing survival of these unproductive firms congests markets and constrains the growth of more productive firms. When zombie firms remain in the market, they trap scarce resources, which imposes an implicit tax on healthy firms, reducing their profit and hence their investment and growth opportunities.

We define a zombie firm as a firm that reports negative profits for three consecutive years (2017, 2018 and 2019). Figure 5.1.6 shows that the expected chance of support does not depend on the productivity level for zombie firms. If we compare the probability of support between the zombie and non-zombie firms (figure 5.1.7), we see that at low productive (the bottom TFP decile) levels, zombie firms seem to have a similar probability of support as the low productive non-zombie firms: 30.4% for the zombie firms and 30.3% for the non-zombie firms. This probability remains quite stable among productivity levels for zombie firms while the probability decreases for non-zombie firms following the general pattern that we observe. his might suggest that the financial support was not distributed efficiently. Nevertheless, we should keep in mind that the number of zombie firms in our sample is rather limited[4] (*N* = 421) and among these firms, the effects are significant only for a small proportion among the low to medium TFP level firms.

Figure 5.1.6 Average Marginal Effects with 95% confidence intervals for total support and TFP deciles, zombie firms

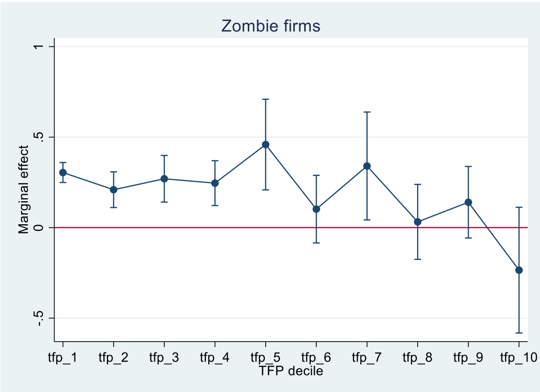
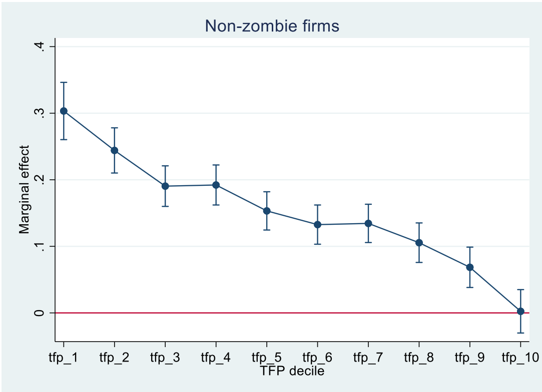


Figure 5.1.7 Average Marginal Effects with 95% confidence intervals for total support and TFP deciles, non-zombie firms



5.2. QUANTILE REGRESSIONS

Most applied econometric research has been concerned with the estimation of *mean* effects—that is, with knowing how changes in an explanatory variable affect the mean of an outcome variable—rather than with *distributional* effects. Due to its singular focus on the mean, the conventional approach (using OLS or other mean estimators) masks the fact that the distribution of the outcome variable may change in ways not revealed by an examination of averages. Thus, in order to see what happens to the *entire* distribution of the dependent variable and to improve our understanding of the varying nature of the relationship between total factor productivity and the coronavirus support and recovery packages, we use the *unconditional quantile regression* (UQR) estimator, recently introduced by Firpo et al. (2009). Good and accessible applications of the UQR can be found in, e.g., Creemers et al. (2022) and Peeters et al. (2017).

[4] This is mainly due to the fact that the PS data was used to define zombies, and therefore a firm has to be present in the PS simple in three consecutive years.

While the analysis in section 5.1 looked at the association between the probability that a firm receives Covid-19 support explained by TFP, recognizing the distributional aspect by breaking down the TFP distribution into discrete categories. The UQR analysis, while reversing the direction of association, allows to infer to the relation between financial support and TFP exploiting the full continuous TFP distribution.

Empirical Model Specification

To guide our empirical analysis of the effect of the coronavirus support and recovery packages on firm-level productivity, we use an augmented Cobb-Douglas production function. The conventional log-linear specification of the production function in total factor productivity (TFP) form, augmented with a binary Covid-19 support indicator, is given by

$$\mathrm{E}[\log(\mathrm{TFP})_{\mathrm{i}}|\mathbf{x}_{\mathrm{i}}] = \beta_0 + \beta_{\mathrm{S}}\mathrm{SUPPORT}_{\mathrm{i}} + \gamma\{\mathrm{Controls}\}, \tag{1}$$

where TFP_i is total factor productivity (pre-pandemic) of firm i. Our key variable of interest is the binary indicator $SUPPORT_i$, which identifies the firms receiving at least one financial support measure (in 2020 and/or 2021) as part of the coronavirus support and recovery packages in the sample population. Equation (1) further includes a set of control variables (industry dummies at SBI 1-digit level and firm size dummies based on number of persons employed) to reduce the influence of potential confounding factors.

The RIF-regression model for each quantile of the productivity distribution is specified as

$$\{\mathrm{RIF}[\log \mathrm{TFP}_{\mathrm{i}}; \mathrm{q}_\tau|\mathbf{x}_{\mathrm{i}}]\} = \beta_{\tau,0} + \beta_{\tau,\mathrm{S}}\mathrm{SUPPORT}_{\mathrm{i}} + \gamma_\tau\{\mathrm{Controls}\} \tag{2}$$

where the coefficient on $\mathrm{SUPPORT}$, $\beta_{\tau,S}$, measures the difference in total factor productivity between supported and non-supported firms *at the τ-th quantile* of the productivity distribution representing the entire sample population of firms under study. The methodology is discussed in more detail in the appendix of the paper.

