Credit Constraints and Firms' Decisions: Evidence from the COVID-19 Outbreak

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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 the lack of access to credit strongly amplifies the negative effects on planned factor demand and expected sales of the pandemic shock. Moreover, credit-constrained firms, in their search for liquidity, plan to charge significantly higher prices relative to their unconstrained counterparts.

JEL Codes: E2, E3, E44

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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 investigate to what extent credit constraints amplify the effects of the shocks associated with the pandemic on firms' sales, employment, and investment. Many of the existing contributions on amplification have focused 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, may differ by geographical location or sector, and occur in the context of a consistently accommodating monetary policy stance.[2] Second, we explore 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 (Gilchrist et al., 2017) or lower (Kim, 2021) prices during a downturn. Our investigation provides new evidence that when faced with an adverse shock, financially-constrained firms tend to reduce employment, investment, and sales more than unconstrained firms. Moreover, we find that financially-constrained firms set higher prices relative to their unconstrained counterparts.

The fact that the COVID-19 shock has an important supply component makes our analysis particularly relevant also for the monetary policy trade-off. Since supply shocks lead to a negative comovement between prices and quantities, and the monetary

[1] The literature on this topic is vast. We briefly discuss the contributions most related to our paper in the next section, including those focusing on the effects of uncertainty shocks.

[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, its efficiency, and the very ability of firms to operate. 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.

authority affects these two variables in the same direction, the central bank has to decide whether to stabilize inflation at the cost of a deeper contraction or to stimulate the economy, causing further upward pressure on prices. Our results suggest that financial frictions are particularly critical in the aftermath of the pandemic also because they may exacerbate the monetary policy trade-off described above.

Our empirical analysis exploits a unique survey on firms' sales and orders expectations as well as plans for prices, employment, and investment. We collected this information 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 one month before the official "case zero" in Italy. The pre-COVID-19 survey is representative of the Italian economy and it 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 5,000 firms 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 a set of methodological challenges, such as: i) the identification of an exogenous shock and of its effects; 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 pandemic represents an ideal laboratory: the outbreak has indeed generated a series of shocks that are exogenous and largely unanticipated, as Italy was the first Western country to be severely hit by the pandemic and to impose national lockdown policies. To identify the effects of these shocks, we focus on how firms revise their expectations and plans, which, unlike realized quantities, respond immediately to a shock. Our identification relies on the assumption that such revisions are entirely due to the pandemic. We regard this assumption to be reasonable considering that the two surveys are taken within a short time interval around the outbreak, and no other significant event occurred during that period. Note also that, at the time of the post-COVID-19 survey, the details and extent of the credit support programs for firms were still largely uncertain.

Regarding the second challenge, we use the pre-COVID-19 survey to construct a measure of credit constraints based on loan applications. The main information we employ in defining our credit-constrained dummy is the answer to the questions whether the loan application was denied, only partly satisfied, or whether firms did not apply because the loan was expected to be turned down. Using a survey measure, as in Campello et al. (2010), allows us to avoid relying on balance-sheet information (e.g., leverage and liquidity), size, or age, all of which are at best imperfect proxies for financial frictions (see Footnote 8 for a fuller discussion). Using our definition, the percentage of financially-constrained firms turns out to be substantial (almost 20%).[3] When comparing the difference in response between financially-constrained firms and the unconstrained ones, we want to make certain that the credit constraints dummy does not simply reflect financial fragility, poor business prospects, or other firms' attributes. For this reason, we control for a rich menu of firms' characteristics (sector, location, size, age, quality of management, type of ownership, among others) and balance-sheet variables (Z-score, liquidity, leverage, cash flow, tangibility) either in a regression framework or, later, in the context of a propensity score matching estimator.

Our results show that financial frictions shape the effect of the COVID-19 outbreak on firms' sales, factor demand, and pricing strategies and that this effect goes over and above observable proxies for firms' riskiness and fundamentals. Credit-constrained firms display a more pessimistic outlook for sales and orders and plan to reduce employment and investment more than unconstrained firms, suggesting that financial frictions amplify the effects of the shocks. In quantitative terms, sales and employment growth are around 9% lower for financially constrained firms, while the corresponding figure is 8% for investment. In addition, we find that credit-constrained firms plan to increase prices by 4% more than their unconstrained counterpart. These results are consistent with the idea that financially-constrained firms have an incentive to increase prices in order

[3]Note that our sample is mostly made of small and privately-held firms that cannot resort to alternative sources of funding.

to boost internal sources of funds, even at the cost of losing part of their customer base in the future (Gilchrist et al., 2017).

We also investigate whether the role of financing constraints in firms' plans depends on whether the firm was allowed to stay open in the initial phase of the pandemic and on the local severity of the outbreak. We find some evidence for heterogeneous effects on quantities, especially based on the local intensity of the outbreak. Moreover, our results suggest that the differential effect on prices 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.

The baseline specification allows for a rich menu of controls in a regression framework. However, we reach similar conclusions when we use propensity score matching estimators (Abadie et al., 2004; Abadie and Imbens, 2011) of the treatment effect. To further assuage concerns about remaining unobserved factors that we may not be controlling for, we also apply the methodology introduced by Altonji et al. (2005, 2008) and refined by Oster (2019). Our results show that the role of financing constraints, under very plausible assumptions, are also robust to the presence of unobservables.

Finally, we present evidence on the information content of post-COVID expectations and plans in 2020 for the realized values of these variables. We do so by first analyzing the correlation between realization and plans, and, then, by re-estimating some of the main specifications using as a dependent variable the realized values instead of the plans made in the immediate aftermath of the COVID-19 shock. While using the revisions of expectations in a narrow window is crucial in identifying the effects of the shock on firms' planned behavior, net of subsequent shocks and policy responses, it is interesting to investigate to what extent credit constraints also played a role for realized variables. The general message conveyed by both the correlation and regression exercises confirms the informativeness and relevance of firm-level expectations and plans for actual economic outcomes, and the important role played by financing constraints during the COVID-19 crisis.

The remainder of the paper is as follows. Section 2 briefly discusses the related literature and our contributions, while Section 3 describes the dataset, the definition of the main variables employed, and provides some descriptive evidence. Section 4 discusses the econometric strategy and results, while Section 5 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 semi-aggregate or 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 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-

[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. (2021).

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 (2021), 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.[10] A key 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 by exploiting the revision of price plans in a narrow window, which can react immediately to the resulting shock. This, together with the survey-based information on financing constraints, allows us to provide novel evidence on the effect of financial frictions on firms' pricing strategies that is largely consistent with the results of Gilchrist et al. (2017).

[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 on 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 greater 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). Similarly, a high level of leverage may either indicate a greater risk of default or simply reflect the ability of the firm to borrow.

[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.

[10]See also Alekseev et al. (2022) who find that in response to the pandemic almost a quarter of the firms reduced their prices (especially firm facing financial constraints and demand shocks) and almost no firms raised prices.

Finally, there is 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 investors initially penalized internationally-oriented firms, but, as the virus spread in Western countries, leverage and internal liquidity emerged as more important value drivers.[11] 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 (2022), Faria-e Castro (2021), Guerrieri et al. (2022), and Woodford (2022).

