COVID-19 and Credit Constraints: Survey Evidence from Italian Firms

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Abstract

This paper takes advantage of unique survey data on Italian firms to investigate the role played by credit constraints in the transmission of the shocks generated by the COVID-19 outbreak. These data, collected just before and just after the onset of the pandemic, allow us to study how revisions of firms' expectations and plans are shaped by a survey-based measure of credit constraints that uses information about the outcome of past loan applications. Our results show that lack of access to credit strongly amplifies the negative effects on planned factor demand and expected sales of the shocks associated with the pandemic. Moreover, credit-constrained firms, in their search for liquidity, plan to charge significantly higher prices relative to their unconstrained counterparts.

JEL Codes: E2, E3, G30, I10

Keywords: COVID-19, pandemic, firms' expectations, firms' plans, credit constraints, prices, employment, investment, sales, orders

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1 Introduction

This paper uses survey data on Italian firms' expectations and plans to investigate the role played by credit constraints in the transmission of the shocks generated by the COVID-19 outbreak. Our analysis addresses two general issues that have received great attention in the literature on the interplay between financial frictions and economic fluctuations.

First, we ask whether credit constraints amplify or mitigate the shocks associated with the pandemic on firms' sales, employment, and investment. Most of the existing evidence on amplification focuses on monetary shocks or financial shocks.[1] The COVID-19 event, instead, generates shocks to firms' supply and demand conditions that originate outside the banking sector, and occur in the context of a consistently accommodating monetary policy stance. Thus, we are able to study whether amplification occurs in response to a different set of shocks and provide empirical evidence in favor of this hypothesis from a novel angle.[2]

Second, we investigate how financial frictions affect firms' pricing strategies. This issue has been debated both theoretically and empirically, and there is an open discussion on whether financially-constrained firms are more likely to charge higher or lower prices during a downturn (see, for instance, the recent contribution by Gilchrist et al., 2017 and Kim, 2020, respectively). Our investigation provides new evidence that when faced with an adverse shock, financially-constrained firms tend to increase prices relatively to unconstrained firms.

[1] The literature on this topic is very vast. We briefly discuss the contributions most related to our paper in the next section.

[2] The COVID-19 outbreak has generated a variety of shocks to supply and demand. On the supply side, the restrictions imposed by governments on labor mobility and directly on businesses, adversely affect the availability of labor or its efficiency. Moreover, the fear and concerns generated by contagion and deaths may lead to a reduction in labor supply even in the absence of restrictions. Finally, implementing transmission reduction strategies in the workplace is associated with additional costs for the firm. On the demand side, the greater uncertainty associated with the pandemic may lead to a postponement of investment projects, or to a decrease in consumption due to a precautionary savings motive. In addition, demand and supply shocks are interlinked: for instance, the disruption to supply in one sector can be felt as a negative demand shocks by upstream firms.

Our empirical investigation exploits a unique survey on firms' sales and orders expectations as well as plans for prices, employment, and investment. We collected this information between March 24 and April 7, 2020 – two weeks after the implementation of the first lockdown policies following the initial explosion in the number of cases and deaths. This survey can be matched with the pre-COVID-19 wave of the Monitoraggio Economia e Territorio (MET) survey completed by mid-January, 2020 – one month before the official "case zero" in Italy. In addition to a broad set of firms' characteristics, the pre-COVID-19 MET survey contains expectations on sales and pricing strategies, together with questions on loan applications that we employ to construct our firm-specific proxy of financing constraints. Our matched dataset is composed of 7,800 firms (5,000 of them with complete balance-sheet information), and it includes many small firms that are privately held and bank dependent, thus more likely to face financial frictions.

In investigating the role of financing constraints on firms' real decisions and pricing strategies, we face two methodological challenges: i) the identification of an exogenous shock as well as its effects on firms' decisions, and ii) the selection of a group of financially-constrained firms to be compared with an unconstrained group. As for the first challenge, the Italian experience at the outset of the COVID-19 pandemic represents an ideal laboratory: the outbreak has indeed generated a series of shocks that are exogenous and unanticipated, as Italy was the first Western country to be severely hit by the pandemic and to impose lockdown policies. To identify the effects of such shocks, we investigate how firms revise their expectations and plans between the two surveys. Our identification relies on the assumption that such revisions are entirely due to the COVID-19 pandemic, which is reasonable considering that the two surveys are taken within a short time interval and no other significant event occurred during that period. In sum, the shortness of this window and the availability of data on expectations and plans (which, unlike realized quantities, can respond immediately to a shock) allow us to identify economic effects that we can uniquely attribute to the pandemic.

Regarding the second challenge, we use the pre-COVID-19 MET survey to construct a measure of credit constraints based on loan applications. The main information employed in the definition of our credit-constrained dummy is whether the loan application was denied, only partly satisfied, or whether firms did not apply because the loan was expected to be turned down.[3] Given that small and privately-held firms are well represented in our sample, the percentage of financially-constrained firms turns out to be substantial (almost 20%). In our empirical strategy, we investigate how such firms (compared to their unconstrained counterparts) revise their expectations and plans due to the pandemic outbreak. We also control for balance-sheet variables and other firm characteristics because we want to make certain that our dummy does not simply reflect financial fragility and poor prospects in the pre-COVID-19 period.

Our analysis delivers a number of important and novel results. At a descriptive level, our data suggest that the COVID-19 outbreak induced a significant leftward shift of the distributions for expected sales, and the worsening in expectations is greater for firms that are financially constrained. Regarding the revision in price plans, we find that its distribution is roughly centered around zero, and that financially-constrained firms are relatively more concentrated in its right tail, meaning that they are more likely to plan price increases compared to unconstrained firms. Finally, once we focus on the actions adopted in response to the outbreak, our data highlight that financially-constrained firms are also less likely to resort to teleworking as a strategy to mitigate the effects of the pandemic.

Motivated by this descriptive evidence, we investigate the determinants of firms' expectations and plans in a multivariate framework where we control for a wide set of firm's characteristics and balance sheet conditions. Our results show that financial frictions shape the effect of the COVID-19 outbreak on firms' sales and orders expectations and on firms' employment, investment, and price plans. Credit-constrained firms display a more pessimistic outlook for sales and orders, and plan to reduce employment and investment more than unconstrained firms. In other words, our results suggest that financial frictions amplify the effects of the shocks generated by the COVID-19 pandemic. In addition, our evidence supports the view that credit-constrained firms

[3] See Section 3 for more details.

plan to increase prices relatively more (or to decrease prices relatively less) than their unconstrained counterpart. These results are consistent with the idea that financially-constrained firms have an incentive to increase prices in order to boost internal sources of funds, even at the cost of losing part of their customer base in the future. This effect is driven by firms that were deemed non-essential and, therefore, temporarily unable to generate cash flow because of the restrictions imposed by the government on their activity. Conversely, the response of essential firms is not affected by their credit-constrained status, possibly because they experienced smaller shocks, could generate internal cash flow, and, thus, were in less dire need of external funds.

Previous results are robust to controlling for firms' characteristics including types of ownership, province and sector dummies, and balance sheet conditions, ensuring that the estimated differences are not due to other factors such as firms' financial fragility and riskiness before the COVID-19 outbreak. We also employ a propensity score matching approach to select a sample of unconstrained firms with characteristics similar to those of the financially-constrained firms. Using different estimators for the average treatment effect, we find that the importance of financial constraints for sales growth expectations and price plans is largely confirmed.

Finally, we perform two additional exercises on the role of financing constraints and firms' response to the pandemic. First, we investigate the determinants of the survey response to the question of whether credit access is one of the firm's major concerns in the aftermath of the outbreak. This variable should not be confused with our proxy for credit constraints, as the latter is based on more detailed information on loan applications during the period immediately preceding the pandemic outbreak. We find that being credit constrained before the pandemic increases the concern about credit access during the COVID-19 crisis. This result helps explaining why our credit-constrained dummy plays an important role in determining firms' expectations and plans after the outbreak. Second, we estimate a series of specifications where the dependent variables capture the adoption of teleworking, the reduction in the number of employees, and the reduction in the number of hours worked in response to the pandemic outbreak. We find that credit-constrained firms are less likely to resort to teleworking, and more likely to reduce labor demand at both the extensive and intensive margin.

The structure of the paper is as follows. Section 2 briefly discusses the related literature and our contributions, while Section 3 explains the data sources used and the definition of the main variables employed. Section 4 provides some descriptive evidence on the effects of the COVID-19 pandemic and how these effects differ for financially-constrained and unconstrained firms. Section 5 presents the econometric strategy, results, and robustness checks, while Section 6 concludes the paper.

2 Related literature

Our paper is related to three main strands of the literature. First, we contribute to the overall debate on the role of capital market imperfections in the amplification or mitigation of macroeconomic shocks. The idea behind amplification (see the seminal papers by Bernanke et al., 1999 and Carlstrom and Fuerst, 1997) is that when a shock occurs, the net worth of the firm (or the bank) is impacted. This leads to a change in the wedge between the cost of internal and external finance that, in turn, has real effects on investment and labor decisions. There has been a lively debate in the context of DSGE models on whether amplification occurs or not.[4] From an empirical standpoint, most of the existing papers focus on monetary policy shocks and provide firm-level evidence in favor of amplification for firms that are more likely to be financially constrained.[5] Moreover, there is evidence that such firms are more sensitive to shocks to banks' balance sheets as well as to uncertainty shocks.[6] Our data and strategy allow us to

[4]The presence or absence of amplification depends upon the nature of the shock itself, the nature of the financial contract, and the parameterization of the model. See, for instance, Gertler and Karadi (2011), Carlstrom et al. (2016), and Dmitriev and Hoddenbagh (2017). See also Khan and Thomas (2013) for a model with both financial frictions and investment irreversibility.