OLS Results

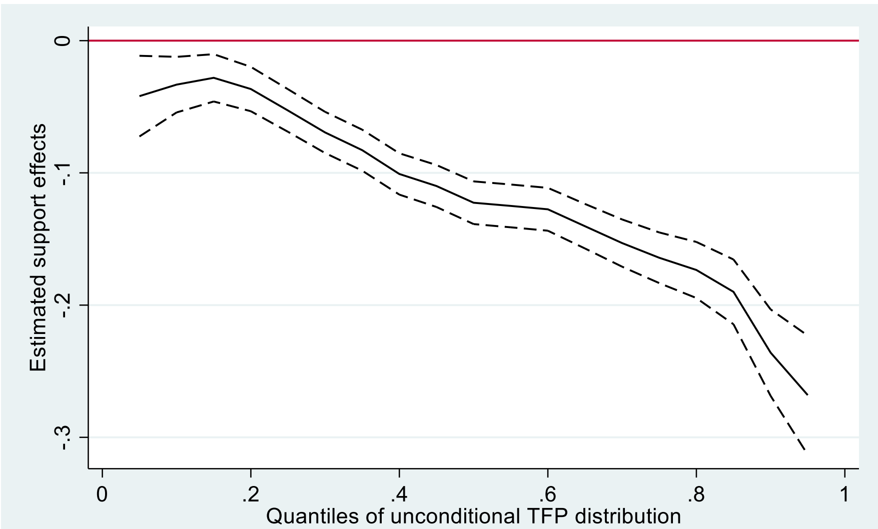
The conventional OLS results are presented in column 1 of Table 5.2.1. They serve as a benchmark against which the productivity gap between supported and non-supported firms at other points of the distribution can be compared. The percentage gap in total factor productivity between supported and non-supported firms is measured as $\hat{\Delta}= [\exp(\hat{\beta}_S) - 1] \times 100$. The estimated coefficient on the indicator is -0.136 (significant at the 1% level), which means that *on average* total factor productivity of supported firms is estimated to be 12.7% lower than that of non-supported firms, other things equal. However, even though this estimate is negative and statistically significant (at the 1% level), a single-point OLS estimator is actually bound to do a poor job in revealing the expected non-uniform TFP gaps between supported and non-supported firms in the tails of the productivity distribution.

Table 5.2.1 Results for Baseline Models – Point Estimates for mean and selected quantiles of TFP distribution

	OLS	RIF-OLS				
	Mean	q10	q25	q50	q75	q90
	(1)	(2)	(3)	(4)	(5)	(6)
SUPPORT	-0.136***	-0.033***	-0.053***	-0.123***	-0.164***	-0.236***
	(-16.79)	(-3.10)	(-6.43)	(-14.89)	(-16.80)	(-14.14)
INDUSTRY dummies	Yes	Yes	Yes	Yes	Yes	Yes
FIRM SIZE dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	21,009	21,009	21,009	21,009	21,009	21,009
$N_{SUPPORT}$	13,673	13,673	13,673	13,673	13,673	13,673
$N_{NO\ SUPPORT}$	7,336	7,336	7,336	7,336	7,336	7,336
R-square	0.128	0.071	0.129	0.152	0.078	0.031

Robust t-statistics in parentheses. *** Significant at 1%, ** 5%, *, 10%.
The dependent variable for the OLS estimation in column 1 is the log of Total Factor Productivity (logTFP). The RIF-OLS regressions in columns 2-6 use the RIFs of logTFP as the dependent variable. The Stata commands used for the mean and quantile regressions are *regress* (OLS, column 1) and *rifreg* (RIF-OLS, columns 2-6). Note that the R-squares are not comparable across the columns in the above table, given that the dependent variables in the UQRs are based on the RIFs of logTFP.

Figure 5.2.2 Estimated support effects along the TFP distribution[1)]



[1)] The black curve represents the estimated productivity effects due to financial Covid-19 support for 19 quantiles of the unconditional productivity distribution. The dashed lines represent the 95% confidence intervals.

UQR Results

We now turn to our key results obtained using the UQR estimator for different quantiles of the productivity distribution, which are more informative about the distributional impacts of financial Covid-19 support than the simple average effect based on conventional mean regression. The quantile estimates obtained using RIF-OLS are presented in columns 2-6 of Table 5.2.1 and are further visualized by means of the quantile plot presented in Figure 5.2.2. The quantile plot shows that the productivity differences between supported relative to non-supported firms decrease monotonically. The UQR estimator provides us with a more informative picture (beyond the simple mean) of the varying impact of financial support on productivity along the productivity distribution.

The estimates of the different quantiles of the productivity distribution are to be interpreted as follows. Supported firms positioned in the lower tail of the productivity distribution, say, at the 10th percentile, tend to exhibit a productivity disadvantage of 3.3% ($[\exp(-0.033) - 1] \times 100$) associated with financial support relative to comparable non-supported firms. However, at the upper tail of the distribution, say, at the 90th percentile, the productivity difference between supported and non-supported firms is much larger. At the 90th percentile, supported firms have a tendency to show a productivity disadvantage of 21.0% ($[\exp(-0.236) - 1] \times 100$) compared to non-supported firms. The point estimate at the 50th percentile (median) is also significantly different from zero.

Thus, in each part of the distribution, support went predominantly to less productive firms, and especially in the high productivity quantiles. Having controlled for industry and size effects, we view this as indicating that more productive firms were in fact more resilient to the negative economic shock, and therefore less likely to need to file to (or be eligible to receive) support.

5.3 SHORT TERM EFFECTS

In this section, we analyze the role played by the financial policy in supporting various outcome measures at the firm level: investment realizations and turnover.

Investment realizations

We focus on actual investments realizations and consider 3 sub-groups: (i) total investment, (ii) investments in computer and IT related materials, and (iii) investments in machines & installations & buildings which we relate to various support measures. Specifically, we postulate that firms with low investments benefitted from financial support less than firms with higher investments. We consider both investments in the pre-pandemic situation (2019), and also consider the period during the pandemic situation (2020).