As to the Italian experience, Brancati (2021) 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 COVID-19. As in our paper, they also find some evidence of amplification of the pandemic shocks as a result of credit constraints. However, 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 – and skewed towards larger firms that are less likely to suffer from financial frictions and more likely to be classified as essential.[12] Moreover, they identify firms as credit-constrained based on post-COVID-19 survey re-

[11] 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.

[12] As we will show, our results for pricing strategies is driven by non-essential firms.

sponses regarding access to liquidity, while our definition of financing constraints uses direct information on the outcome of loan applications before the pandemic. Finally, the nature of our dataset allows us to use a short window identification strategy, based on the availability of firm-level expectations and plans taken just before and just after the COVID-19 outbreak.

3 Data and descriptive evidence

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, as well as the local severity of the pandemic. Finally, we describe how the revisions in expectations and plans differs between credit-constrained and unconstrained 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.[13] 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.[14] As such, the survey does not contain information on food and hospitality, travel, and other consumer services. Consistently with the timing of the previous waves, the administration of the

[13] 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 administered in a single European country, with an original sample comprising eight waves – 2008, 2009, 2011, 2013, 2015, 2017, 2019, and 2021 – 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.

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

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-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 administered 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 two-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 policy measures, involving the provision of public guarantees on bank loans, were only introduced later on April 9 ("*decreto liquidità*") and converted into law, in an expanded form, on June 5.[15] See Section 4.3 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 about 7,800 completed interviews.[16] We use two sets

[15] 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 24. However, the full extent of the credit support became clearer only with the subsequent "*decreto liquidità*". Therefore, the content of the credit programs was largely unanticipated at the time of our survey. The measures provided a public guarantee of 80% for loans up to 5 million euro and 90% on loans up to 25,000, increased to 30,000 in June. No formal credit assessment was necessary and application fees were waved. The decision on whether or not to extend a loan was left to banks. See Core and De Marco (2021) for evidence on the Italian public guarantee scheme during the COVID-19 pandemic.

[16] 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.

of questions from the survey. The first set 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 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' (continuous) expectations and plans for the growth rate of new orders, number of workers employed, expenditure in tangible and intangible investments over the next 12 months, in addition to sales growth in the following three and 12 months.[17]

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 relevance of expectations, and of their revision following a shock, would be substantially reduced. We assuage this concern with two exercises. First, we exploit the waves of the biannual MET survey in the period 2008-2019 and show that sales expectations have a strong predictive power for future realized sales (see the Online Appendix, Table C1). Second, in Section 4.5, we present evidence in favor of the information content and relevance of post-COVID expectations and plans for the realized values of quantities and prices in 2020.

In completing the data set used in our analysis, 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, and balance-sheet conditions. As a result of this matching, the number of firms was reduced to about

[17] 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.

5,000.[18] Summary statistics for the firm-level survey and balance-sheet data are presented in Table B2.

3.2 Definition of the main variables

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 the 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.[19]

In order 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,

[18] 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).

[19] 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 4.3 for a discussion on further robustness tests and the Online Appendix for the complete set of results.

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. Moreover, we use the estimated number of COVID-19-related deaths (or positive cases) at the provincial level to obtain a proxy for the local severity of the pandemic, which is likely to capture the geographic-specific component of the COVID-19 shock.[20]

3.3 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 the 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. 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 thicker right tail for constrained firms. The difference in the distribution of expected price changes between financially-constrained and uncon-

[20]We use data on the number of cases in each of the 107 provinces and the cumulative deaths in each of the 20 regions. We use the number of cases to project the regional deaths to a provincial level. While both variables are measured with error, the number of deaths is likely to be more accurate. In constructing our measure, we employ data for the day before the interview of each firm, but we also tested other timings with no significant change in the results. We find that our conclusions are robust to different choices and using only the number of cases, but are sharpest when we employ reported deaths as a proxy.

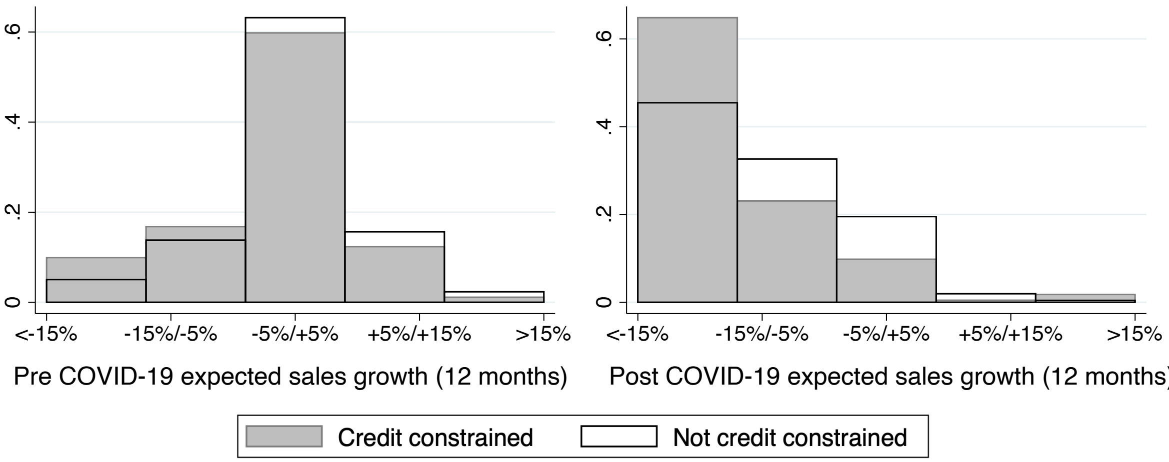

Figure 1: Expected sales growth by credit-constrained status

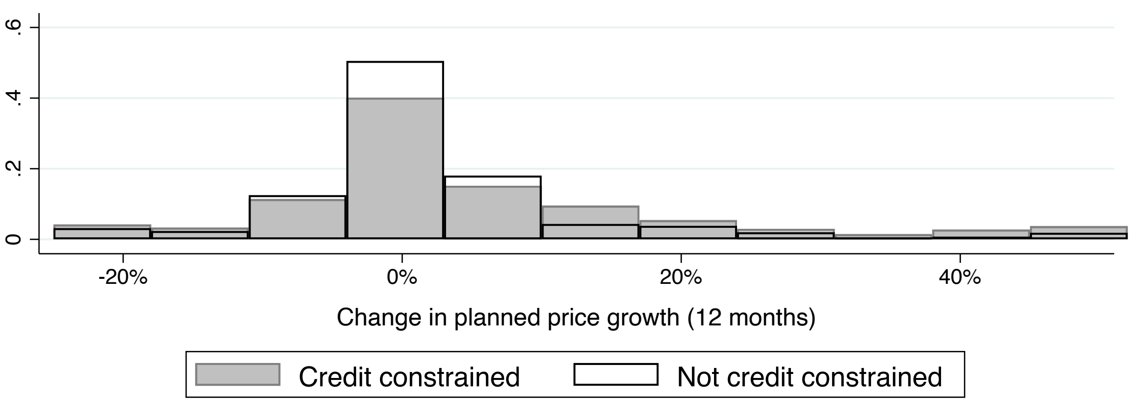

Figure 2: Planned price growth revision by credit-constrained status

strained firms is highly significant according to the Kolmogorov-Smirnov test (p-value effectively equal to zero).