[5]See the seminal contributions by Gertler and Gilchrist (1994) using semi-aggregate data, and Kashyap et al. (1994) using firm-level data. See also, among others, the recent contributions by Cloyne et al. (2018), Ottonello and Winberry (2020), and Jeenas (2019) for panel-data evidence on the role of firms' characteristics and/or balance-sheet variables for the amplification (mitigation) of monetary shocks.

[6]For evidence on the effects of shocks to the banking system during the financial crisis or the sovereign debt crisis see Chodorow-Reich (2014) and Balduzzi et al. (2018), among others. For evidence on the effects of uncertainty shocks in presence of financing constraints see Alfaro et al. (2018).

identify the effects of adverse supply and demand shocks that originate outside the banking sector and are not due to monetary policy. Thus, we contribute to the existing literature by providing new evidence supportive of the amplification role of financing constraints for the transmission mechanism of such shocks. Another distinguishing feature, analogously to Campello et al. (2010), is that we identify credit-constrained firms from direct survey measures rather than proxies based on (firm or bank) balance-sheet variables or other characteristics of the firm.[7] This issue is central given the risk of misclassification attached to measures that are derived from balance-sheet information.[8]

Second, our paper is related to the literature that studies the effect of financing constraints on firms' pricing strategies. The seminal papers by Gottfries (1991) and Chevalier and Scharfstein (1995) argue that, during a downturn, credit-constrained firms have an incentive to increase prices to raise current liquidity instead of investing in building their customer base. A recent important contribution providing empirical evidence in support of this mechanism is Gilchrist et al. (2017), who find that liquidity-constrained firms raised prices more than their unconstrained counterparts at the time of the financial crisis.[9] Kim (2020), instead, provides evidence that firms whose lender banks were more affected by the Lehman collapse decreased prices in the short run to liquidate inventories and generate additional cash flow. The challenge in this field of research is the availability of high-frequency firm-level information on prices and of reliable indicators of financing constraints. We contribute to this strand of the literature by taking advantage of the unique features of our dataset centered around an exogenous event and exploiting price plans that react immediately to the resulting shock. This, together with the survey-based information on financing constraints, allows

[7]The definition of financially-constrained firms in Campello et al. (2010) is based on the answer by CFOs during the financial crisis to the question whether a company's operations was "not affected," "somewhat affected," or "very affected" by difficulties in accessing the credit markets. Their evidence shows that constrained firms plan upper cuts in tech spending, employment, and capital spending.

[8]For instance, classifying firms according to their stock of liquidity may be problematic. On the one hand, high liquidity may indicate balance-sheet strength and the absence of constraints. On the other, large liquidity holdings may also arise from the precautionary accumulation by informationally impaired firms that are less likely to receive credit. See, for instance, the paper by Bates et al. (2009).

[9]See also Asplund et al. (2005), de Almeida (2015), Kimura (2013), Lundin et al. (2009), Montero and Urtasun (2021), Duca et al. (2017), and Brianti (2021) for additional evidence supporting this mechanism.

us to provide novel evidence on the effect of financing constraints on firms' pricing strategies that is consistent with the results of Gilchrist et al. (2017).

Finally, there is a growing literature on the economic effects of COVID-19 using micro-level data. However, only a few papers explore financing constraints and even fewer focus on their impact on firm-level outcomes or expectations. Our findings are broadly in line with Acharya and Steffen (2020) who show that, at the onset of the COVID-19 outbreak, the US stock market had higher valuations for firms with access to liquidity through cash holdings or credit lines. We are also related to Ramelli and Wagner (2020) who use US stock prices and corporate conference calls to show that initially investors penalized internationally-oriented firms, but, as the virus spread in Western countries, leverage and internal liquidity emerged as more important value drivers.[10] Together with these papers, our micro-level findings support the importance of including financial frictions in models that investigate the effects of COVID-19 at the macro level; see, for instance, Baqaee and Farhi (2020), Faria-e Castro (2020), Guerrieri et al. (2020), and Woodford (2020).

As to the Italian experience, Brancati (2020) uses our same dataset to provide evidence on the effects of the pandemic on innovative and internationally-oriented companies, while Lamorgese et al. (2021) employ the Bank of Italy INVIND survey data to study how managerial quality affects firms' response to news about the pandemic. None of these papers explore the role of financing constraints. Our study is closer to Bottone et al. (2021), who use the Bank of Italy Survey on Inflation and Growth Expectations (SIGE) to analyze firms' inflation expectations and pricing strategies during the COVID-19. Consistent with our paper, they also find some evidence of amplification of the pandemic shocks as a result of credit constraints. However, differently from our analysis, they find no evidence that financing constraints affected firms' pricing decisions during the pandemic. We attribute this diverging result to the different composition of the two samples: their sample is substantially smaller – roughly 1,000 firms

[10] Other papers worth citing include Balleer et al. (2020), who focus on German firms' price plans, Baert et al. (2020), who investigate Flemish employees' decisions to telework, and Brinca et al. (2021), who investigate labor demand and supply shocks at the sector level around the COVID-19 outbreak.

– and skewed towards larger firms that are less likely to suffer from financial frictions. Moreover, they identify firms as credit-constrained based on the post-COVID-19 survey responses regarding access to liquidity, while our definition of financing constraints uses direct information on the actual and expected outcome of loan applications prior to the pandemic.

3 Data

This section presents the data used in the empirical analysis. First, we discuss the unique features of our dataset containing information on the revision in firms' expectations and plans around the COVID-19 outbreak. We then provide details on how we define financially-constrained and essential firms.

3.1 Data sources

Our main data source is a firm-level survey designed to explore the consequences of the COVID-19 outbreak, combined with the 2019-wave of the MET survey on the Italian industrial system.[11] Unlike other surveys, MET provides information on every size class including micro-sized companies with less than ten employees. The survey is representative of the manufacturing sectors (60% of the sample) and the production-service industry (40%), with total coverage of 38 NACE Rev.2 3-digit sectors.[12] Consistent with the timing of the previous waves, the administration of the 2019-survey ended in mid-January of the following year, right before the outbreak of the COVID-19 pandemic in Italy (the first reported case was on February 1, 2020).

The original questionnaire contains a wealth of information on firms' performance and strategies, including data on direct proxies for firms' financial constraints, bank-

[11] MET, *Monitoraggio Economia e Territorio*, is a private research center regularly surveying a large number of Italian companies. It is one of the most comprehensive surveys administrated in a single European country, with an original sample comprising seven waves – 2008, 2009, 2011, 2013, 2015, 2017, and 2019 – and roughly 25,000 observations in the cross-section. The survey follows a sampling scheme representative at the firm size, geographic region, and industry levels.

[12] Production services sectors are: distributive trades, transportation and storage services, information and communication services, administrative and support service activities.

lending relationships, internationalization, and R&D processes. This information is supplemented with a second survey specifically conceived to study the effect of the COVID-19 pandemic and administrated to the entire sample of respondents of the original questionnaire. This allows us to have information on both the pre- and post-COVID-19 expectations and plans for each company. To avoid excessive variation in the information set of the respondents, the timing of the survey was restricted to a 2-week window between March 24, and April 7, 2020. The administration started 13 days after the generalized initial lockdown imposed by the Italian government (March 11, then revised on March 22), so as to leave each firm enough time to update its beliefs and plans. At the same time, there was still a large degree of uncertainty on the extent of financial support that firms could receive from the government. The main measures, involving the provision of public guarantees on bank loans, were only introduced later on April 8 ("*decreto liquidità*") and converted into law on June 5.[13] See Section 5.3 for further discussion and evidence on whether firms internalized government support measures into their expectations and plans.

The post-COVID-19 survey had a response rate of 33%, which is substantial for such a small time window, with a final number of completed interviews for about 7,800 companies.[14] The survey is composed of three main sets of questions. The first one replicates the original questions in the pre-COVID-19 survey on expected changes in future sales and prices allowing us to construct the revision in firms' expectations and plans around the COVID-19 outbreak. For sales, firms were allowed to give a categorical answer on their expected change: i) very negative (below -15%); ii) negative (between -15% and -5%); iii) stable (between -5% and +5%); iv) positive (between 5% and

[13] An initial outline of measures of support for firms was also contained in the March 17 decree ("*decreto cura Italia*"), which was converted into law on April 9. However, the full extent of the credit support became clearer only with the "*decreto liquidità*". See Core and De Marco (2021) for evidence on the effects of the Italian public guarantee scheme during the COVID-19 pandemic.

[14] While the distribution of respondents across macro-sectors, geographical macro-regions, and size classes is similar to that of the 2019 MET survey, in principle endogenous selection of the respondents is still possible. We address this issue by employing ex-post stratification weights for the post-COVID-19 survey that are calibrated to reproduce the population aggregates from the sample of respondents (see the discussion in Solon et al., 2015). However, in estimation, we used both weighted and unweighted data with similar results.

15%); and v) very positive (above 15%). As for prices, firms were directly asked for the planned (continuous) percentage change over the next 12 months. The second set of questions asks about firms' expectations and plans on new orders, the number of workers employed, expenditure in tangible and intangible investments over the next 12 months, in addition to sales growth in the following 3 and 12 months.[15] Finally, the third set of questions directly asks about actual measures undertaken or planned (such as teleworking, shutdown, and reduction in hours or workers), as well as the main challenges expected in the aftermath of the COVID-19 outbreak (access to credit, difficulties in obtaining inputs, reduction in demand, etc.).

While not reported in the main text, we performed some preliminary exercises to assess the properties of our survey data. In particular, we are interested in understanding whether past expectations predict realized outcomes. Indeed, if past beliefs turned out to be uncorrelated with realizations, the informativeness of expectations, and of their revision following a shock, would be substantially reduced. We assuage this concern by exploiting previous waves of the biannual MET survey and showing that sales expectations have a strong predictive power for future realized sales. Further details are provided in Appendix A.