Specifically, at lower investment levels, a type of support will facilitate access to credits or may be relaxing liquidity problems which in term lead to higher investing possibilities. This is in line with the findings that financially distressed firms with lower investment opportunities will benefit more from loans with public guarantees (Goodhart et al., 2020; Schivardi et al., 2020; Greenwald et al., 2020), taking therefore into account the impact of financial support at different margins of outcomes. Related is the work of Buchheim et al. (2020) and Fernández-Cerezo et al. (2021) who show with a panel of respectively German and Spanish firms that firms which are in financial distress were cancelling investments, face more competition and uncertainty, and face larger unpaid receivables.

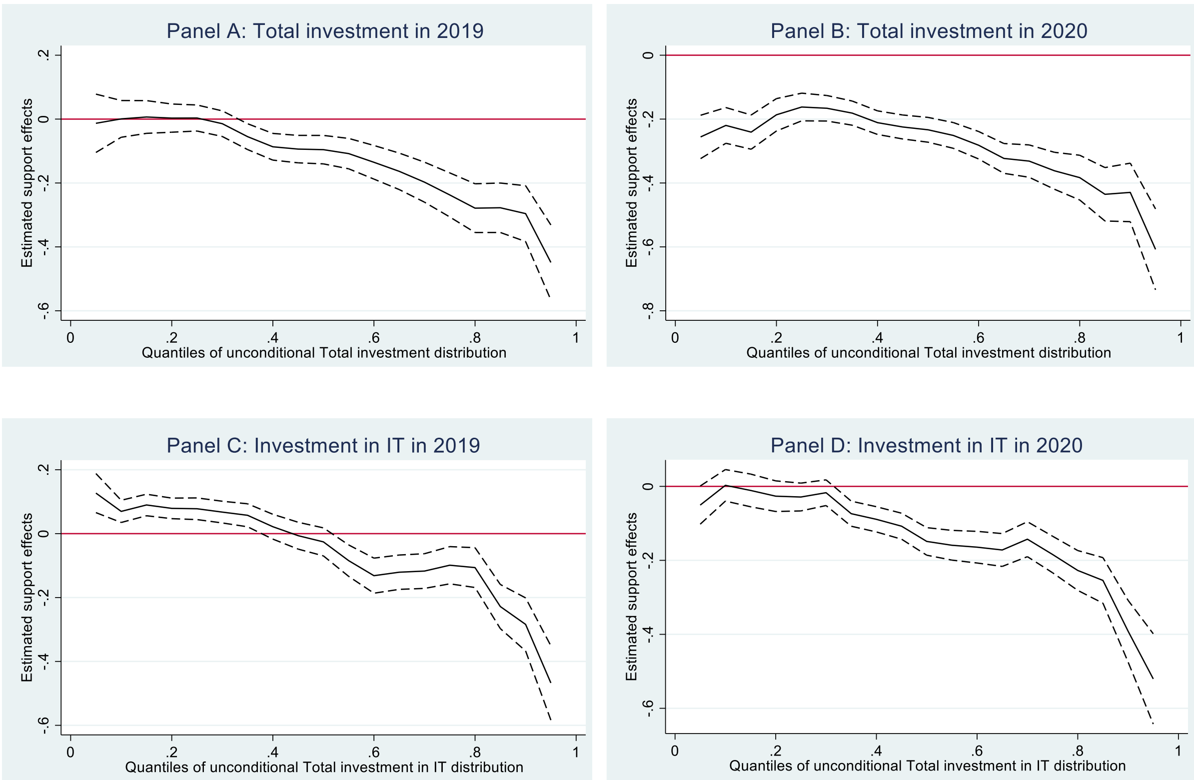
Table 5.2.2 Results for Baseline Models – Point Estimates for mean and selected quantiles of Investment (realizations) distribution

	OLS	RIF-OLS				
	Mean	q10	q25	q50	q75	q90
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: logINVESTMENT in 2019 as dependent variable						
SUPPORT	-0.142***	0.0007	0.0035	-0.0956***	-0.2374***	-0.2958***
	(-7.39)	(0.02)	(0.17)	(-4.21)	(-6.74)	(-6.63)
INDUSTRY dummies	Yes	Yes	Yes	Yes	Yes	Yes
FIRM SIZE dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	24,788	24,788	24,788	24,788	24,788	24,788
$N_{SUPPORT}$	15,916	15,916	15,916	15,916	15,916	15,916
$N_{NO\ SUPPORT}$	8,872	8,872	8,872	8,872	8,872	8,872
R-square	0.401	0.082	0.179	0.317	0.323	0.256
Panel B: logINVESTMENT in 2020 as dependent variable						
SUPPORT	-0.304***	-0.2197***	-0.1621***	-0.2335***	-0.3617***	-0.4294***
	(-16.93)	(-7.70)	(-7.33)	(-11.80)	(-12.26)	(-9.19)
INDUSTRY dummies	Yes	Yes	Yes	Yes	Yes	Yes
FIRM SIZE dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	26,050	26,050	26,050	26,050	26,050	26,050
$N_{SUPPORT}$	16,182	16,182	16,182	16,182	16,182	16,182
$N_{NO\ SUPPORT}$	9,182	9,182	9,182	9,182	9,182	9,182
R-square	0.405	0.105	0.213	0.328	0.313	0.261
Panel C: logINVESTMENT_IT in 2019 as dependent variable						
SUPPORT	-0.0751***	0.0697***	0.0780***	-0.0258	-0.0988***	-0.2841***
	(-4.71)	(3.93)	(4.51)	(-1.15)	(-3.32)	(-6.71)
INDUSTRY dummies	Yes	Yes	Yes	Yes	Yes	Yes
FIRM SIZE dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	20,509	20,509	20,509	20,509	20,509	20,509
$N_{SUPPORT}$	13,251	13,251	13,251	13,251	13,251	13,251
$N_{NO\ SUPPORT}$	7,258	7,258	7,258	7,258	7,258	7,258
R-square	0.532	0.082	0.244	0.459	0.372	0.319
Panel D: logINVESTMENT_IT in 2020 as dependent variable						
SUPPORT	-0.1639***	0.0029	-0.0288	-0.1488***	-0.1841***	-0.3915***
	(-11.39)	(0.13)	(-1.50)	(-7.83)	(-7.31)	(-9.21)
INDUSTRY dummies	Yes	Yes	Yes	Yes	Yes	Yes
FIRM SIZE dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	21,824	21,824	21,824	21,824	21,824	21,824
$N_{SUPPORT}$	14,164	14,164	14,164	14,164	14,164	14,164
$N_{NO\ SUPPORT}$	7,660	7,660	7,660	7,660	7,660	7,660
R-square	0.573	0.254	0.320	0.447	0.391	0.351