Taken together, our descriptive evidence suggests a difference in the behavior of sales growth expectations and price plans. We will explore more formally the role of credit constraints in the transmission mechanism of the COVID-19 shocks in a multivariate framework in which we control for a large number of firms' characteristics in Section 4.

4 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. In Section 4.3, we present additional exercises to further investigate the heterogeneous response of credit-constrained firms depending on their essential status and geographic location. Finally, in Section 4.4, we provide evidence on the informativeness of post-COVID-19 expectations and plans for the actual values realized in 2020.

4.1 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. Since for the other continuous variables we do not have the corresponding expectations formed before the COVID-19 episode, we use past categorical sales expectations to control for the pre-COVID-19 information set.[21] Importantly, the narrow time window between surveys and the fact that no other major economic events took place in-between surveys, support our assumption that the pandemic is the dominant factor in determining firms' expectation revisions.

[21]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.

Our empirical specifications is based on variants of the following model:

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

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.[22]

Credit constrained ($CC_{i,t-1}$) is an indicator variable that equals one if the firm is financially constrained before entering the pandemic based on the questions on loan applications in the MET 2019 survey. In the model, we also control for a wide set of firms' characteristics and initial conditions $x_{i,t-1}$. In our baseline specification, $x_{i,t-1}$ 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); the education (Manager education) and experience of managers (Manager past exp.); and a summary measure of the creditworthiness of the firm (Z-score).[23] 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, or a more granular definition of the sectoral dummies (six-digit level). Our baseline model is estimated using ex-post

[22] For notation simplicity, $\mathbb{E}_{i,t}(\cdot)$ indicates 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.

[23] 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 the 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.

stratification weights calibrated to reproduce known population aggregates (see Footnote 16). Results are similar if we use unweighted regressions instead (see the Online Appendix).

The key variable in our specification is the survey-based measure for financing constraints, $CC_{i,t-1}$. In order to study the effect of credit constraints on the response to the COVID-19 shock, one has to address two important issues. First, there may be other confounding factors that are correlated with the credit-constrained status. The inclusion of a rich set of firms' characteristics and of 2019 balance-sheet variables allows us to focus on the determinants of access to credit that go beyond pre-COVID-19 firms' riskiness, financial fragility, and other confounding factors.[24] Thus, we contrast the expectations and plans of firms with similar characteristics but that differ in the degree to which they say they have been credit constrained. The remaining variation in the credit constrained status is likely to reflect either the willingness/ability of banks to supply enough funds to satisfy the demand for credit by apparently-equivalent firms, or the quality of the bank-firm relationship that may affect the access/cost of credit.[25] Second, the size or the nature of the COVID-19 shock may differ across firms, for instance, depending upon their sectoral and their geographic location. For this reason, in Section 4.4 we interact the credit-constrained status with a dummy that captures the essential vs non-essential status of the firm and with a measure of the severity of the pandemic at the provincial level.

4.2 Main results

The first two columns of Table 1 present the results of OLS models for the one-year ahead categorical expected sales growth (numbered from one to five according to in-

[24] In the same spirit of Campello et al. (2010), we also present estimates of the average treatment effect of being credit constrained based on propensity-score matching. The conclusion on the important role of financing constraints is robust to this variation and results are reported in Section 4.3.

[25] For instance, in Stiglitz and Weiss (1981), banks' profit maximization under asymmetric information about clients' riskiness may result in rationing of some applicants that appear to be identical to others that, instead, receive credit. As for relationship lending, see Section 4.3 for a further discussion on this issue and an empirical exercise in which we control for proxies of the nature of the firm-bank relationship.

creasing levels of optimism), while columns 3 and 4 report the estimates for ordered logit models for the same variable. For both models, we present standard errors clustered at the two-digit sector level when using both a narrow and wide set of controls.

In all specifications, firms that were deemed to be credit constrained before the outbreak are significantly more pessimistic about their future sales. This is consistent with firms decreasing production more when they face financial frictions.[26] 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 play the most important role: larger firms hold more optimistic expectations about sales, while family-owned firms have more pessimistic expectations. 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.[27]

We now move to Table 2 where we present OLS estimates using a wider set of continuous dependent variables: expected sales at three 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

[26]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.

[27]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 measures of plans and expectations instead.

Table 1: Model for expected sales growth

Model	WLS		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	-0.309***	-0.302***	-1.056***	-1.062***
	[0.0426]	[0.0400]	[0.161]	[0.148]
Essential	0.414***	0.410***	1.264***	1.299***
	[0.0166]	[0.0154]	[0.134]	[0.119]
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Very Negative	-0.194***	-0.191***	-0.715***	-0.814***
	[0.0357]	[0.0328]	[0.205]	[0.161]
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Negative	-0.297***	-0.284***	-0.933***	-0.912***
	[0.0422]	[0.0399]	[0.174]	[0.165]
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Positive	0.124***	0.134***	0.408***	0.429***
	[0.0265]	[0.0260]	[0.0897]	[0.0876]
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Very Positive	0.407***	0.434***	0.848***	0.932***
	[0.106]	[0.107]	[0.211]	[0.219]
Size	0.174***	0.155***	0.528***	0.396***
	[0.0167]	[0.0168]	[0.0630]	[0.0813]
Age	-0.0330	-0.0336	-0.109*	-0.0929
	[0.0240]	[0.0249]	[0.0660]	[0.0770]
Group	0.128***	0.148***	0.281***	0.420***
	[0.0284]	[0.0309]	[0.0742]	[0.0947]
Family firm	-0.147***	-0.145***	-0.426***	-0.410***
	[0.0356]	[0.0359]	[0.0755]	[0.0732]
Manager past exp.	0.000446	0.000443	0.00138	0.00181*
	[0.000322]	[0.000296]	[0.000941]	[0.000953]
Manager education	0.000430	0.000492	0.00214	0.00171
	[0.000630]	[0.000629]	[0.00161]	[0.00165]
Z-score	-0.0199***	-0.00556	-0.139***	-2.449***
	[0.00340]	[0.00357]	[0.0363]	[0.602]
Liquidity		0.0328		0.309
		[0.0597]		[0.209]
Leverage		0.00350		-1.788***
		[0.0519]		[0.420]
Cash flow		-0.304***		16.80***
		[0.0396]		[4.356]
Tangible		0.407***		0.953***
		[0.0515]		[0.290]
Trade credit		-0.00330		-0.0604
		[0.115]		[0.349]
Province (NUTS3) FE	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓
R-squared (Pseudo R2)	0.333	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 Least Squares (WLS) and Ordered Logit estimates. Additional controls (unreported): export and import status, R&D activity, and the share of graduate employees. Standard errors (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2: Model for continuous measures for sales, orders, employment, and investment