In completing the data set used in our analyses, we match the pre- and post-COVID-19 surveys with the 2019 official balance-sheet data (CRIF-Cribis D&B database) to control for predetermined firm characteristics such as size and age. As a result of this matching, the number of firms was reduced by roughly 35%, resulting in a final sample of about 5,000 firms.[16] Summary statistics for the firm-level survey and balance-sheet data are presented in Table A2.

[15] These variables are effectively continuous because firms were asked to provide a numerical value for expected changes below -5% or above +5%. For values within this range, they could simply indicate no change, even though some firms still provided a numerical answer. Overall, only 20% of the companies in our data set reported a value of zero and our results are not sensitive to their exclusion from the estimating sample.

[16] As usual, balance-sheet data is not available for unincorporated firms (*società di persone*), which causes most of the reduction in our sample size. Moreover, to reduce the influence of outliers, balance-sheet variables are censored at the 1% and some observations are excluded because of measurement errors (negative or nil assets, negative or nil sales).

3.2 Definition of credit-constrained and essential firms

In constructing our measure for credit constraints we exploit the unique information on bank-loan applications available in the 2019 MET survey. Specifically, firms were asked if they applied for a loan in the past year and what the resulting outcome was. In case of a loan application, firms were allowed to choose one of the following options: (i) the loan was granted at favorable conditions; (ii) the loan was granted at slightly less favorable conditions; (iii) the loan was granted but for an amount substantially lower than requested, or at very unfavorable conditions; iv) the loan was denied. Moreover, in absence of a loan application, the questionnaire asks firms whether they did not apply because: (v) there was no need for external funds; or (vi) they knew the application would have been denied. Exploiting this information, we classify as credit constrained those firms that replied either (iii), (iv), or (vi). In other words, we regard a company to be financially constrained if the loan application was rejected, accepted but for a substantially lower amount (or at a higher price), or if the firm did not apply because it expected to be rejected. Overall, almost one-fifth of the firms in our sample (18%) are classified as constrained.[17]

Finally, to capture the sectoral heterogeneity of the restrictions on production imposed by the Italian government, we identify firms as essential (non-essential) using the same 6-digit sectoral classification (ATECO class from the ASIA registry) adopted by the Italian government in the March 22 decree. Essential firms were allowed to continue operations, while non-essential firms had to temporarily shut down. Moreover, main suppliers to firms in essential sectors were also allowed to stay in business and were also classified as essential. We can identify this additional set of companies because the post-COVID-19 survey has information on whether a firm stayed open despite belonging to a non-essential sector. Overall, 59% of the firms in our sample are classified as essential.

[17] Our findings are largely robust if we exclude discouraged borrowers (option vi) or if we exclude discouraged borrowers and partial rejections (options iii and vi) from the definition of financially-constrained firms. See Section 5.3 for a discussion on further robustness tests and the online appendix for the complete set of results.

4 Descriptive evidence

In this section, we provide a set of descriptive statistics to highlight changes in the distribution of expectations that occurred after the COVID-19 outbreak and differences between financially-constrained and unconstrained firms.

Figure 1 reports their conditional distributions of expected sales growth before and after the pandemic. The data show a generalized leftward shift of expectations, confirming the large impact of the pandemic outbreak on firms' information set, and, hence, on their beliefs. Most importantly, Figure 1 also shows that the shift relative to the pre-COVID-19 distribution is larger for financially-constrained firms than for unconstrained firms.

In Figure 2 we report the change in the planned price growth between the pre- and post-COVID-19 surveys.[18] The distribution is centered around zero, and there is a larger fraction of financially-constrained firms (49%) that plan to revise their prices upwards compared to the fraction of unconstrained firms (40%). Moreover, the distribution of the price revisions displays a ticker right tail for constrained firms. The difference in the distribution of expected price changes between financially-constrained and unconstrained firms is highly significant according to the Kolmogorov-Smirnov test (p-value effectively equal to zero).

Additional evidence on the role of financing constraints is contained in Figure 3 that shows which mixture of actions the firms in our sample adopted, or intended to adopt, in response to the outbreak. The data suggest that financially-constrained firms were much less likely to adopt teleworking as a strategy to mitigate the effects of the COVID-19 epidemic. It also appears that constrained firms were also more likely to lay off workers, while the difference in other strategies is less pronounced.

Taken together, our descriptive evidence suggests a difference in the behavior of sales growth expectations, price plans, and measures adopted between credit-constrained and unconstrained firms around the COVID-19 outbreak. We will explore more for-

[18]Recall that for prices we have the actual numerical value of the planned price changes, which we have grouped in 11 categorizes in Figure 2.

mally the role of credit constraints in the transmission mechanism of the COVID-19 shocks in a multivariate framework in Section 5.

5 Empirical analysis

This section discusses our econometric strategy and empirical results. We first outline our baseline model and present the core findings of the paper. We then show the results obtained using different estimation procedures and some robustness checks. Moreover, we present some additional exercises to further investigate the heterogeneous response of credit-constrained firms. Finally, we provide additional evidence on the interpretation and role of our credit-constrained dummy.

5.1 Econometric strategy

Our empirical analysis takes advantage of the availability of pre- and post-COVID-19 sales expectations and price plans (at a one-year horizon) to model their revisions around the COVID-19 outbreak in Italy. For other continuous variables, such as sales over the next three months, orders, employment, and investment over the next 12 months, we do not have the correspondent expectations formed before the COVID-19 episode. In this case, we use past sales expectations to control for the pre-COVID-19 information set. Recall that the two surveys were taken only two months apart and, therefore, we assume that they reflect expectations of the yearly growth rate over approximately the same time horizon. As discussed in the introduction, the narrow time window between surveys and the fact that no other major economic events took place in-between surveys, supports our assumption that the pandemic is the dominant factor in determining firms' expectation revisions.

Our empirical specifications will be based on variants of the following model:

$$\mathbb{E}_{i,t}(y_{i,t+1}) = \alpha + \beta \mathrm{CC}_{i,t-1} + \delta\, \mathbb{E}_{i,t-1}(y_{i,t+1}) + \gamma^{\top} x_{i,t-1} + \lambda_s + \lambda_p + \varepsilon_{i,t}, \quad (1)$$

where $y_{i,t+1}$ represents the growth rate of sales, prices, orders, employment, investment in tangible assets, and investment in intangible assets of firm i; and $\mathbb{E}_{i,t}(\cdot)$ is the expectation operator of firm i using the information set at time t.[19]

Credit constrained ($\mathrm{CC}_{i,t-1}$) is an indicator variable that equals one if the firm is deemed to be financially constrained before entering the pandemic based on the questions on loans applications in the MET 2019 Survey. In the model, we also control for a set of firms' characteristics and initial conditions $x_{i,t-1}$. We start from a specification where $x_{i,t-1}$ includes: an indicator variable that equals one if the firm was classified as essential (Essential); the log of total assets (Size); the log of one plus age (Age); indicator variables on whether the firm belongs to a group (Group) or is family owned (Family firm); and a summary measure of the creditworthiness of the firm (Z-score).[20] Although we do not present the coefficient estimates, we always include a set of dummies indicating whether firm i is importing, exporting, and investing in R&D, as well as a continuous variable for the share of graduate employees. In all specifications, we also control for 88 two-digit sector dummies (λ_s), and 107 province fixed effects (λ_p), to account for sources of sectoral and geographical heterogeneity. In a richer specification, we also include a set of balance sheet variables such as Liquidity, Leverage, Cash Flow, Tangible assets, and Trade Credit, all relative to total assets.[21]

The key variable in our specification is the survey-based measure for financing constraints. The inclusion of 2019 balance-sheet variables and other firms' characteristics allows us to focus on the determinants of access to credit that go beyond pre-COVID-

[19] For notation simplicity, $\mathbb{E}_{i,t}(\cdot)$ represents expectations formed by firm i in the post-COVID-19 survey, while $\mathbb{E}_{i,t-1}(\cdot)$ represents expectations formed by firm i in the pre COVID-19 survey.

[20] Z-score is the first principal component of the factors specifically chosen to capture financial fragility among Italian firms by Altman et al. (2013): working-capital-to-total-assets, retained-earnings-to-total-assets, EBIT-to-total-assets, and book-value-of-equity-to-total-liabilities ratios. It loads positively on each factor and explains 56% of their total variance. We chose to employ the first principal component of balance-sheet variables rather than the linear combination with weights estimated in Altman et al. (2013) because it better captures firms' creditworthiness in our sample. In any case, our results on credit constraints are not affected by the choice of weights.

[21] We estimate our model both with the unweighted and the weighted sample, using the ex-post stratification weights for the COVID-19 survey. The results are similar, and we use the weighted results as our benchmark throughout the main body of the paper. We present results for the unweighted sample in the online appendix.

19 firm's riskiness and financial fragility. In other words, by including a large menu of controls, we want to ensure that we do not attribute to financing constraints differences in behavior that are due to other factors.[22]

5.2 Main results

In this section, we present our main results for sales and orders expectations, and for investment, employment, and prices plans.

The first two columns of Table 1 present the results of OLS models for the one-year ahead expected sales growth (numbered from one to five according to increasing levels of optimism), while columns 3 and 4 report the estimates for ordered logit models for the same variable. For both models, we present results clustered at the two-digit sector level using both a narrow and wide set of control.

In all specifications, firms that were deemed to be credit constrained before the outbreak are significantly more pessimistic about their future sales, after controlling for summary measures of firms' financial conditions, size, age, and ownership structure. This is consistent with firms decreasing employment and investment due to the financial frictions they face and, hence, decreasing production. Given that our variable is nominal sales, this could be also consistent with financially-constrained firms expecting lower price growth, but we will show below that this is not the case. There is therefore evidence that the existence of financing constraints amplifies the adverse effects of the shocks related to the COVID-19 outbreak.