Robust t-statistics in parentheses. *** Significant at 1%, ** 5%, *, 10%.
The dependent variable for the OLS estimation in column 1 is the log of investment realizations (logINVESTMENT). The RIF-OLS regressions in columns 2-6 use the RIFs of logINVESTMENT as the dependent variable. The Stata commands used for the mean and quantile regressions are *regress* (OLS, column 1) and *rifreg* (RIF-OLS, columns 2-6). Note that the R-squares are not comparable across the columns in the above table, given that the dependent variables in the UQRs are based on the RIFs of logINVESTMENT.

First, considering total investment, we find that for investment in the 2019 pre-pandemic period and during the 2020 Covid-19 period, supported firms at lower investment levels tend to have an investment disadvantage that is lower compared to firms at higher ends of the distribution (see panel A and B in Table 5.2.2 and Figure 5.2.3). In other words, at higher ends of the investment distribution, those firms that did receive support have a larger investment disadvantage compared to those firms that did not apply for financial support. This pattern is similar to what we observed considering productivity measures (TFP and labour productivity) as an output measure. In addition, we also see that these more negative effects have become more pronounced during the pandemic period. Second, we find a similar pattern for investments in computers & IT related services. Again, as expected there is a notable higher impact between support and varying investment level during the pandemic period (see panel C and D in Table 5.2.2 and Figure 5.2.3).

Figure 5.2.3 Estimated support effects along the investment (realizations) distribution[1)]



[1)] The black curve represents the estimated investment effects due to financial Covid-19 support for 19 quantiles of the unconditional investment distribution. The dashed lines represent the 95% confidence intervals.

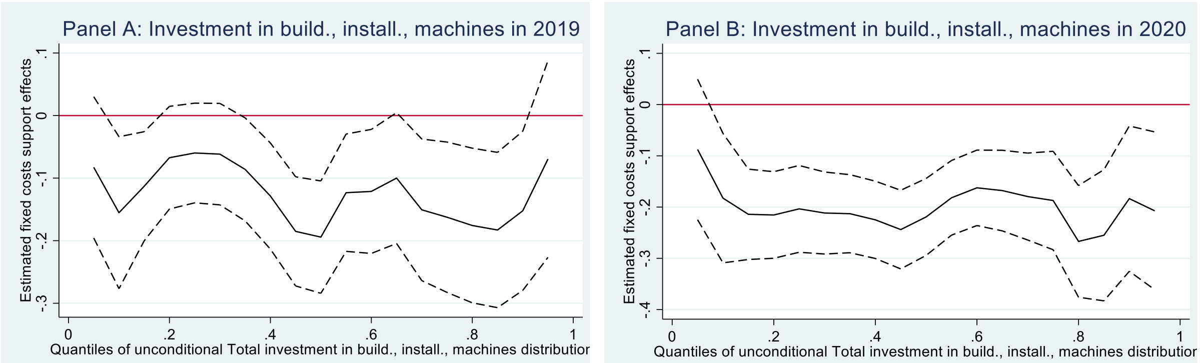
Lastly, we document some heterogeneity of the financial support where we perform the UQR considering the reimbursement of the fixed costs scheme (TVL + TOGS) as an effect on fixed tangible assets (investment in buildings, installations, machines). This analysis serves to verify to what extent financial support may influence specific investments that involve sunk costs and therefore involve long-term planning. We clearly see that, in contrast to the previous results, at various levels of this particular investment distribution, the effect of the support remains quite stable across deciles (see Table 5.2.4 and Figure 5.2.5). These latter results provide evidence that the financial support has enabled firms to retain a particular type of an investment plan that is structurally viable for all firms across the distribution. The implication of this result may suggest that financial support corrects investments that incorporate sunk costs and long-term planning, irrespective the nature of the firms' balance sheet situation. Taking together our results provide an indication that the deadweight loss for those firms that received the policy support is minimized and that there is a longer term allocation efficiency in terms of subsidies.

Table 5.2.4 Results for Baseline Models – Point Estimates for mean and selected quantiles of Investment (in buildings, installations and machines) distribution

	OLS	RIF-OLS				
	Mean	q10	q25	q50	q75	q90
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: logINVESTMENT_BUILDINGS_INSTALLATIONS_MACHINES in 2019 as dependent variable						
FIXED COSTS SUPPORT	-0.1238***	-0.1553**	-0.0598	-0.1943***	-0.1625***	-0.1522**
	(-3.84)	(-2.51)	(-1.47)	(-4.24)	(-2.65)	(-2.35)
INDUSTRY dummies	Yes	Yes	Yes	Yes	Yes	Yes
FIRM SIZE dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	12,300	12,300	12,300	12,300	12,300	12,300
$N_{\text{FIXED COSTS SUPPORT}}$	3,754	3,754	3,754	3,754	3,754	3,754
$N_{\text{NO FIXED COSTS SUPPORT}}$	8,546	8,546	8,546	8,546	8,546	8,546
R-square	0.434	0.275	0.231	0.342	0.297	0.206
Panel B: logINVESTMENT_BUILDINGS_INSTALLATIONS_MACHINES in 2020 as dependent variable						
FIXED COSTS SUPPORT	-0.2076***	-0.1825***	-0.2035***	-0.2192***	-0.1872***	-0.1835**
	(-7.13)	(-2.83)	(-4.71)	(-5.72)	(-3.82)	(-2.54)
INDUSTRY dummies	Yes	Yes	Yes	Yes	Yes	Yes
FIRM SIZE dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	13,712	13,712	13,712	13,712	13,712	13,712
$N_{\text{FIXED COSTS SUPPORT}}$	4,547	4,547	4,547	4,547	4,547	4,547
$N_{\text{NO FIXED COSTS SUPPORT}}$	9,165	9,165	9,165	9,165	9,165	9,165
R-square	0.471	0.225	0.300	0.352	0.312	0.236