	(1) $\mathbb{E}_{i,t}(\text{Sal}^g\text{3M})$	(2) $\mathbb{E}_{i,t}(\text{Sal}^g\text{1Y})$	(3) $\mathbb{E}_{i,t}(\text{Ord}^g)$	(4) $\mathbb{E}_{i,t}(\text{Emp}^g)$	(5) $\mathbb{E}_{i,t}(\text{ITan}^g)$	(6) $\mathbb{E}_{i,t}(\text{IInt}^g)$
Credit constrained	-14.05***	-9.149***	-10.61***	-9.004***	-8.425***	-7.369***
	[1.850]	[1.930]	[1.924]	[2.163]	[1.845]	[1.733]
Essential	10.36***	9.113***	7.270***	1.786	7.084***	6.370***
	[1.923]	[0.875]	[1.069]	[1.135]	[0.690]	[1.109]
$\mathbb{E}_{i,t-1}(\text{Sales}^g\text{1Y})$: Very Negative	-9.797***	-6.704***	-3.456	-7.010***	-3.997***	-3.252
	[1.866]	[1.741]	[2.502]	[2.188]	[1.384]	[2.172]
$\mathbb{E}_{i,t-1}(\text{Sales}^g\text{1Y})$: Negative	-5.655***	-8.832***	-7.889***	-6.466**	-4.121*	-5.528**
	[1.856]	[1.803]	[2.165]	[3.211]	[2.215]	[2.263]
$\mathbb{E}_{i,t-1}(\text{Sales}^g\text{1Y})$: Positive	0.659	1.299	1.804	0.760	4.011**	1.646
	[1.322]	[1.642]	[1.617]	[1.128]	[1.877]	[1.788]
$\mathbb{E}_{i,t-1}(\text{Sales}^g\text{1Y})$: Very Positive	-7.422***	0.0953	3.309	0.844	10.11***	6.451***
	[2.370]	[1.549]	[2.504]	[1.429]	[1.518]	[2.118]
Size	5.218***	4.517***	3.402***	1.098*	1.236**	1.058***
	[0.833]	[0.475]	[0.399]	[0.579]	[0.558]	[0.277]
Age	-1.478**	-1.767*	-1.446*	1.872*	1.376	3.458**
	[0.720]	[0.928]	[0.757]	[1.090]	[1.067]	[1.661]
Group	-1.674	-0.502	-2.110***	1.213**	5.100***	4.292***
	[1.099]	[1.091]	[0.687]	[0.530]	[0.680]	[0.700]
Family firm	-2.674***	-2.163	-1.627**	-1.259	-3.519**	-0.187
	[0.667]	[1.400]	[0.618]	[0.884]	[1.354]	[0.949]
Manager past exp.	-0.0268***	-0.0117	0.00204	-0.00393	0.0553***	0.0553***
	[0.00760]	[0.00937]	[0.00889]	[0.0121]	[0.0137]	[0.0129]
Manager education	-0.0491***	-0.0163*	-0.0266**	-0.000617	-0.0209	0.0452***
	[0.00980]	[0.00895]	[0.0122]	[0.0169]	[0.0163]	[0.0100]
Z-score	1.557***	1.532***	1.535***	0.199	0.668**	0.805***
	[0.269]	[0.197]	[0.157]	[0.219]	[0.312]	[0.180]
Liquidity	6.600**	5.483**	6.060***	0.197	3.130	3.692
	[2.539]	[2.659]	[1.936]	[2.310]	[2.948]	[2.353]
Leverage	2.056	1.138	-0.616	-2.478	-0.761	-1.016
	[3.944]	[3.379]	[2.025]	[1.620]	[2.580]	[2.730]
Cash flow	-13.77***	-12.24***	-15.16***	4.873***	-6.590**	-8.632***
	[2.268]	[2.014]	[1.235]	[1.595]	[2.644]	[1.467]
Tangible	0.448	6.261***	7.503***	-4.209*	2.668	4.326
	[1.403]	[1.279]	[0.978]	[2.155]	[3.326]	[3.226]
Trade credit	-6.459**	-6.780**	-4.975**	-0.194	1.172	-2.767
	[2.633]	[2.689]	[2.228]	[3.781]	[3.120]	[3.970]
Province (NUTS3) FE	✓	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓	✓
R-squared	0.402	0.422	0.356	0.351	0.298	0.266
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. WLS estimates. Additional controls (unreported): export and import status, R&D activity, and the share of graduate employees. Standard errors (in square brackets) are clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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 conclusions we have reached 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 about 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 employment, intangible investment, and tangible investment substantially more than unconstrained firms by an amount of 9%, 8.4%, and 7.4%, respectively. In addition, the essential designation is associated with significantly fewer negative outcomes with the only exception of employment. Note that the inclusion of past sales expectations as control is perfectly appropriate for sales 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 outbreak 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 measured continuously, 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. 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

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	3.569***	4.074***	3.774***
	[0.966]	[0.935]	[1.131]
Essential	-4.027***	-4.038***	-4.513***
	[1.030]	[0.926]	[0.844]
$\mathbb{E}_{i,t-1}(\mathrm{P}^g)$	0.0349	0.0306	
	[0.0809]	[0.0801]	
Size	-1.177***	-1.203***	-1.190***
	[0.194]	[0.173]	[0.188]
Age	-0.399	-0.429	0.105
	[0.427]	[0.424]	[0.461]
Group	0.0634	0.343	0.229
	[1.501]	[1.389]	[1.424]
Family firm	0.639	0.543	0.0270
	[0.652]	[0.703]	[0.837]
Manager past exp.	0.0136	0.0137	0.0159
	[0.0111]	[0.0107]	[0.0130]
Manager education	-0.00528	-0.00706	-0.0150
	[0.0123]	[0.0126]	[0.0184]
Z-score	-0.214**	-0.104	-0.159
	[0.0965]	[0.104]	[0.145]
Liquidity		0.817	0.789
		[1.762]	[2.365]
Leverage		-1.490	-1.235
		[0.919]	[1.103]
Cash flow		-1.811	-1.160
		[1.321]	[1.843]
Tangible		0.231	-0.780
		[1.148]	[1.312]
Trade credit		-0.294	0.432
		[1.778]	[2.097]
Province (NUTS3) FE	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓
R-squared	0.226	0.230	0.213
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. WLS estimates. Additional controls (unreported): export and import status, R&D activity, and the share of graduate employees. Standard errors (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

lower prices (see the seminal papers by Gottfries, 1991 and Chevalier and Scharfstein, 1995, and the recent contribution by Gilchrist et al., 2017).

Note that an alternative explanation for the relatively higher price plans may be the higher expected costs for financially constrained firms in the aftermath of the crisis. While potential heterogeneities in the cost shocks are controlled for by our rich menu of fixed effects and firm-level controls, we further rule out this channel using a direct proxy for the expected change in input costs. The COVID-19 survey provides information on firms' expectations about total input costs related to materials, semifinished goods, and intermediate products over the following 12 months. We rescale this measure by orders to retrieve a proxy for the expected change in material and intermediate input costs per unit of product. Results show a positive and significant effect of this variable on firms' pricing plans, but the effect of credit constraints is found to be largely unchanged (see column 1 of Table C2 in the Online Appendix). This exercise assuages potential concerns about the interpretation of our findings.

Among the other regressors, essential firms appear to charge significantly lower prices. As for the other controls, we document lower prices for larger firms, while past price plans do not appear to have a significant effect, which is somewhat surprising. Finally, 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.

4.3 Different estimators and robustness

In the previous section, we used a regression approach with a large menu of controls to address the potential issue of confounding factors affecting our conclusion on the role of financing constraints. In this section, we provide further evidence on their importance.