As for the other controls, the negative effect of the COVID-19 event is significantly attenuated if the firm is classified as essential. This result underscores the importance of the restrictions imposed by the Italian government in shaping the economic effects of the COVID-19 outbreak. Moreover, we find that firms with more pessimistic (optimistic) pre-COVID-19 expectations are more (less) likely to be pessimistic about post-COVID-19 expected sales. Among the other characteristics, firms' size and being family owned

[22] In the same spirit, following Campello et al. (2010), we present estimates of the average treatment effect of being credit constrained based on propensity-score matching. Results are robust to this variation and are reported in Section 5.3.

play the most important role: larger firms hold more optimistic expectations about sales, while family-owned firms have more pessimistic expectations possibly due to a less sophisticated management style. Finally, focusing on balance-sheet variables, firms that have a larger share of tangible assets appear to be relatively more optimistic. The coefficient of the Z-score is either not significant or has a counter-intuitive negative sign, as firms with better balance sheet conditions have a higher z-score. We will return to the role of the Z-score when commenting on the results in Table 2.[23]

To provide more details on the effects of the COVID-19 pandemic, we now move to Table 2 where we present OLS estimates using a wider set of dependent variables: expected sales at 3 and 12 months, expected orders, as well as plans for employment, and investment in both tangibles and intangibles, all at a 12-month horizon. The results for these variables allow us to shed light on additional aspects of firms' planned response, and to make more precise statements regarding the quantitative effect of the COVID-19 pandemic, as they are continuous and expressed in percentage point changes relative to the pre COVID-19 situation.

This additional analysis confirms the results discussed so far. In particular, being credit constrained negatively and significantly affects all the dependent variables. The effect of financial frictions is important both over the three- and 12-month horizons. In the short run, we observe a fall in expected sales for credit-constrained firms that is almost 14 percentage points higher than for unconstrained companies. Although this difference is somewhat reduced over the 12-month horizon, it is still quite sizable (about 9%). Financially-constrained firms also plan to reduce investment and employment substantially more than unconstrained firms by an amount that varies between 6.8% and 9%. In addition, the essential designation is associated with significantly fewer negative outcomes (with the only exception of employment), with a reduction in the expected fall in sales of approximately ten percentage points for both horizons. Note that the inclusion of past sales expectations as control is perfectly appropriate for sales

[23]Given the categorical nature of the dependent variable, it is not straightforward to make statements about the size of the effects. We will do so later in the discussion of Table 2 where we employ continuous variables instead.

expectations at 12 months and approximately so for the other dependent variables. In terms of the additional controls, the role of size is confirmed, while the Z-score enters now with an expected positive coefficient and is significant in most cases. This indicates the relevant role played by financial fragility and firms' riskiness in determining firms' outlook.

In Table 3 we analyze the effect of the COVID-19 event on domestic price plans. In terms of included regressors, this specification is similar to the one in Tables 1 and 2, except for having included lagged expected price changes, as opposed to lagged sales growth, as a control. Since price plans are continuous, we only estimate an OLS specification.

Regarding the role of credit constraints, we find that, everything else equal, price growth tends to be higher for financially-constrained firms. Quantitatively speaking, a credit-rationed firm plans a price growth about 4 percentage points higher than its non-rationed counterpart. This result is consistent with previous theoretical and empirical work on the price-setting behavior of financially-constrained firms.[24] The basic logic is that financially-constrained companies have an incentive to increase prices in order to boost their internal liquidity as opposed to investing in their customer base by charging lower prices (see the seminal papers by Gottfries, 1991 and Chevalier and Scharfstein, 1995, and the recent contribution by Gilchrist et al., 2017).

Among the additional controls, essential firms appear to charge significantly lower prices. Specifically, a firm deemed to be essential plans a price growth of about four percentage points less than its non-essential counterpart. Finally, among the controls, it is somewhat surprising that past price plans are not significant. In column 3, we present estimates when we use the revision in planned price growth as an alternative dependent variable (which implies imposing a unitary coefficient on the lagged dependent variable in our baseline price model). Results are unchanged and our conclusions are largely confirmed.

[24]Note that, since the interval between the beginning of the pandemic and the time of the interview is very short (on average two/three weeks), it is highly unlikely that the recorded stronger increase in price by financially-constrained firms follows a hypothetical price drop occurring between these two periods.

5.3 Different estimators and robustness

In this section, we make sure that our financial-constrained variable does not simply capture other confounding factors. More specifically, we use a propensity score matching approach to select a sample of constrained and unconstrained firms that are similar along a broad set of characteristics but differ for their actual condition of being financially constrained. We then implement two types of estimators for the average treatment effect, one based on nearest neighbor matching with bias correction as in Abadie and Imbens (2011) and Abadie et al. (2004), and the other based on the radius matching. In computing the propensity score, we employed the full set of firms' characteristics in $x_{i,t-1}$.[25]

Table C3 of the online appendix reports the balancing properties of the sample after matching. Importantly, it shows no statistical difference in firms' characteristics between the financially-constrained firms and unconstrained firms, thus reassuring about the success of the matching procedure. Table 4 in the text presents the results for expected sales and price growth. The importance of financial constraints for sales growth is largely confirmed as the average treatment effect is always negative and significant at least at the 5% level.[26] It is positive and almost always significant for prices. We have also repeated the same exercises for the continuous measures of sales, orders, employment, and investment. Results of radius matching are largely consistent with those presented in Section 5.2, while the Abadie and Imbens (2011) estimator yields coefficients that are, in some cases, less precisely estimated (in Table C4).

In addition, we have implemented a series of exercises to test the robustness of our results using the same models presented in the previous section. First, we have experimented with alternative definitions of credit-constrained firms. Results are robust if we construct our credit-constrained dummy: (i) excluding firms that did not apply

[25] In this case, geographical controls are at a regional level while industrial sectors follow the original classification in 12 macro industries of the MET sampling.

[26] The categorical sales-growth variable has been transformed into a continuous one with values that go from 1 to 5, like in the first two columns of Table 1.

because they knew the application would have been denied; and (ii) including only the cases in which the loan was fully denied.

Our conclusions are also robust to: (i) using unweighted data in the estimation; (ii) clustering at the provincial (NUTS-3) level as opposed to the two-digit sector; (iii) removing firms that did not report an actual figure for the minus/plus five percent categories of the effectively continuous variables, instead of imputing to them a value of zero; and (iv) using six-digit sectoral dummies as a control, instead of the indicator variable identifying the firm as essential. All these results are presented in the online appendix.

Finally, one may wonder whether the estimate of the coefficient of credit constraints is contaminated by firms' expectations about access to financial aid through government programs, such as those providing credit guarantees. If credit-constrained firms expect greater access to such programs, that would generate an attenuation bias and we would underestimate the effect of financial constraints.[27] However, if we allow the coefficient of $CC_{i,t-1}$ to vary depending upon the response date, the coefficient for the sample of firms that answered in the second half of the interview period (when information about policy measures may have become clearer) is not significantly different from that obtained using the group of firms that answered in the first half.[28] The most likely explanation for these results is that, throughout our survey administration period, the uncertainty regarding policy measures was still large for all firms, making it difficult for them to evaluate the extent of and access to government financial support. See the online appendix for the results.

5.4 Models with interactions

It is possible that the effects of financing constraints depend upon other firms' characteristics such as the sector a firm operates in and, more specifically, whether it was classified as essential. This may be the case because the nature or size of the shocks

[27]See the timing of the policy measures and of the data collection period in Section 3.

[28]In the equation we also include a set of dummies for the date on which each firm responded.

depend upon such characteristic. In a more complex specification, therefore, we have interacted our credit constraints status with the essential dummy.

In Table 5 we present results for categorical sales (Column 1) and our set of continuous variables (Columns 2 to 7). The interaction terms with essential are typically not significant, which implies that the negative effect of credit constraints does not depend upon the essential status of the firm. However, there are two exceptions, expected categorical sales and plans for tangible investment, which suggest that the effect of financing constraints is substantially smaller for essential firms.[29]

In Column 1 of Table 6, we report the results for the price equation when we interact the credit-constrained dummy with the essential status of the company. In this case, the coefficient of the main effect of credit constraints continues to be positive and significant, while the interaction term is significant with a magnitude similar to the coefficient of credit constraints but with an opposite sign. This result highlights that among credit-constrained firms, those identified as non-essential are the ones responsible for the price increase estimated in our baseline specification. This is consistent with the idea that credit-constrained non-essential firms (limited in their credit access and temporarily unable to generate cash flow) are the ones under a greater pressure to set higher prices in order to boost liquidity once they reopen. At the same time, the overall effect of credit constraints for essential firms is not statistically different from zero. This result is consistent with adverse supply shocks being smaller for companies allowed to operate and generate cash flow. It is also likely that the demand outlook for such firms were comparatively more favorable, for instance, because they were located in sectors producing necessities that are less subject to demand swings.

In Table 6, we further explore the mechanism through which financial frictions affect pricing strategies. In particular, in Columns 2 to 6 we also allow for the interaction between credit constraints and the HHI index at the 2-digit sectoral level (Concentra-

[29]The overall effect of credit constraints for essential firms remains negative and significant for categorical sales but not for investment. On a different note, we have experimented with interactions between the credit constrained variable and proxies for the geographical heterogeneity in the severity of the pandemic. The interaction terms with variables such as mortality or contagions are, again, largely insignificant.

tion) and firms' inventories over total assets (Inventories). Results show that credit-constrained firms that operate in more concentrated markets tend to increase prices relatively more. It is in sectors with higher concentration, and hence characterized by larger market power, that financially-constrained firms have a greater incentive to increase prices in order to boost internal liquidity. Finally, among credit-constrained firms, the ones with a higher stock of inventories tend to increase prices relatively less. This result has some affinity with the mechanism outlined in Kim (2020), who shows that credit-constrained firms have an incentive to lower prices during a downturn in order to liquidate their inventories to raise current liquidity. However, at the observed level of inventories in our sample, being financially constrained is always associated with relatively higher prices for non-essential firms. For essential firms, the marginal effect of being constrained is negative and significant only for the very right tail of the inventories distribution (99th percentile).