Robust t-statistics in parentheses. *** Significant at 1%, ** 5%, *, 10%.
The dependent variable for the OLS estimation in column 1 is the log of investment realizations (logINVESTMENT). The RIF-OLS regressions in columns 2-6 use the RIFs of logINVESTMENT as the dependent variable. The Stata commands used for the mean and quantile regressions are *regress* (OLS, column 1) and *rifreg* (RIF-OLS, columns 2-6). Note that the R-squares are not comparable across the columns in the above table, given that the dependent variables in the UQRs are based on the RIFs of logINVESTMENT. Fixed costs support is a combination of the The Reimbursement Fixed Costs Scheme (in Dutch: TVL) and The Direct compensation for entrepreneurs in affected sectors (in Dutch: TOGS).

Figure 5.2.5 Estimated fixed costs support effects along the investment (realizations) distribution[1)]

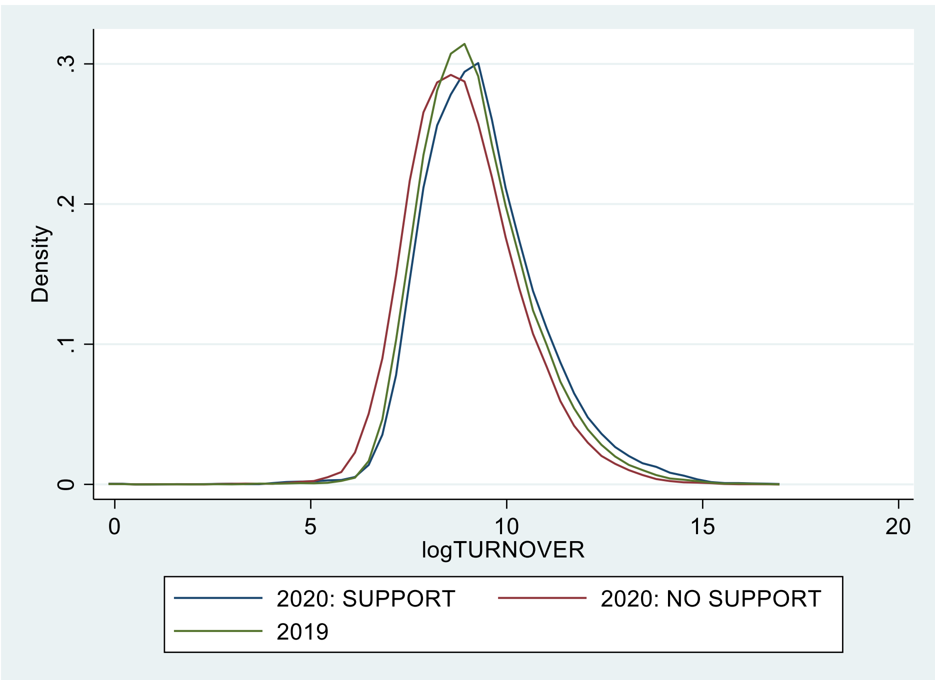


[1)] The black curve represents the estimated investment effects due to financial Covid-19 support for 19 quantiles of the unconditional investment distribution. The dashed lines represent the 95% confidence intervals. Fixed costs is a combination of the The Reimbursement Fixed Costs Scheme (in Dutch: TVL) and The Direct compensation for entrepreneurs in affected sectors (in Dutch: TOGS).

Turnover distributions

We now quantify the effects of the financial support by looking at various distributions using the information on turnover.[5] We estimate turnover distributions in the pre-pandemic year 2019 and the pandemic year 2020 where we consider a breakdown between those firms that did and did not apply for financial Covid-19 support (see Figure 5.2.5).

Figure 5.2.5 Turnover Kernel densities.



[5] It is important to note that the Covid support measures are not part of a firm's turnover in PS, as they are part of other revenue, or are deducted from the cost side (NOW).

Our results first suggest that the pandemic created some distributional shift that is clearly visible. Almost at all levels of turnover, there is an adverse effect between the pre-pandemic situation in 2019 and for those firms who did not receive any support in 2020. Despite the fact that access to financial support was not complicated, there were eligibility criteria, such as a minimum loss of turnover. By contrast, our results further suggest that the turnover distribution for firms receiving subsidies lies somewhere close but even slightly to the right of the pre-pandemic distribution. We do not observe any kinked shifts along the distribution of turnover. Given the criterion of a minimum loss of turnover of 20% to be eligible for various support measures, it is striking that the turnover distribution has shifted out to the right for these firms. This deserves further investigation: for 2019 we could make a distinction between the 2020 support and no support firms, to see if the pre-pandemic turnover level was in fact already higher. In addition, the turnover figures are not corrected for inflation, which may also contribute to the higher turnover.

5.4. LONGER TERM EFFECTS

Using the COEN data, we are able to indicate a relationship between productivity, receiving Covid-19 support and the expectation about investments in the upcoming year. Using data on enterprise deaths, we are also able to indicate whether or not businesses that have received Covid-19 support have been terminated after they have received support.

Investment expectations

To get an insight into the longer term effects of Covid-19 support and productivity of an enterprise, we have conducted an exploratory data analysis. For a subset of the enterprises that have received Covid-19 support, we have productivity (TFP) available, as well as information on the direction of investment expectations in 2021, based on COEN data from 2020.

COEN data is aggregated to the enterprise level, and in 2020 an enterprise could expect to invest less (-1), the same (0) or more (+1) in 2021. We exploit the 2020 data, because that is the year in which most enterprises received support for the first time. By taking an average of the expected investments in a subset of enterprises, we obtain a general investment expectation for each group. We consider low and high TFP (below or above the median by industry), together with receiving support or no support in 2020.