First, 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 in their actual condition of being financially constrained. We present two types of estimators for the average treatment effect based on nearest neighbor matching without and with bias correction (Abadie et al., 2004; Abadie and Imbens, 2006; Abadie and Imbens, 2011). In computing the propensity score, we employed the full set of firms' characteristics in $x_{i,t-1}$. Table C3 of the Online Appendix reports the balancing properties of the sample after matching. Importantly, it shows no statistical difference in most firms' characteristics between the financially-constrained firms and unconstrained firms, thus reassuring us about the success of the matching procedure. Table 4, Panel A, presents the results for expected sales, orders, employment, investment, and prices of the nearest neighbor matching estimator. The importance of financial constraints for all the variables is confirmed as the average treatment effect is always negative and significant, while it is positive and significant for prices.[28] Actually, the coefficients of the matching estimator are always greater in absolute value than those in our original estimate. When using the bias-corrected estimator (Abadie and Imbens, 2011) presented in Panel B, the coefficients are negative and significant for quantities, except for investment, and positive and significant for prices. The magnitudes are similar, although slightly smaller than the bias-corrected matching estimator. Overall, this exercise confirms the significance of the effect of financing constraints.

Second, we follow Altonji et al. (2005, 2008) and Oster (2019) to evaluate the importance of unobservable factors in affecting the inference on the treatment effect. In Panel C of Table 4, we report the ATE ratio (Altonji et al., 2005) between the coefficient of the regression with the full set of controls and the difference between this estimate and that obtained in a regression including only the fixed effects. A large value of the ratio indicates that observables remove only a small fraction of the effect of credit constraints. Therefore, the unobservables would need to have a disproportionate effect relative to observables to completely eliminate the effect of financing constraints (2.3-to-3.8 times for quantities, 11.3 times for prices). Oster (2019) extends this approach by using the information about the explanatory power of the regression. In Panel D, we report the identified set for the treatment effect and the importance of unobservable

[28]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.

Table 4: Matching estimator and the role of unobservables

	$\mathbb{E}_{i,t}(\text{Sales}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{3M})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Ord}^g)$	$\mathbb{E}_{i,t}(\text{Emp}^g)$	$\mathbb{E}_{i,t}(\text{ITan}^g)$	$\mathbb{E}_{i,t}(\text{IInt}^g)$	$\mathbb{E}_{i,t}(\text{P}^g)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Nearest Neighbor matching estimator (no bias correction)								
ATT	-0.395***	-24.714***	-18.971***	-18.865***	-17.911***	-16.547***	-14.223***	6.210***
	[0.127]	[4.762]	[3.991]	[4.193]	[4.534]	[5.555]	[5.112]	[2.362]
Panel B: Abadie and Imbens (2002) estimator								
ATT	-0.277**	-22.500***	-16.775***	-15.348***	-15.012***	-9.140	-7.289	5.178**
	[0.142]	[4.929]	[3.905]	[4.196]	[4.564]	[5.954]	[5.611]	[2.496]
Panel C: Altonji at al. (2005) AET ratio								
AET ratio	3.732	3.428	2.298	2.578	3.013	3.817	2.836	11.371
Panel D: Oster (2019) test								
Identified set	[-0.30,-0.26]	[-14.05,-10.98]	[-9.15,-6.57]	[-10.61,-7.92]	[-9.00,-6.74]	[-8.43,-6.39]	[-7.37,-5.79]	[3.89,4.07]
$\tilde{\delta}$ for $\beta = 0$	9.040	4.438	3.489	3.784	3.726	4.311	4.906	261.9

Notes: Panel B presents the result of the Abadie and Imbens (2011) nearest neighbor matching with bias correction (one matched control per treated firm), while Panel A reports the non-bias-corrected version of the same matching. Standard errors in square brackets. Panel C presents the Altonji et al. (2005) (AET) ratio, which compares the size of the credit constraints in a restricted regression including only the constant term and the fixed effects with that of the regression including the full set of controls ($\beta_{full}/(\beta_{restr} - \beta_{full})$). In panel D, we present the results of the Oster (2019) test for unobservable selection and coefficient stability. The identified set for CC is bounded between the estimated coefficients in Tables 1, 2, and 3 (i.e., β_{full}) and the $\tilde{\beta}$ calculated based on $\tilde{\delta} = 1$ and $R^2_{max} = 1.3R^2$ (as suggested by Oster, 2019). $\tilde{\beta}$ is the upper bound in columns 1-7 and the lower bound in column 8. $\tilde{\delta}$ for $\beta = 0$ reports the estimated value of $\tilde{\delta}$ that would reduce the credit constraints coefficient to zero. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

relative to observable factors that would render the estimated treatment effect non-significantly different from zero. The identified set does not contain zero and is very tight, confirming the significance and the size of our estimated coefficients. Moreover, the estimated effect of credit rationing becomes insignificant for an unrealistic value of the relative importance of unobservables.[29] This set of results suggests that our baseline conclusions regarding the significance and size of the coefficients on credit constrained status reached hold and are unlikely to be driven by unobservable omitted variables.

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 because they knew the application would have been denied; and ii) including only the cases in which the loan was fully denied (see Tables C4 and C5).

Our conclusions are also robust to: i) using unweighted data in the estimation; ii) clustering at the provincial (NUTS-3) level or six-digit sectors as opposed to the two-digit sector; iii) using six-digit sectoral dummies as a control, instead of the indicator variable identifying the firm as essential; and iv) controlling for proxies for relationship lending, such as the length of the firm-bank relationship (in log years) and the number of lender banks (in log, see Tables C6–C10, respectively). Our results are largely unchanged, while suggesting a minor role for the proxies for relationship lending.[30] Note, however, that these measures capture only imperfectly the strength of the relationship with a bank, which is likely to be reflected in our CC dummy.

Furthermore, 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

[29] Recall that the upper limit (in absolute value) of the identified set is given by the estimated effects contained in Tables 1-3.

[30] The exceptions are a positive effect of number of banks on sales at a 12-month horizon, and of the length of the relationship on sales at a three-month horizon and intangible investment.

and we would underestimate the effect of financial constraints.[31] 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 (see Table C11 in the Online Appendix). 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.

Finally, we check the informativeness of our $CC_{i,t-1}$ dummy by exploiting information on firms perceiving credit access as a major concern in the aftermath of the pandemic. 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.[32] While this variable is not the post-COVID-19 counterpart of our proxy, it signals the relevance of financing constraints in the aftermath of the outbreak. We find that past credit constraints increase the concern of getting access to credit during the COVID-19 crisis by 21 percentage points (relative to an unconditional average of 37%). Therefore, our proxy is very informative about the likelihood of experiencing difficulties in accessing credit in the during the first stage of the pandemic (see Table C12 in the Online Appendix).

4.4 Models with interactions

It is possible that the role of financing constraints depends on other firms' characteristics such as the sector a firm operates in – and, more specifically, whether it was classified as essential – or the local severity of the pandemic. This may be the case because the

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

[32] 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.

nature or size of the shocks depends upon such characteristics and firms respond to both the common and sector- or geographic-specific components of the shock. For instance, non-essential firms suffer an extreme form of supply shock because they were prevented from operating at all for some time. Moreover, the local severity of the pandemic may have adverse effects on labor supply either because of the restriction to mobility or the perceived risk of infections or deaths. In a more complex specification, therefore, we have interacted our credit-constrained status with both the essential dummy and the log of the number of COVID-19 deaths at the provincial level.