5.5 More on the interpretation and role of the credit-constrained dummy

In this subsection, we discuss two additional exercises that shed more light on the information contained in our credit constrained dummy and its role in explaining firms' response to the pandemic.

In Table 7, we investigate the determinants of considering credit access as one of the firm's major concerns in the aftermath of the pandemic outbreak. This binary variable from the COVID-19 survey takes value of one if the firm mentions access to credit as one of the main critical factors affecting its choices.[30] Note that this variable is not the post-COVID-19 counterpart of our proxy for credit constraints in the pre-COVID-19 period, as the latter is based on more detailed information about loan applications. However, it gives a summary indication about the relevance of financing constraints in the aftermath of the outbreak. We employ a linear probability model controlling for

[30]Firms could select up to three major concerns associated with the pandemic event. Available options were about difficulties in (i) purchasing inputs/semi-finished products, (ii) the relationship with usual suppliers, (iii) finding skilled workforce, (iv) accessing credit, (v) the availability of services (transportation and logistic), (vi) the reorganization of work tasks and production, and (vii) the need of product diversification.

lagged firms' financial variables, measures of banking relationships, our pre-COVID-19 measure of credit constraints, and other firms' characteristics. We find that past credit constraints (measured from the 2019 MET survey) increase the concern of getting access to credit during the COVID-19 crisis. For instance, having been constrained in the past increases the probability that firms mention the existence of financial constraints as a critical issue by 20 percentage points (relative to a weighted mean value of 37%). In sum, our dummy of having experienced credit constraints in the past is very informative about the likelihood of experiencing difficulties in accessing credit during the pandemic. At the same time, it is a predetermined variable that, given our set of controls, is unlikely to be correlated with unobservable factors that may drive firms' response to the pandemic. As for the other estimates, there is evidence that having a higher stock of liquidity at the end of 2019 is negatively associated with the concern of getting access to credit. This result is in line with the idea that firms with more internal sources of finance are less concerned about the availability of external funds. Finally, it appears that having a longer-lasting lending relationship increases the concerns of being financially constrained in the aftermath of the pandemic outbreak. This result is somewhat counter-intuitive, unless the length of the relationship reflects the monopoly power of the bank over the firm (i.e., a lock-in effect).

While the emphasis of our analysis is on expectations one-year out, the post-COVID-19 survey also has information on measures immediately taken as a reaction to the crisis. In Table 8, we estimate a series of logit specifications where the outcome variables are dummies representing the use of teleworking, reduction in the number of employees, and reduction in the number of hours worked per employee. The results reported in the table highlight how credit-constrained firms are less likely to resort to teleworking, and more likely to reduce labor demand at both the extensive and intensive margin. The effects are non-trivial. For instance, being credit constrained translates into a reduction of 10 percentage points in the probability to convert to teleworking. Analogously, being credit constrained raises by 10 percentage points both the probability of reducing the number of employees and the number of working hours. Interestingly, being part of a group and having a larger stock of liquidity facilitates the conversion to teleworking.

6 Conclusions

In this paper, we have taken advantage of a unique survey of pre- and post-COVID-19 expectations and plans to study the role of credit constraints in the transmission of the shocks generated by the pandemic outbreak.

There is strong evidence pointing to the importance of financial frictions in shaping the effects of the COVID-19 outbreak: credit-constrained firms hold more pessimistic expectations about future sales and orders, and plan to reduce employment and investment more, relatively to unconstrained firms. In other words, our results suggest that financial frictions amplify the effects of the shocks generated by the COVID-19 pandemic. These findings emphasize the importance of firms' access to credit in the immediate aftermath of the COVID-19 outbreak and provide support for the policy measures introduced in many countries to improve access to credit and liquidity.

Our analysis also sheds light on the way financial frictions affect firms' pricing strategies. We provide evidence that credit-constrained firms expect to increase prices more than their unconstrained counterpart, and this is especially so if they operate in more concentrated sectors. Such results are consistent with the idea that financially-constrained firms have an incentive to increase prices in order to boost internal sources of funds, even at the cost of losing part of their customer base in future. This effect is driven by non-essential firms that were temporarily unable to generate cash flow, while for essential firms, experiencing smaller supply and demand shocks, financing constraints are found to play no role in the revision of pricing strategies.

There is much more to learn about the effects of the COVID-19 outbreak on firms' strategies and decisions. Its effect will be felt not only on quantity and prices but also on the very organization of the firm and on the nature of its relationship with other firms, domestically and internationally. These topics are very important, but are left for future analysis.

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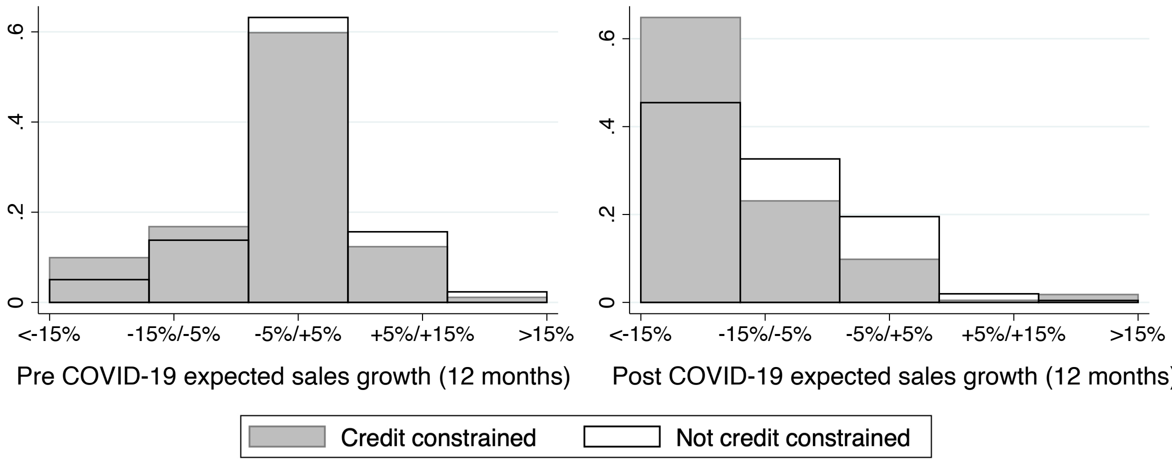