Table 5.4.1 shows the mean expected investment of each subset of enterprises. The number of observations amounts to 1,195. On average, enterprises with relatively high TFP and no Covid-19 support expect to perform best in terms of investments next year (in fact, they expect their investment levels to be on par on average). These are firms that were performing relatively well pre-pandemic, and did not suffer such turnover losses to have to apply for support. However, high productive firms that filed for support, do expect to invest less on average, indicating that the support does not necessarily overcome the uncertainty around the economic situation. Low productive enterprises and with no support on average also expect to invest less next year. The decrease is more pronounced when there was a need to ask for Covid-19 support: enterprises that received Covid-19 support in 2020 on average expect to invest less in 2021 than enterprises with no support. Indeed, the group with low productivity and Covid-19 support expects to perform worst in 2021 in terms of investments. This is an intuitive observation. If an enterprise feels the need to ask for support, there are hardships in terms of paying wages or fixed charges, leading to less available means for investments. And especially when an enterprise is not performing well compared to other enterprises, the expectation of investments declines even more.

Table 5.4.1 Average investment expectations for 2021 (*N* = 1,195).[1]

	No support	Support
High productivity	0	-0.053
Low productivity	-0.015	-0.089

[1] Productivity refers to 2019; support refers to 2020. Expectations are averaged across three possible value (-1 = less investment; 0 = similar investment; 1 = more investment)

In short, we find that especially firms that had to file for support expect to invest less on average, and in particular those with lower pre-pandemic productivity levels. While we could establish a pattern in these data, we do not find the differences to be significant, possibly due to the limited number of observations. We note that these results are in line with the work of Harasztosi et al. (2022), but in contrast to work where it is found that firms that receive support are expected to invest more relatively to firms that did not get any support (e.g., Jibril et al., 2021). These initial observations pave the way to continue to investigate this further in the future with more recent support and COEN data available, as well as data on realized investments.

Enterprise deaths

Another way to look at long term effects in terms of Covid-19 support is to view enterprise deaths. Enterprise deaths are a portion of the population of enterprises that will not continue their economic activities, so it filters the population, leaving enterprises that will still be economically active in the longer term. These data are available for the population of enterprises in the Netherlands, and the relationship between Covid-19 support and enterprise death is established only if enterprise death happened after having applied for Covid-19 support.

In the business economy, 7.2% (= 6.9% + 0.3%) of the enterprises in 2020 ceased to exist. Only about 4% (= 0.3/7.2) of these enterprise deaths received support. This is a small share, although in an ideal scenario this would be zero: from a social planner's point of perspective firms that exit should not receive any support. The exit rate however nicely aligns with the long-year average from 2011 to 2019 (7.3%), and is actually a bit higher than the most recent years before the pandemic (6.4% in 2019).

In 2021, only 5.9% of enterprises died, but the share of enterprise deaths that had received support increased to 15%, almost 1% of the enterprise population in 2021. Looking forward to 2022, in the first quarter 2.8% died, of which almost 18% received support. Thus, the share of firms that have to leave the market despite having received support seems to be growing. Moreover, the share of continuing firms receiving support is relatively high (about 24% in 2021), resulting in a high share of continuing firms from a historical perspective (the mirror image of the low exit rate). This could indicate that still more firms with support will be forced to exit when support schemes are abolished.

Table 5.4.2. Population shares of exits and continuing firms with and without support.

		2020		2021		2022Q1	
NACE	Support	No death (%)	Death (%)	No death (%)	Death (%)	No death (%)	Death (%)
Mining and quarrying	No	73.1	7.9	74.8	5.5	77.4	2.8
	Yes	18.6	0.3	18.6	1.1	19.8	0.0
Manufacturing	No	68.0	5.4	69.3	3.8	71.3	1.8
	Yes	26.4	0.2	26.1	0.8	26.5	0.4
Electricity, gas, steam and air conditioning supply	No	86.7	5.3	85.3	6.5	85.8	6.0
	Yes	7.8	0.1	7.7	0.5	8.0	0.2
Water supply; sewerage; waste management and remediation activities	No	65.6	4.4	65.0	4.5	67.4	2.1
	Yes	29.8	0.2	29.6	0.9	29.8	0.8
Construction	No	77.1	4.6	77.5	3.9	79.7	1.7
	Yes	18.2	0.2	18.1	0.5	18.3	0.3
Wholesale and retail trade; repair of motor vehicles and motorcycles	No	62.4	7.5	62.8	6.1	66.3	2.6
	Yes	29.6	0.4	30.1	1.1	30.5	0.6
Transporting and storage	No	56.0	6.5	56.7	5.0	59.8	1.9
	Yes	36.7	0.7	36.5	1.8	37.5	0.8
Accommodation and food service activities	No	32.2	5.7	31.8	3.6	34.1	1.3
	Yes	60.8	1.3	61.5	3.2	63.2	1.4
Information and communication	No	76.7	8.3	79.2	5.1	81.7	2.7
	Yes	14.8	0.2	15.1	0.5	15.3	0.3
Professional, scientific and technical activities	No	78.6	8.0	81.1	5.1	83.7	2.6
	Yes	13.2	0.2	13.3	0.5	13.5	0.3
Administrative and support service activities	No	67.8	7.3	68.8	5.6	72.0	2.4
	Yes	24.5	0.4	24.6	1.0	25.0	0.6
Total B-N excl. K & L	**No**	**70.0**	**6.9**	**71.2**	**5.0**	**74.0**	**2.3**
	Yes	**22.7**	**0.3**	**22.9**	**0.9**	**23.3**	**0.5**

In 2020, most enterprise deaths that had received support were found in accommodation and food service activities, 1.3%. This increased in 2021 to 3.2%. Not surprisingly, this is the section in which the highest share of enterprises received support. In most major sectors, we find a pattern of 1. an increasing share of firms with support among exits, and 2. a relatively large share of firms with support among continuing firms.