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 mostly not significant but there are two interesting exceptions: categorical sales and tangible investment. In these cases, the amplification effect of financing constraints is substantially smaller for essential firms. For the geographical severity of the pandemic, instead, the interaction effect with credit constraints is negative and significant in the majority of cases. This is consistent with the shocks being more adverse in areas where COVID-19 was more severe, and the credit-constrained status amplifying both the common and geographical-specific component of the shock.[33]

In Column 1 of Table 6, we report the results for the price equation when we interact the credit-constrained dummy with both the essential status of the company and the local number of deaths. In this case, the coefficient of the main effect of credit constraints continues to be positive and significant, while the interaction term containing essential 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 greater pressure to set higher prices in order to boost

[33]The negative sign of the coefficient of the interaction term between $\text{Essential}_{i,t}$ and $\text{CC}_{i,t}$ for employment is somewhat puzzling but this term is not precisely estimated and is significant only at the 10% level.

Table 5: Model with interactions for quantities

	(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	-1.393***	-5.985**	-8.296***	-7.131***	2.807	-9.119***	-6.901***
	[0.127]	[2.604]	[2.078]	[1.982]	[3.015]	[1.759]	[1.997]
Essential	1.231***	10.57***	8.472***	6.777***	3.780***	5.475***	4.384***
	[0.142]	[1.001]	[0.481]	[0.651]	[0.713]	[0.783]	[0.680]
Constrained × Essential	0.658***	-1.089	2.296	1.898	-10.00*	8.281**	9.421*
	[0.253]	[4.432]	[4.479]	[5.369]	[5.509]	[3.608]	[5.173]
Constrained × Deaths	-0.0707	-7.552***	-1.580	-3.615*	-5.473***	-3.348**	-5.331***
	[0.0609]	[1.360]	[1.887]	[1.948]	[1.860]	[1.571]	[1.968]
Province (NUTS3) FE	✓	✓	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓	✓	✓
Wide Controls	✓	✓	✓	✓	✓	✓	✓
R-squared (Pseudo R2)	(0.202)	0.404	0.388	0.328	0.322	0.302	0.266
N obs.	4942	4942	4940	4941	4941	4938	4937

Notes: Weighted Ordered Logit (column 1) and WLS estimates (columns 2 to 7). Additional controls (unreported) are listed in Table 1. Standard errors (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

liquidity once they reopen. This result is consistent with adverse supply shocks being much smaller for companies allowed to operate and generate cash flow. The coefficient of the interaction term with deaths is, instead, never significant.

Table 6: Model with interactions for planned price growth

Dependent variable:	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\mathbb{E}_{i,t}(\mathrm{P}^g)$	$\mathbb{E}_{i,t}(\mathrm{P}^g)$
	(1)	(2)	(3)	(4)
Credit constrained	8.408***	8.118***	13.72***	12.19***
	[1.417]	[1.319]	[3.107]	[3.131]
Essential	-1.925**	-1.835**	-2.493***	-2.312***
	[0.823]	[0.816]	[0.430]	[0.430]
Constrained × Essential	-8.949***	-10.09***	-13.42***	-14.12***
	[2.318]	[2.314]	[3.064]	[3.040]
Constrained × Deaths	0.777	-0.0884	0.314	-0.0941
	[0.898]	[1.037]	[1.550]	[1.446]
Constrained × Concentration		1.943***		2.605***
		[0.439]		[0.596]
Constrained × Inventories			-14.18**	-11.15
			[6.738]	[7.152]
Inventories			2.150	0.208
			[7.220]	[7.369]
Province (NUTS3) FE	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓
Wide Controls	✓	✓	✓	✓
R-squared	0.295	0.301	0.376	0.382
N obs.	4932	4932	3591	3591

Notes: WLS estimates. Additional controls (unreported) are listed in Table 1. Standard errors (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

In Columns 2 to 6, we further explore the mechanism through which financial frictions affect pricing strategies. In particular, we allow for the interaction between credit constraints and the HHI index at the 2-digit sectoral level (Concentration) 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 provides some support for the mechanism outlined in Kim (2021), 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, the significance of inventories disappears when the interaction with concentration is also included.[34]

4.5 Information content of expectations and plans for actual outcomes

In this final section, we present evidence on the information content of post-COVID-19 expectations and plans for the realized values over the same period. We do this in two steps. First, we analyze the correlation between realizations and plans. Then, we replicate some of the main specifications using as a dependent variable the realized values of sales, employment, investment, and prices rather than the plans made in the immediate aftermath of the COVID-19 outbreak. The advantage of using revisions of expectations and plans is that they can immediately react to the shock and they are much less likely to be contaminated by subsequent shocks and unanticipated policy responses. It is, however, interesting, to analyze the importance of credit constraints also for the actual values of the variables of interest.

In section 3.1, we have already shown that firms' expectations are informative about their sales realizations over the period 2008–2019. In Table 7, we report, instead, the correlation (and its p-value) between planned/expected values from the post COVID-19 survey and actual outcomes that are calculated using December 2020 balance sheet data for sales, employment, and investment. For prices, instead, we employ information on the actual growth in firm-level prices from the 2021 MET survey, in which we added a specific question on realized prices charged in 2020. In the first row, we report the raw correlation between expected and realized outcomes, while in the bottom row we control for firm-level variables, industry, and province. The cross-sectional correlation is very high for sales and varies between 0.287 and 0.241. It is also quite sizable for employment growth (0.082–0.108), while for investment in tangible and intangible assets

[34] Our conclusions are unchanged if we control for our proxy for expected unit costs (see columns 2-6 of Table C2).

it is somewhat smaller (around 0.05 and 0.03, respectively).[35] Finally, for prices, the correlation is substantial and varies between 0.082 and 0.094. In all cases, the associated p-values are essentially zero. These results confirm the informativeness of firms' plans and expectations for the realizations of most variables.

Table 7: Expectations and realized measure: correlations

	(1)	(2)	(3)	(4)	(5)
Variable:	$Sales^g 1Y$	Emp^g	$ITan^g$	$IInt^g$	P^g
Pure correlation	0.287	0.108	0.049	0.035	0.094
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
Controlling for firm-variables	0.241	0.082	0.049	0.026	0.082
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)

Notes: correlation between post-COVID expectations and realized outcomes. In the first row, we report the raw correlation coefficient between expected and realized outcomes. In the second raw, the correlation is computed between the error terms obtained regressing post COVID expectations and realized variables on the same set of firm-level variables used in Table 1.

As a second exercise, we re-estimate our baseline specifications in Tables 1, 2, and 3 but replace post-COVID-19 plans and expectations with their realized counterparts. The purpose of this exercise is to gauge whether credit constraints played a role not only for plans but also for realizations. The results, reported in Table 8, clearly show that this is the case for sales and price growth. The coefficient of the credit constraint dummy is highly significant in both cases, negative for sales and positive for price growth. The size of the coefficient in the sales growth equation is very similar to the one obtained when using expected sales, while the coefficient in the price equation is smaller. The estimate for employment is negative and significant, but only at the 10% level, while the ones for tangible investment are similar in magnitude but are imprecisely estimated. On the whole, there is strong evidence that credit constraints played a role also for the realization of sales and prices, while results for employment and investment are somewhat weaker. The general message conveyed by both the correlation and

[35] The lower correlation for investment should not be surprising as the investment process consists of several stages (going from initial plans to orders and expenditures) that are distributed over a considerable time span. Note that, while our survey questions refer to plans, our ex-post data captures actual investment expenditures.