Figure 1: Post-COVID-19 expected sales growth by credit-constrained status

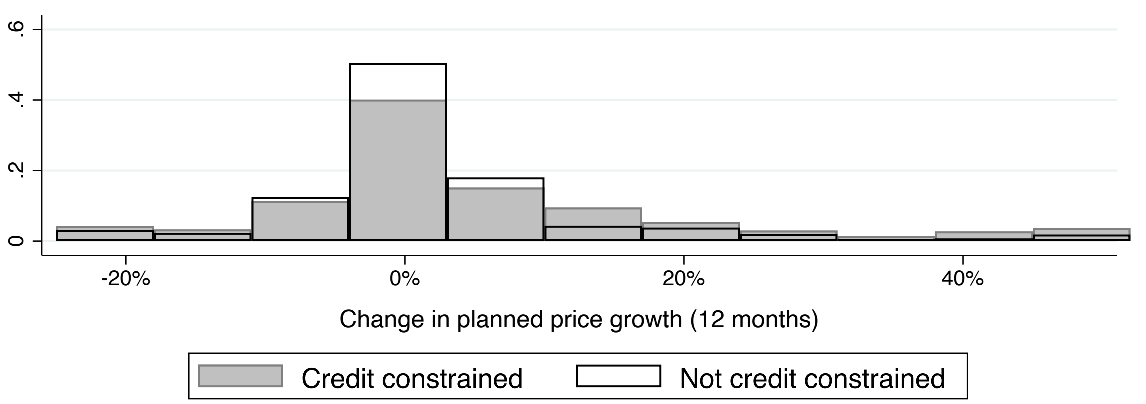

Figure 2: Planned price growth revision by credit-constrained status

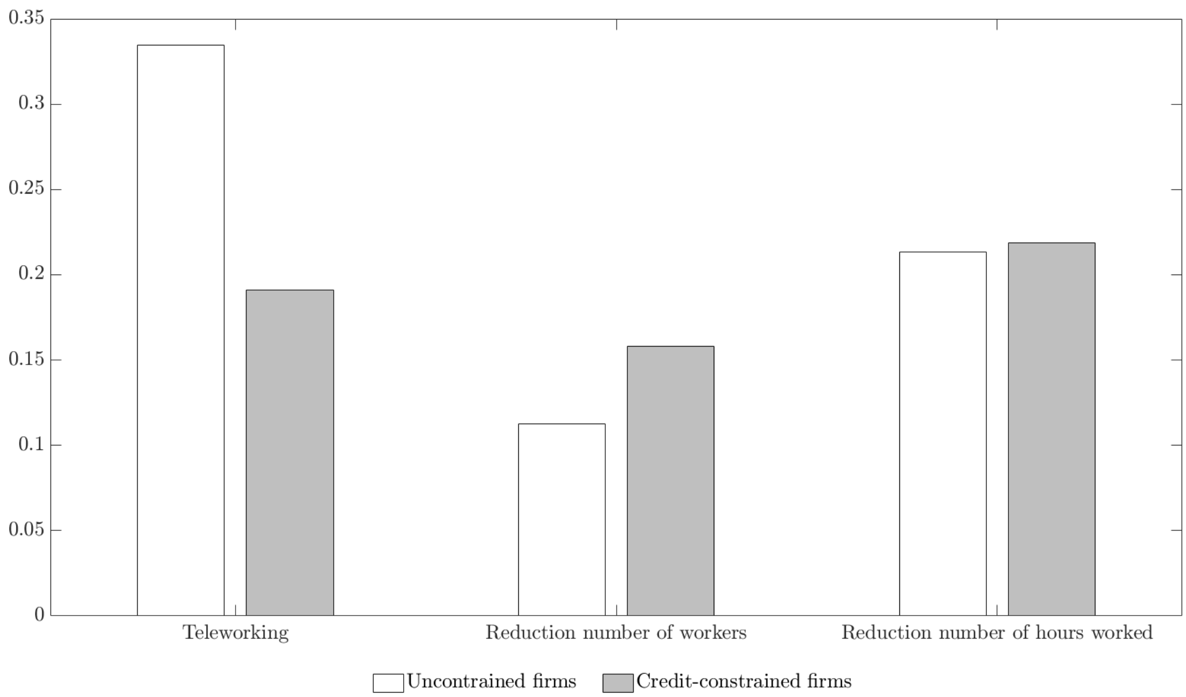

Figure 3: Measures adopted in response to COVID-19 outbreak

Table 1: Model for Expected Sales Growth

Model	OLS		Ordered Logit	
Dependent variable:	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$
	(1)	(2)	(3)	(4)
Credit constrained	-0.305***	-0.298***	-1.047***	-1.043***
	[0.0435]	[0.0405]	[0.164]	[0.152]
Essential	0.417***	0.413***	1.278***	1.310***
	[0.0171]	[0.0157]	[0.140]	[0.126]
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Very Negative	-0.188***	-0.186***	-0.696***	-0.791***
	[0.0359]	[0.0323]	[0.207]	[0.164]
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Negative	-0.296***	-0.284***	-0.936***	-0.911***
	[0.0449]	[0.0424]	[0.185]	[0.180]
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Positive	0.124***	0.134***	0.406***	0.432***
	[0.0265]	[0.0263]	[0.0844]	[0.0826]
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Very Positive	0.414***	0.441***	0.865***	0.953***
	[0.105]	[0.105]	[0.224]	[0.232]
Size	0.175***	0.157***	0.530***	0.404***
	[0.0170]	[0.0174]	[0.0617]	[0.0808]
Age	-0.0361	-0.0367	-0.117*	-0.105
	[0.0227]	[0.0237]	[0.0616]	[0.0716]
Group	0.136***	0.156***	0.315***	0.455***
	[0.0260]	[0.0285]	[0.0676]	[0.0890]
Family firm	-0.150***	-0.149***	-0.440***	-0.422***
	[0.0330]	[0.0331]	[0.0694]	[0.0703]
Z-score	-0.0197***	-0.00484	-0.138***	-2.382***
	[0.00362]	[0.00363]	[0.0396]	[0.572]
Liquidity		0.0351		0.328
		[0.0596]		[0.209]
Leverage		0.00269		-1.742***
		[0.0526]		[0.402]
Cash flow		-0.313***		16.29***
		[0.0397]		[4.117]
Tangible		0.404***		0.953***
		[0.0523]		[0.291]
Trade credit		0.000688		-0.0232
		[0.113]		[0.347]
Province (NUTS3) FE	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓
R-squared (Pseudo R2)	0.332	0.342	(0.193)	(0.202)
N obs.	5037	5037	5037	5037

Notes: $\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$ denotes the post-COVID-19 expectations for sales growth over a 12-month horizon. Weighted OLS and ordered logistic estimates. Standard error (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 2: Model for Continuous Measures for Sales, Orders, Employment, and Investment

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{E}_{i,t}(\text{Sal}^g\text{3M})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Ord}^g)$	$\mathbb{E}_{i,t}(\text{Emp}^g)$	$\mathbb{E}_{i,t}(\text{ITan}^g)$	$\mathbb{E}_{i,t}(\text{IInt}^g)$
Credit constrained	-14.29***	-9.261***	-10.57***	-9.045***	-7.815***	-6.812***
	[1.835]	[1.900]	[1.883]	[2.149]	[1.811]	[1.694]
Essential	10.11***	9.025***	7.163***	1.776	7.093***	6.652***
	[1.897]	[0.870]	[1.060]	[1.169]	[0.752]	[1.120]
$\mathbb{E}_{i,t-1}(\text{Sales}^g\text{1Y})$: Very Negative	-10.22***	-6.866***	-3.561	-7.042***	-3.675***	-2.631
	[1.792]	[1.721]	[2.502]	[2.159]	[1.378]	[2.252]
$\mathbb{E}_{i,t-1}(\text{Sales}^g\text{1Y})$: Negative	-5.637***	-8.838***	-7.809***	-6.481**	-3.832	-5.414**
	[1.787]	[1.772]	[2.165]	[3.241]	[2.399]	[2.425]
$\mathbb{E}_{i,t-1}(\text{Sales}^g\text{1Y})$: Positive	0.684	1.301	1.853	0.753	4.165**	1.689
	[1.367]	[1.655]	[1.639]	[1.116]	[1.887]	[1.707]
$\mathbb{E}_{i,t-1}(\text{Sales}^g\text{1Y})$: Very Positive	-7.973***	-0.107	3.120	0.813	10.32***	7.162***
	[2.371]	[1.554]	[2.484]	[1.376]	[1.421]	[2.043]
Size	5.139***	4.482***	3.411***	1.086*	1.411**	1.226***
	[0.822]	[0.491]	[0.384]	[0.602]	[0.566]	[0.268]
Age	-1.310*	-1.688*	-1.491*	1.904*	0.897	3.050*
	[0.782]	[0.906]	[0.763]	[1.033]	[1.000]	[1.554]
Group	-2.255*	-0.730	-2.225***	1.161**	5.666***	5.202***
	[1.177]	[1.073]	[0.665]	[0.543]	[0.618]	[0.569]
Family firm	-2.358***	-2.057	-1.454**	-1.256	-3.378**	-0.477
	[0.657]	[1.393]	[0.606]	[0.947]	[1.339]	[0.908]
Z-score	1.502***	1.511***	1.522***	0.194	0.710**	0.885***
	[0.275]	[0.191]	[0.154]	[0.215]	[0.324]	[0.172]
Liquidity	6.369**	5.407**	5.929***	0.196	3.009	3.895
	[2.478]	[2.626]	[1.937]	[2.262]	[2.991]	[2.591]
Leverage	2.108	1.160	-0.615	-2.472	-0.848	-1.114
	[3.911]	[3.348]	[2.073]	[1.601]	[2.826]	[2.888]
Cash flow	-13.24***	-12.01***	-15.24***	4.959***	-7.834***	-9.792***
	[2.364]	[1.891]	[1.149]	[1.511]	[2.528]	[1.348]
Tangible	0.605	6.333***	7.470***	-4.181*	2.259	3.961
	[1.407]	[1.300]	[0.959]	[2.190]	[3.279]	[3.136]
Trade credit	-6.796**	-6.902**	-5.099**	-0.211	1.266	-2.346
	[2.592]	[2.691]	[2.227]	[3.739]	[3.301]	[4.166]
Province (NUTS3) FE	✓	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓	✓
R-squared	0.399	0.422	0.355	0.351	0.292	0.259
N obs.	5037	5035	5036	5036	5033	5032

Notes: $\mathbb{E}_{i,t}(Y)$ denotes the post-COVID-19 expectations and plans for variable Y. Sal3M^g denotes sales growth at a three-month horizon, Sal1Y^g denotes sales growth at a 12-month horizon. Ord^g, Emp^g, ITan^g, and IInt^g denote the 12-month growth rate for orders, employment, investment in tangible assets, and investment in intangible assets. Weighted OLS estimates. Standard error (in square brackets) are clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 3: Model for Planned Price Growth

Dependent variable:	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\Delta\mathbb{E}_{i,t}(\mathrm{P}^g)$
	(1)	(2)	(3)
Credit constrained	3.754***	4.250***	3.984***
	[0.889]	[0.870]	[1.039]
Essential	-4.059***	-4.076***	-4.597***
	[0.995]	[0.896]	[0.808]
$\mathbb{E}_{i,t-1}(\mathrm{P}^g)$	0.0313	0.0267	
	[0.0850]	[0.0842]	
Size	-1.172***	-1.198***	-1.197***
	[0.196]	[0.174]	[0.191]
Age	-0.501	-0.540	-0.0317
	[0.401]	[0.393]	[0.422]
Group	0.253	0.501	0.388
	[1.502]	[1.404]	[1.477]
Family firm	0.681	0.603	0.146
	[0.580]	[0.621]	[0.753]
Z-score	-0.218**	-0.102	-0.159
	[0.0969]	[0.102]	[0.143]
Liquidity		0.712	0.628
		[1.650]	[2.202]
Leverage		-1.529*	-1.287
		[0.832]	[0.985]
Cash flow		-2.048	-1.464
		[1.302]	[1.857]
Tangible		0.154	-0.882
		[1.072]	[1.216]
Trade credit		-0.228	0.537
		[1.837]	[2.179]
Province (NUTS3) FE	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓
R-squared	0.224	0.228	0.210
N obs.	4993	4993	4993

Notes: $\mathbb{E}_{i,t}(P^g)$ denotes the post-COVID-19 plans for firm-level price over a 12-month horizon. Weighted OLS estimates. Standard error (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 4: Average Treatment Effect

Outcome:	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$			$\mathbb{E}_{i,t}(\text{P}^g)$		
Abadie and Imbens (2002)	N=1	N=2	N=3	N=1	N=2	N=3
Credit constrained	-0.120**	-0.124***	-0.122***	1.404**	1.373**	1.123**
	[0.0502]	[0.043]	[0.0406]	[0.692]	[0.604]	[0.575]
Outcome:	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$			$\mathbb{E}_{i,t}(\text{P}^g)$		
Radius Matching (std)	0.1 std	0.25 std	0.5 std	0.1 std	0.25 std	0.5 std
Credit constrained	-0.145***	-0.175***	-0.204***	0.986*	1.125**	1.178**
	[0.0393]	[0.0382]	[0.0377]	[0.560]	[0.556]	[0.554]