In general, the portion of enterprises deaths that received support, is lowest. This is not surprising, because the share of enterprises that dies is not so high, and the share that receives support are likely to prolong their existence. However, as noted, the exit rate is relatively low, at least in 2021. Together with the finding that less productive firms had a higher probability of support, this indicates that to a certain extent some firms were allowed to continue, where they would have exited under ordinary market conditions. Care must be taken in the interpretation of these numbers, because firm characteristics may also play a role in explaining these patterns (Roelandt et al., 2022).

Overall, our results suggest the that receiving support increases the chance of survival, but reduces the expectation of investing.

6. SUMMARY AND CONCLUSION

The Covid-19 crisis has confronted firms with uncertainty and unforeseen economic challenges, restructuring, and pushing most economies into recessions. Government financial support measures were offered as an important mitigation of the negative economic shocks that firms faced. The economic firm-level effects of these support measures are the topic of an ongoing international research agenda. Our paper adds to this literature by considering the case of the Netherlands.

We consider a broad range of support measures and relate it to the (pre-pandemic) productivity of firms, their current and expected investment behaviour, as well as to turnover, and enterprise deaths. This analysis sheds light on both the short and potential long-term effects of support measures, by assessing the pre-pandemic, pandemic, and post-pandemic period. Unlike previous studies, we use Total Factor Productivity (TFP), which is a more comprehensive measure of productivity than labour productivity, since it takes into account the capital intensity of firms. Finally, by exploiting the method of Unconditional Quantile Regression (UQR), we exploit the full distributional aspects of TFP and investment when assessing the effect of financial support. To our knowledge this method has not been used in this context.

Comparable to previous studies, both for the Netherlands and other countries, we observe a (steeply) declining relationship between the incidence of receiving Covid-19 financial support and pre-pandemic firm productivity. This is the case in most sectors; although, in some sectors that were hit particularly hard by the crisis, even high productivity firms had to apply for support. There is indicative evidence that low productive zombie firms seem to have a similar probability of support as their more viable counterparts, suggesting that the distribution of financial support could have been more sufficient from this perspective, although the share of such zombie firms is quite low in these data.

The overall relation between TFP, in 2019, and the incidence of receiving report, in 2020, is negative and statistically significant. The UQR results reveal further TFP gaps between supported and non-supported firms along the productivity distribution. The productivity differences between supported and non-supported firms decrease monotonically. Thus, in each part of the distribution, predominantly less productive firms were supported, and especially in the high productivity quantiles. Having controlled for industry and size effects, we view this as indicating that more productive firms were in fact more resilient to the negative economic shock, and therefore less likely to file for (or be eligible to receive) support.

For investment, the pattern resulting from the UQR results is similar to what we observed considering productivity measures. In addition, looking at 2020 investment (i.e. during the pandemic), we find that these negative effects have become more pronounced. Thus, firms that were investing more before the pandemic, were less likely to ask support, and more so when moving up in the investment distribution and during the pandemic. Again, this is indicative for the fact that firms investing more are better able to cope with negative shocks, and less likely to file for support. Apparently, when firms do get support, investments are still being scaled downwards. For investment in buildings, installations, and machinery, which require relative larger sunk costs; however, the effect of the support remains quite stable across deciles, also during the pandemic. This suggests that the financial support may have enabled firms to retain investments in this type of assets, while downscaling investment in other assets such as transport and IT equipment.

In line with the UQR results, based on information about investment expectations, we find that especially firms that had to file for support in 2020 expect to invest less on average in 2021. The results suggest that in particular those with lower pre-pandemic productivity levels indicate that they are likely to invest less over the coming year, although the differences are not statistically significant.

Finally, we find an increasing share of firms that have received support but nonetheless exit the market: up to 18% of firm exits in the first quarter of 2022 had received support at some point. Overall, the exit rate was rather low in 2021, or vice versa the share of continuing firms rather high. The share of supported firms is relatively high among the latter, which might indicate that still more firms with support will exit when support schemes are abolished. We find similar patterns in most major sectors.

Our results suggest that the financial support has increased the chance of survival for firms, but also potentially reduced aggregate productivity by keeping alive the less viable firms, and supporting lower productive firms. Investments have been scaled back, regardless of receiving support, and investment expectations are also lower for those firms with support. Nevertheless, while our results suggest that the support may not always have been allocated in an efficient way from the perspective of aggregate productivity, one should bear in mind that these support measures have allowed many firms to pay wages to their employees, and to pay their fixed costs. A full quantification of the effects of the support measures is yet to be provided.

However, one thing is quite clear from our results, and that is that firms that are more productive and have invested more, are better able to survive a crisis, even without any financial support. This is a strong message to policy makers and the business environment to remain focusing on improving firm productivity, so as to make our economy more resilient in the face of future crises.

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APPENDIX: UNCONDITIONAL QUANTILE REGRESSION (UQR)

The UQR estimator builds upon the concept of *re-centered influence function* (RIF). In practice, the RIF is established as a particular transformation of the outcome variable Y for different quantiles of its unconditional distribution. Following Firpo et al. (2009), the RIF of the τ-th quantile of the distribution of Y, for $\tau \in [0,1]$, is defined as

$$\mathrm{RIF}(Y; q_\tau) = q_\tau + \frac{\tau - I\{Y \leq q_\tau\}}{f_Y(q_\tau)}, \tag{1}$$

where a *feasible* RIF can be computed on the basis of the sample data (as the true RIF is not observed) by estimating the *sample* quantile $\hat{q}_\tau$, estimating the density $f_Y(q_\tau)$ at the point $\hat{q}_\tau$ using a (Gaussian) kernel method, and forming an indicator function $I\{Y \leq \hat{q}_\tau\}$, which indicates whether the value of the outcome variable Y is below $\hat{q}_\tau$.