regression results is consistent with the conclusions in Gennaioli et al. (2016) on the informativeness and relevance of firm-level expectations for economic analysis.[36]

Table 8: Credit constraints and realized outcomes

Variable:	(1) $Sales^g 1Y$	(2) Emp^g	(3) $ITan^g$	(4) $IInt^g$	(5) P^g
Credit constrained	-7.887***	-1.488*	-7.739*	-9.260	1.216***
	[2.149]	[0.842]	[4.463]	[16.33]	[0.430]
$\mathbb{E}_{i,t-1}(Sales^g 1Y)$	6.028***	4.729***	8.937***	-1.557	
	[0.431]	[0.410]	[1.156]	[7.427]	
$\mathbb{E}_{i,t-1}(P^g)$					0.227**
					[0.111]
Essential	3.594***	1.975**	-21.55***	9.152	-2.245***
	[0.852]	[0.791]	[2.516]	[8.387]	[0.451]
Province (NUTS3) FE	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓
Wide Controls	✓	✓	✓	✓	✓
R-squared	0.347	0.326	0.203	0.241	0.339
N obs.	4806	3322	4850	4869	2648

Notes: WLS estimates. Additional controls (unreported) are listed in Table 1. Standard errors (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

The fact that credit constraints have, in some cases, stronger effects on expectations and plans than on realizations should not be surprising as a lot happened between March and December 2020. The most important change is, perhaps, the introduction and implementation of credit programs designed to assist firms in accessing credit, which was mostly unanticipated at the time of the survey. An analysis of the effect of these credit programs on firms' choices and behavior and how well they explain the difference between realizations and expectations is an important research topic that is worth pursuing.

[36]Gennaioli et al. (2016) show that expectations matter for actual decisions, in the sense that corporate investment plans and actual investment are well explained by CFOs' expectations of earnings growth.

5 Conclusions

In this paper, we take 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 amplifying 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. These findings emphasize the importance of firms' access to credit in the immediate aftermath of the COVID-19 outbreak and provide indirect 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 or if they were temporarily unable to generate cash flow. This evidence is 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.

There is much more to learn about the effects of the COVID-19 outbreak on firms' strategies and decisions. The consequences of the shocks associated with the pandemic will be felt not only on quantities and prices but also on the very organization of the firm and on the nature of its relationship with other companies, domestically and internationally. Moreover, the pandemic has spawned a series of interventions by governments to support firms and facilitate their access to credit. The analysis of all these topics is very important, but it is left for future research.

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 Table C1 in the 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 about previous years does not allow for a validation exercise at the micro-level for the period 2008–2019. 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.[37] 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. For the year 2020, we can, instead, compare price realizations and plans because a special question has been introduced in the 2021 MET survey (see Section 4.5).

[37] 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

Table B1: Variable description

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).
Deaths	Log of (1+) COVID-19 cumulative deaths at the provincial level (imputed from number of cases, https://github.com/pcm-dpc/COVID-19).
Population	Log of population at the provincial level (ISTAT).
Post-COVID-19 credit access concerns	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).
Size	Log of assets (2019 firm balance sheets, Crif-Cribis D&B).
Age	Log of (1+) age of the firm (2019 MET survey).
Manager past exp	Percentage of managers with past managerial experience, continuous variable (2019 MET survey).
Manager education	Percentage of graduated managers, continuous variable (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).
Concentration	Two-digit sectoral Herfindahl-Hirschman Index (entire population of 2019 Italian balance sheets, Crif-Cribis D&B).
Inventories	Stock of inventories to total assets ratio (2019 firm balance sheets, Crif-Cribis D&B).

Table B2: Summary statistics

Variable	Type	Mean	Q1	Q2	Q3	Stdev
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Very Negative	Categorical	0.489	0.000	0.000	1.000	0.500
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Negative	Categorical	0.309	0.000	0.000	1.000	0.462
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Constant	Categorical	0.178	0.000	0.000	0.000	0.382
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Positive	Categorical	0.017	0.000	0.000	0.000	0.129
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Very Positive	Categorical	0.007	0.000	0.000	0.000	0.082
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Very Negative	Categorical	0.059	0.000	0.000	0.000	0.236
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Negative	Categorical	0.143	0.000	0.000	0.000	0.350
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Constant	Categorical	0.626	0.000	1.000	1.000	0.484
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Positive	Categorical	0.151	0.000	0.000	0.000	0.358
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Very Positive	Categorical	0.021	0.000	0.000	0.000	0.144
$\mathbb{E}_{i,t}$(P^g)	Continuous	6.519	0.000	0.000	9.500	14.195
$\mathbb{E}_{i,t-1}$(P^g)	Continuous	1.167	0.000	0.000	1.000	6.144
$\mathbb{E}_{i,t}$(Sal^{g}3M)	Continuous	-23.994	-40.000	-15.000	0.000	29.042
$\mathbb{E}_{i,t}$(Sal^{g}1Y)	Continuous	-19.278	-30.000	-10.000	0.000	23.498
$\mathbb{E}_{i,t}$(Ord^g)	Continuous	-17.385	-30.000	-10.000	0.000	24.447
$\mathbb{E}_{i,t}$(Emp^g)	Continuous	-8.838	0.000	0.000	0.000	23.650
$\mathbb{E}_{i,t}$(ITan^g)	Continuous	-14.561	-10.000	0.000	0.000	32.296
$\mathbb{E}_{i,t}$(IInt^g)	Continuous	-13.087	-6.000	0.000	0.000	31.228
Credit constrained	Categorical	0.178	0.000	0.000	0.000	0.382
Post-COVID-19 credit access concerns	Categorical	0.372	0.000	0.000	1.000	0.483
Deaths	Continuous	0.087	0.009	0.026	0.062	0.151
Population	Continuous	11.445	10.873	11.505	12.289	1.035
Essential	Categorical	0.540	0.000	1.000	1.000	0.498
Size	Continuous	6.612	5.370	6.517	7.667	1.703
Age	Continuous	2.936	2.565	3.045	3.466	0.778
Group	Categorical	0.068	0.000	0.000	0.000	0.252
Family firm	Categorical	0.770	1.000	1.000	1.000	0.421
Manager past exp	Continuous	55.201	0.000	100.000	100.000	48.731
Manager education	Continuous	5.358	0.000	0.000	0.000	19.354
Z-score	Continuous	0.078	-0.291	-0.032	0.353	2.806
Liquidity	Continuous	0.164	0.012	0.071	0.247	0.211
Leverage	Continuous	0.634	0.426	0.649	0.828	0.282
Cash flow	Continuous	0.010	0.000	0.016	0.056	0.192
Tangible	Continuous	0.205	0.014	0.089	0.335	0.244
Trade credit	Continuous	-0.085	-0.160	0.000	0.000	0.148
Inventories	Continuous	0.024	0.000	0.000	0.000	0.075
Export	Categorical	0.146	0.000	0.000	0.000	0.353
Import	Categorical	0.119	0.000	0.000	0.000	0.323
R&D	Categorical	0.155	0.000	0.000	0.000	0.361
% graduated employment	Continuous	15.468	0.000	0.000	8.333	31.496
N of Lender Banks	Continuous	0.833	0.693	0.693	1.099	0.356
Lending Relationship (Years)	Continuous	0.484	0.251	0.415	0.604	0.479

Notes: Weighted summary statistics.