Notes: Propensity Score Matching. Standard error (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 5: Model with Interactions for Categorical Expected Sales Growth and Continuous Measures of Sales, Orders, Employment, and Investment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$	$\mathbb{E}_{i,t}(\text{Sal}^g 3\text{M})$	$\mathbb{E}_{i,t}(\text{Sal}^g 1\text{Y})$	$\mathbb{E}_{i,t}(\text{Ord}^g)$	$\mathbb{E}_{i,t}(\text{Emp}^g)$	$\mathbb{E}_{i,t}(\text{ITan}^g)$	$\mathbb{E}_{i,t}(\text{IInt}^g)$
Credit constrained	-1.476***	-13.95***	-11.01***	-11.59***	-4.421	-12.58***	-12.33***
	[0.124]	[3.522]	[4.062]	[4.102]	[5.402]	[3.347]	[4.206]
Essential	1.225***	9.888***	8.168***	6.420***	3.370***	5.522***	4.587***
	[0.151]	[1.101]	[0.492]	[0.675]	[0.771]	[0.902]	[0.732]
Constrained × Essential	0.647***	0.372	3.542	3.268	-7.367	9.321**	10.57
	[0.237]	[5.604]	[5.337]	[6.582]	[7.240]	[4.655]	[6.442]
Province (NUTS3) FE	✓	✓	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓	✓	✓
Wide Controls	✓	✓	✓	✓	✓	✓	✓
R-squared (Pseudo R2)	(0.202)	0.418	0.432	0.374	0.375	0.329	0.297
N obs.	5037	5037	5035	5036	5036	5033	5032

Notes: Weighted ordered logistic (column 1) and OLS estimates (columns 2 to 7). Standard error (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 6: Model with Interactions for Planned Price Growth

Dependent variable:	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\mathbb{E}_{i,t}(\mathrm{P}^g)$
	(1)	(2)	(3)	(4)	(5)	(6)
Credit constrained	8.320***	8.420***	7.129***	7.256***	12.97***	11.13***
	[1.455]	[1.473]	[1.425]	[1.436]	[2.429]	[2.648]
Essential	-2.201**	-2.265***	-2.134**	-2.180**	-2.744***	-2.591***
	[0.955]	[0.851]	[0.949]	[0.852]	[0.494]	[0.497]
Constrained × Essential	-8.558***	-8.171***	-9.660***	-9.303***	-12.81***	-13.38***
	[2.599]	[2.444]	[2.633]	[2.485]	[3.145]	[3.181]
Constrained × Concentration			2.081***	2.067***		2.489***
			[0.320]	[0.340]		[0.541]
Constrained × Inventories					-20.08***	-17.21**
					[7.203]	[7.421]
Inventories					4.053	2.344
					[7.017]	[7.026]
Province (NUTS3) FE	✓	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓	✓
Wide Controls	X	✓	X	✓	✓	✓
R-squared	0.275	0.277	0.282	0.283	0.356	0.357
N obs.	5026	5026	4989	4989	3659	3629

Notes: Weighted OLS estimates. Standard error (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 7: Determinants of Post-COVID-19 Credit Access Concerns

Dependent Variable:	Post-COVID-19 credit access concerns			
	(1)	(2)	(3)	(4)
Credit constrained	0.227***	0.198***	0.216***	0.219***
	[0.0340]	[0.0294]	[0.0269]	[0.0249]
Essential	-0.00192	0.00340	0.0136	0.0158
	[0.0269]	[0.0247]	[0.0210]	[0.0166]
Z-score	-0.0199***	-0.274*	-0.159	-0.195
	[0.00478]	[0.155]	[0.118]	[0.135]
Size	0.000546	-0.0260	-0.0300*	-0.0231
	[0.0140]	[0.0180]	[0.0172]	[0.0170]
Age	0.0168	0.0215	-0.0141	-0.0136
	[0.0173]	[0.0160]	[0.0138]	[0.0229]
Group	-0.0562***	-0.0571***	-0.0530***	-0.0810***
	[0.0126]	[0.0116]	[0.00908]	[0.00932]
Family firm	0.00816	0.00651	0.0346*	0.0240
	[0.0183]	[0.0186]	[0.0185]	[0.0212]
Liquidity		-0.326***	-0.380***	-0.324***
		[0.0354]	[0.0351]	[0.0377]
Leverage		-0.151	-0.0503	-0.0829
		[0.114]	[0.0845]	[0.104]
Cash flow		1.970*	1.162	1.395
		[1.121]	[0.853]	[0.989]
Tangible		-0.00511	-0.0669**	-0.0815**
		[0.0414]	[0.0287]	[0.0326]
Trade credit		-0.00878	0.0753*	0.0229
		[0.0449]	[0.0425]	[0.0402]
Lending Relationship (Years)			0.0661***	0.0625***
			[0.0130]	[0.00524]
N of Lender Banks			-0.0216***	-0.0173*
			[0.00827]	[0.00884]
Distance with lender bank			0.0261*	0.0693**
			[0.0154]	[0.0311]
Province (NUTS3) FE	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓
Pseudo R2	0.218	0.236	0.251	0.288
N obs.	5021	5021	4621	4381

Notes: The dependent variable is a dummy variable representing whether or not the firm has included access to credit as one of the three main concerns in the aftermath of the COVID-19 outbreak. Logit marginal effects for weighted sample. Standard error (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 8: Actions in Response to the COVID-19 Outbreak

Dependent variable:	Teleworking	Employment reduction	Hours reduction
	(1)	(2)	(3)
Credit constrained	-0.102***	0.117***	0.113***
	[0.0241]	[0.0302]	[0.0106]
Age	-0.0134	-0.0265***	0.0142
	[0.0115]	[0.00449]	[0.0142]
Group	0.156***	-0.0142	-0.0681***
	[0.0254]	[0.0125]	[0.0190]
Family_firm	-0.0166	-0.0555***	-0.0329***
	[0.0138]	[0.00915]	[0.0104]
Z-score	-0.00589	-0.00750	-0.0158***
	[0.00420]	[0.0172]	[0.00452]
Liquidity	0.352***	0.0660**	0.0442
	[0.0389]	[0.0328]	[0.0482]
Leverage	0.110***	-0.0619*	-0.00320
	[0.0330]	[0.0369]	[0.0348]
Cash flow	-0.112	0.160	0.414***
	[0.0903]	[0.102]	[0.0422]
Tangible	-0.186***	0.0861	0.0964**
	[0.0313]	[0.0552]	[0.0419]
Trade credit	0.191***	-0.174***	-0.0558*
	[0.0672]	[0.0448]	[0.0304]
Province (NUTS3) FE	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓
Wide Controls	✓	✓	✓
Pseudo R-squared	0.262	0.158	0.189
N obs.	4720	4652	4720

Notes: Logit estimates for weighted sample. Standard error (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Appendix

A Informativeness of the MET survey

We have performed several validation exercises to evaluate the informativeness of the expectations and plans data of past waves of the MET survey for actual outcomes. This appendix summarizes such exercises.

First of all, we exploit the panel dimension of the original data set (between 2008 and 2019) and regress realized sales growth on the expectations held at the beginning of the period, together with province, sector, and year dummies. We show that firms' expectations are positively and significantly correlated with realized future sales, with a sizable predictive power. For instance, if we run an OLS regression of the categorical outcome and expectation variable (transformed to a -2, -1, 0, +1, +2 linear scale), the R-square increases from 0.039 to 0.210 when they are included as regressors, more than a five-fold increase. This R-square is quite high because we are dealing with firm-level data and because of the linear approximation that we have adopted. Importantly, if we restrict the analysis to the sovereign debt crisis only, firms' expectations gain even more significance and the incremental R-squared reaches 0.333 (see online appendix). Useful indications can also be derived from the aggregation of our ordinal measure of expectations and its comparison with the reported increase in realized sales (classified consistently). In aggregating the two firm-level data sets, we employ sampling weights to reproduce the number of companies in the population and weigh each observation by the beginning-of-period level of sales. Repeating this exercise for all the waves of the MET survey (seven data points between 2008 and 2019) we estimate a correlation coefficient between aggregate realized and expected sales of about 0.72, which further reassures us of the high informativeness of our expectational data for aggregate outcomes.

When it comes to pricing plans, the lack of firm-level data on realized prices does not allow for a validation exercise at the micro-level. However, once we aggregate firm-level expectations for the manufacturing sector (from the 2017-wave of the MET survey, performed in January 2018) we obtain an expected inflation rate of 1.39%, which is close to the 1.1% observed inflation for domestic manufacturing goods in 2018.[31] Note that, because price expectation data is available only starting from the 2017 wave, we cannot calculate the correlation between expected and realized series as we have done for sales. Nevertheless, the big picture emerging from this set of exercises suggests that firms' expectations are informative about the future dynamics of the actual variables and that this is especially true in times of crisis.

[31] For price plans we use the same aggregation weights that we have used for sales. See also https://www.istat.it/it/files//2019/03/PPI_CPP_PPS_0219_IVtrim18.pdf for the Producer Price Index.