A useful feature of the RIF of the dependent variable Y is that its expectation is equal to the specified quantile; that is, $E[\mathrm{RIF}(Y; q_\tau)] = q_\tau$. This means that the RIF of Y represents the expected value of the productivity outcome at the τ-th quantile of the productivity distribution, q_τ, even if the RIF of Y is *conditioned* on a key independent variable *X* and a set of control variables *W*; that is, $E_X\{E[\mathrm{RIF}(Y; q_\tau)|X, W]\} = q_\tau$ (which clearly contrasts with the properties of CQR). Then, if the expectation of $\mathrm{RIF}(Y; q_\tau)$ is modeled as a function of covariates X, we obtain the UQR equation, given by

$$E[\mathrm{RIF}(Y; q_\tau)|X, W] = X\beta_\tau + W'\gamma_\tau, \tag{2}$$

where β_τ measures the change in the τ-th quantile of the unconditional distribution of Y resulting from a marginal change in the key variable of interest, X, while holding the other covariates (control variables), W, constant.[6]

Conditional versus unconditional

Since estimation and correct interpretation of conditional quantiles can be difficult, many researchers have turned to unconditional quantile regression models (Porter, 2015). Unlike CQR, including any control variables does not change the definition of the quantile (Borgen, 2016). This is a major advantage of UQR over CQR, as the estimated effects on Y of incremental changes in X can be directly interpreted; i.e., adding control variables or changing the set of control variables does not change the interpretation of the parameter of

[6] We emphasize that despite the fact that the RIF of Y is *conditioned* on the covariates X, the coefficients remain to be referred to as *unconditional* quantile effects. It should further be noted that our distributional analysis is distinct from studying varying impacts on productivity across *subgroups* of supported and non-supported firms. The quantile estimators always and invariably use the *full* sample population of firms under study.

interest (Porter, 2015). The interpretation of the UQR coefficient directly measures how a marginal change in the level of one variable will affect the distribution of productivity in the population, keeping the distribution of other characteristics equal. So, the interpretation is not within groups, as with the CQR. The UQR will estimate a separate regression model for every specific quantile (Porter, 2015).

The conditional quantile regression (CQR) developed by Koenker and Bassett (1978) can be used to examine how the effect of Covid-19 support varies across the conditional distribution of productivity. The interpretation of the CQR coefficient is in relation to the quantiles of the distributions defined by the covariates, rather than the unconditional distribution of the outcome variable (Porter, 2015). In CQR, the quantiles are defined conditional on the control variables (Borgen, 2016). Specifically, CQR focuses on the conditional quantile of an individual firm, which is its position in a virtual distribution in which all firms are assumed to have the same observed characteristics (Fournier & Koske, 2012). For example, if firms would differ only with respect to their export level, the conditional quantile of a low-exporting firm would be its productivity quantile among all low-exporting firms, whereas the conditional quantile of a high-exporting firm would be its productivity quantile among all high-exporting firms.

Unconditional quantile regressions (UQR) focus on the unconditional quantile of an individual firm, which is its productivity quantile in the overall productivity distribution, not controlling for observed and unobserved characteristics (Fournier & Koske, 2012). For example, the unconditional quantiles of the two firms with respectively low and high export levels would be their productivity quantiles among all firms in the population. Conclusions based on results obtained using CQR cannot be framed in terms of the unconditional distribution. Moreover, conditional quantile regression and unconditional quantile regression are designed to answer different research questions.

It should be emphasized that the widely-used *conditional quantile regression* (CQR) estimator, proposed by Koenker & Bassett (1978) _ENREF_59, is *not* appropriate for answering our central research questions (and therefore not used here), as the latter are clearly posed in terms of the entire, *unconditional* productivity distribution, representing all the firms in the population, rather than in terms of the distribution associated with a given set of values of the covariates, showing only the heterogeneity *within* selected *subgroups* of firms in the population. Moreover, within the CQR framework any change in the covariates would redefine the quantiles of the unconditional distribution of the outcome variable and, therefore, complicate the interpretation of the CQR results. Good and accessible expositions of the difference between UQR and CQR can be found in, e.g., Mueller (2015); Porter (2015); Peeters et al. (2017).

Advantages UQR

"On the average" has never been a satisfactory statement with which to conclude a study on heterogeneous populations. If we acknowledge that firms are heterogeneous, we have reasons to suspect that the difference in productivity between supported firms and nonsupported firms does not need to be the same for all firms (Powell & Wagner, 2014). For example, it might be the case that the productivity difference between firms receiving Covid-19 support and firms not receiving Covid-19 support is higher for firms at the lower end of the productivity distribution. Quantile regression allows the researcher to understand how an independent variable affects the entire distribution of an outcome, rather than just the average. Quantile regression is more powerful than linear regression due to its insensitivity to outliers on the outcome variable, and its ability to see how the entire distribution of the outcome variable changes when the independent variable changes rather than just seeing how the mean changes (Porter, 2015).

The use of UQR has several important advantages over conventional mean regressions. First, by relying on UQR, we are able to provide a more informative picture of the non-uniform responses along the entire productivity distribution. Thus, by going beyond the mean, the UQR estimates are able to account—at least partly—for the unobserved heterogeneity firms. Second, the UQR estimator, the implementation of which boils down to the application of OLS to the RIF-transformed dependent variable in Equation (1), has the useful property of combining the attractive features of both OLS and quantile regression. The "quantile part" is related to the fact that UQR enables us to estimate the effects at different quantiles of the unconditional productivity distribution. The "OLS part", on the other hand, refers to the fact that the RIF of *Y* respects the *Law of Iterated Expectations* (LIE), hence allowing us to estimate the *expected value* of *Y* at each quantile of the unconditional productivity distribution. This property further provides us with a direct interpretation of the UQR estimates (alien to the CQR estimates), similar to that of the OLS estimates at the *mean*. That is, by virtue of the LIE, the OLS estimator has the property of yielding the (well-known) result that $E_X[E(Y|X)] = E_X[X\beta] = E(X)\beta = E(Y)$, which implies that the value of the *conditional* and the *unconditional* mean of Y are equal. Finally, the UQR estimator also reduces the susceptibility of the estimates to influential observations.