B Data Appendix

Table A1: Variable definition and sources

Variable name	Definition
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$	Pre COVID-19 expected sales growth over the next 12 months (2019 MET survey). Ordinal variable taking values: Very negative (below -15%), Negative (-15%,-5%), Constant [-5%,+5%], Positive (+5%,+15%), Very positive (above 15%).
$\mathbb{E}_{i,t}(\text{Sales}^g 1\text{Y})$	Post COVID-19 expected sales growth over the next 12 months (COVID-19 survey). Ordinal variable taking values: Very negative (below -15%), Negative (-15%,-5%), Constant [-5%,+5%], Positive (+5%,+15%), Very positive (above 15%).
$\mathbb{E}_{i,t-1}(\text{P}^g)$	Pre COVID-19 plans on the change in domestic prices over the next 12 months (2019 MET survey). Continuous variable.
$\mathbb{E}_{i,t}(\text{P}^g)$	Post COVID-19 plans on the change in domestic prices over the next 12 months (COVID-19 survey). Continuous variable.
$\mathbb{E}_{i,t}(\text{Sal}^g 3\text{M})$	Post COVID-19 expected change in sales over the next 3 months (COVID-19 survey). Continuous variable.
$\mathbb{E}_{i,t}(\text{Sal}^g 1\text{Y})$	Post COVID-19 expected change in sales over the next 12 months (COVID-19 survey). Continuous variable.
$\mathbb{E}_{i,t}(\text{Ord}^g)$	Post COVID-19 expected change in orders over the next 12 months (COVID-19 survey). Continuous variable.
$\mathbb{E}_{i,t}(\text{Emp}^g)$	Post COVID-19 adjustment plans on employment over the next 12 months (COVID-19 survey). Continuous variable.
$\mathbb{E}_{i,t}(\text{Tan}^g)$	Post COVID-19 adjustment plans on investment in tangibles over the next 12 months (COVID-19 survey). Continuous variable.
$\mathbb{E}_{i,t}(\text{Int}^g)$	Post COVID-19 adjustment plans on investment in tangibles over the next 12 months (COVID-19 survey). Continuous variable.
Credit constrained	Pre COVID-19 binary variable taking value of one if the firm i. did not applied for a bank loan because it would have been denied, ii. applied for a loan and it was denied, or iii. applied for a loan and it was accepted with unfavorable conditions; it takes zero otherwise (2019 MET survey).
Essential	Binary variable taking value of one if the firm i. is deemed to be essential in the 6-digit sectoral classification of of the Italian government's decree for the lockdown or ii. is deemed to be non-essential and declares to have not shut down during the lock down; it takes zero otherwise. (COVID-19 survey and Italian government's decree of March 22).
Teleworking	Binary variable taking value of one if the firm is employing or planning to employ teleworking to face the crisis; it takes zero otherwise (COVID-19 survey).
Employment reduction	Binary variable taking value of one if the firm is reducing or planning to reduce employment to face the crisis; it takes zero otherwise (COVID-19 survey).
Hours reduction	Binary variable taking value of one if the firm is reducing or planning to reduce the amount of hours worked by its employees to face the crisis; it takes zero otherwise (COVID-19 survey).

Variable name	**Definition**
Size	Log of assets (2019 firm balance sheets, Crif-Cribis D&B).
Age	Log of (1+) age of the firm (2019 MET survey).
Import	Binary variable taking value of one if the firm is an importer; it takes zero otherwise (2019 MET survey).
Export	Binary variable taking value of one if the firm is an exporter; it takes zero otherwise (2019 MET survey).
Group	Binary variable taking value of one if the firm is part of a corporate group; it takes zero otherwise (2019 MET survey).
Family firm	Binary variable taking value of one if the firm is a family business; it takes zero otherwise (2019 MET survey).
% graduated employment	Percentage of graduated employment in the firm, continuous variable (2019 MET survey).
R&D	Binary variable taking value of one if the firm performs activity of Research and Development; it takes zero otherwise (2019 MET survey).
Liquidity	Liquid assets + short-term credit – short-term debt to total assets ratio (2019 firm balance sheets, Crif-Cribis D&B).
Cash flow	Cash flow to total assets ratio (2019 firm balance sheets, Crif-Cribis D&B).
Tangible assets	Tangible assets to total assets ratio (2019 firm balance sheets, Crif-Cribis D&B).
Leverage	Total debt to equity ratio (2019 firm balance sheets, Crif-Cribis D&B).
N. of Lender Banks	Number of banks the firm is borrowing from as of January 2020 (2019 MET survey).
Lending relationship (years)	Duration of the relationship with the lender bank as of January 2020 (2019 MET survey). For firms borrowing from multiple banks (roughly 30% of the sample) this measure is computed as the equally-weighted average across the outstanding relationships.
Distance lender-bank	Distance in log-Km between the firm and the headquarter of the lender bank (2019 MET survey). For firms borrowing from multiple banks (roughly 30% of the sample) this measure is computed as the equally-weighted average across the outstanding relationships.
Trade credit	Net accounts payable (accounts payable net of accounts receivable) to total assets ratio (2019 firm balance sheets, Crif-Cribis D&B).
Credit constrained (post COVID-19)	Binary variable taking value of one if the firm expects credit constraints to be a potential issue after the COVID-19 pandemic; it takes zero otherwise (COVID-19 survey).
Concentration	two-digit sectoral Herfindahl-Hirschman Index (entire population of 2019 Italian balance sheets, Crif-Cribis D&B).

Table A2: Summary statistics

		Raw Sample					Weighted Sample				
Variable	Type	Mean	Q1	Q2	Q3	Stdev	Mean	Q1	Q2	Q3	Stdev
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Very Negative	Categ.	0.440	–	–	–	–	0.489	–	–	–	–
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Negative	Categ.	0.323	–	–	–	–	0.309	–	–	–	–
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Constant	Categ.	0.197	–	–	–	–	0.178	–	–	–	–
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Positive	Categ.	0.025	–	–	–	–	0.016	–	–	–	–
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Very Positive	Categ.	0.008	–	–	–	–	0.006	–	–	–	–
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Very Negative	Categ.	0.047	–	–	–	–	0.059	–	–	–	–
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Negative	Categ.	0.134	–	–	–	–	0.143	–	–	–	–
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Constant	Categ.	0.581	–	–	–	–	0.625	–	–	–	–
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Positive	Categ.	0.208	–	–	–	–	0.151	–	–	–	–
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Very Positive	Categ.	0.031	–	–	–	–	0.021	–	–	–	–
$\mathbb{E}_{i,t}$(P^g)	Cont.	0.047	0.000	0.000	0.100	0.147	0.071	0.000	0.000	0.100	0.183
$\mathbb{E}_{i,t-1}$(P^g)	Cont.	0.015	0.000	0.000	0.030	0.068	0.011	0.000	0.000	0.010	0.061
$\mathbb{E}_{i,t}$(Sal^{g}3M)	Cont.	-0.226	-0.300	-0.150	0.000	0.265	-0.239	-0.400	-0.150	0.000	0.294
$\mathbb{E}_{i,t}$(Sal^{g}1Y)	Cont.	-0.169	-0.250	-0.100	0.000	0.208	-0.193	-0.300	-0.100	0.000	0.234
$\mathbb{E}_{i,t}$(Ord^g)	Cont.	-0.156	-0.220	-0.100	0.000	0.221	-0.174	-0.300	-0.100	0.000	0.244
$\mathbb{E}_{i,t}$(Emp^g)	Cont.	-0.069	0.000	0.000	0.000	0.191	-0.088	0.000	0.000	0.000	0.236
$\mathbb{E}_{i,t}$(Tan^g)	Cont.	-0.139	-0.100	0.000	0.000	0.307	-0.146	-0.100	0.000	0.000	0.322
$\mathbb{E}_{i,t}$(Int^g)	Cont.	-0.121	-0.060	0.000	0.000	0.293	-0.131	-0.060	0.000	0.000	0.312
Credit constrained	Categ.	0.163	–	–	–	–	0.178	–	–	–	–
Credit constrained (post)	Categ.	0.354	–	–	–	–	0.372	–	–	–	–
Deaths	Cont.	4.143	3.018	4.114	5.046	1.552	4.207	3.077	4.162	5.046	1.639
Cases	Cont.	6.687	5.793	6.729	7.488	1.291	6.732	5.823	6.738	7.525	1.361
Population	Cont.	13.39	12.79	13.35	13.92	1.190	13.62	12.94	13.69	14.63	1.232
Essential	Categ.	0.595	–	–	–	–	0.540	–	–	–	–
Size	Cont.	14.73	13.54	14.61	15.78	1.745	13.55	12.32	13.43	14.56	1.672
Age	Cont.	3.010	2.639	3.178	3.555	0.823	2.936	2.565	3.044	3.466	0.778
Z-score	Cont.	0.034	-0.164	-0.018	0.182	1.573	0.521	-0.173	-0.003	0.200	7.232
Export	Categ.	0.299	–	–	–	–	0.146	–	–	–	–
Import	Categ.	0.246	–	–	–	–	0.119	–	–	–	–
R&D	Categ.	0.241	–	–	–	–	0.154	–	–	–	–
Group	Categ.	0.125	–	–	–	–	0.068	–	–	–	–
% graduated empl.	Cont.	0.112	0.000	0.000	0.117	0.220	0.154	0.000	0.000	0.083	0.315
Family firm	Categ.	0.707	–	–	–	–	0.769	–	–	–	–
Leverage	Cont.	0.667	0.506	0.704	0.855	0.234	0.643	0.446	0.675	0.866	0.262
Liquidity	Cont.	0.113	-0.073	0.106	0.318	0.113	0.137	-0.058	0.108	0.381	0.137
Tangible ass.	Cont.	0.211	0.037	0.143	0.329	0.207	0.197	0.014	0.079	0.313	0.241
Trade credit	Cont.	-0.111	-0.222	-0.048	0.000	0.147	-0.087	-0.149	0.000	0.000	0.141
N banks	Cont.	1.008	0.693	1.098	1.386	0.468	0.833	0.693	0.693	1.098	0.355
Length bank rel.	Cont.	0.597	0.251	0.470	0.775	0.535	0.484	0.251	0.415	0.604	0.479
Distance bank	Cont.	5.424	5.024	5.669	6.236	1.218	5.248	4.787	5.606	6.276	1.456