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Credit Constraints and Firms' Decisions: Evidence from the COVID-19 Outbreak

Online Appendix

Table C1: Validation for expected sales growth

Dependent Variable:	Realized sales growth (categorical)					
Panel A: full sample 2008–2019						
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Very Negative		-7.102***		-6.495***		-2.678***
		[0.0877]		[0.131]		[0.0375]
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Negative		-2.240***		-1.572***		-1.059***
		[0.0569]		[0.0820]		[0.0216]
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Positive		2.569***		1.986***		1.344***
		[0.0436]		[0.0639]		[0.0170]
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Very Positive		7.028***		5.537***		3.038***
		[0.110]		[0.167]		[0.0470]
Time FE	✓	✓	✓	✓	✓	✓
Province FE	✓	✓	X	X	✓	✓
Industry (2 Digit) FE	✓	✓	X	X	✓	✓
Firm FE	X	X	✓	✓	X	X
Estimator	OLS		Within		Ordered Logit	
R-squared (Pseudo R2)	0.039	0.210	0.034	0.140	(0.017)	(0.105)
N obs.	91540	91540	91540	91540	91540	91540
Panel B: sovereign-debt crisis only (2011)						
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{E}_{i,t-1}(\text{Sales}1\text{Y})$: Very Negative		-10.56***		–		-4.457***
		[0.164]		–		[0.0985]
$\mathbb{E}_{i,t-1}(\text{Sales}1\text{Y})$: Negative		-2.009***		–		-1.240***
		[0.128]		–		[0.0602]
$\mathbb{E}_{i,t-1}(\text{Sales}1\text{Y})$: Positive		2.698***		–		1.735***
		[0.110]		–		[0.0542]
$\mathbb{E}_{i,t-1}(\text{Sales}1\text{Y})$: Very Positive		5.590***		–		3.331***
		[0.404]		–		[0.231]
Province FE	✓	✓	X	X	✓	✓
Industry (2 Digit) FE	✓	✓	X	X	✓	✓
Estimator	OLS		–		Ordered Logit	
R-squared (Pseudo R2)	0.012	0.345	–	–	(0.005)	(0.155)
N obs.	14760	14760	–	–	14760	14760

Notes: the dependent variable is the realized categorical growth rate of sales. The explanatory variable is the expectations of future sales growth at the one-year horizon formed the previous period ($\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$). Both variables are categorical and take a value from one to five if the firm reported expected or realized sales growth to be: i) very negative (less than -15%); ii) negative (between -15% and -5%); iii) stable (between -5% and +5%); iv) positive (between 5% and 15%); and v) very positive (more than 15%). The estimator varies across columns: WLS in columns 1 and 2, within estimator with firm and time fixed effects in columns 3 and 4, and weighted Ordered Logit (estimates) in columns 5 and 6. Standard errors (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. In Panel A we report the results for the entire sample (combination of all the waves of the MET survey), while Panel B presents results for the sovereign debt crisis only (expectations formed at the end of 2011 for 2012).

Table C2: Controlling for expected unitary costs

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	5.003***	6.943***	6.971***	6.461***	13.84**	11.88**
	[1.241]	[1.914]	[1.614]	[1.799]	[5.639]	[5.458]
Essential	-5.850***	-4.649***	-4.469***	-4.414***	-5.685***	-5.513***
	[1.132]	[1.134]	[1.055]	[1.086]	[1.448]	[1.362]
Constrained × Essential		-5.796***	-7.541***	-7.145***	-10.85***	-11.12***
		[1.909]	[1.848]	[1.917]	[3.833]	[4.058]
Constrained × Deaths		1.249	0.481	0.423	1.358	1.327
		[1.103]	[1.120]	[1.169]	[1.857]	[1.825]
Constrained × Concentration			1.877***	1.923***		2.427***
			[0.390]	[0.426]		[0.780]
Constrained × Inventories					-6.743	-2.588
					[13.82]	[12.69]
Inventories					-2.357	-4.128
					[6.780]	[6.007]
Expected unit input costs	3.467***	3.454***	3.600***	3.572***	4.404***	4.307***
	[0.536]	[0.604]	[0.564]	[0.591]	[0.768]	[0.785]
Province (NUTS3) FE	✓	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓	✓
Wide Controls	✓	✓	✓	✓	✓	✓
R-squared	0.293	0.295	0.298	0.301	0.376	0.382
N obs.	4932	4932	4932	4932	3591	3591

Notes: WLS estimates. $\mathbb{E}_{i,t}(P^g)$ denotes the post-COVID-19 plans for firm-level price over a 12-month horizon. In this table, we control for the expected change in material and intermediate input costs per unit of product. As a proxy, we use *Expected unit input costs*, a measure obtained by dividing the expected growth of input costs (materials, semifinished goods, and intermediate products) by the expected growth of orders (both related to the following 12 months). Additional controls (unreported) are listed in Table 1. Standard errors (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C3: Post-matching balancement

	Mean		t-test	
	Treated	Control	t	$p >\mid t \mid$
Z-score	-0.169	-0.159	-0.55	0.584
Size	7.543	7.527	0.18	0.859
Age	2.895	2.806	1.83	0.067
Liquidity	-0.052	-0.035	-0.37	0.709
Leverage	0.855	0.857	-0.04	0.969
Cash flow	-0.027	-0.008	-1.61	0.107
Tangible	0.227	0.227	-0.01	0.988
Trade credit	-0.110	-0.113	0.26	0.796
Essential	0.601	0.613	-0.45	0.654
Export	0.321	0.276	1.80	0.073
Import	0.265	0.259	0.25	0.804
R&D	0.288	0.258	1.23	0.219
Group	0.134	0.132	0.16	0.872
Manager past exp.	62.1	65.95	-1.55	0.120
Manager education	15.65	17.15	-0.87	0.385
Family firm	0.698	0.694	0.18	0.858
Graduated empl.	12.402	14.185	-1.38	0.167
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Very Negative	0.072	0.066	0.43	0.666
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Negative	0.160	0.156	0.22	0.822
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Positive	0.219	0.207	0.53	0.593
$\mathbb{E}_{i,t-1}(\text{Sales}^g 1\text{Y})$: Very Positive	0.033	0.027	0.64	0.521

Notes: Post-matching balancing properties from nearest neighbor matching for expected sales in Panel B of Table 4.

Table C4: Alternative definition of credit constrained: no discouraged borrowers

Dependent variable:	$\mathbb{E}_{i,t}(\text{Sales}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{3M})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Ord}^g)$	$\mathbb{E}_{i,t}(\text{Emp}^g)$	$\mathbb{E}_{i,t}(\text{Tan}^g)$	$\mathbb{E}_{i,t}(\text{Int}^g)$	$\mathbb{E}_{i,t}(\text{P}^g)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit constrained	-0.358***	-10.15***	-8.222***	-7.244***	-5.215**	-9.458***	-5.262***	1.989**
	[0.0489]	[1.963]	[1.837]	[2.055]	[2.107]	[2.563]	[1.977]	[0.949]
Essential	0.401***	10.17***	8.929***	7.146***	1.717	6.841***	6.275***	-5.291***
	[0.0170]	[2.099]	[1.022]	[1.221]	[1.235]	[0.768]	[1.232]	[0.614]
Province (NUTS3) FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓	✓	✓	✓
Wide controls	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.341	0.383	0.413	0.340	0.336	0.296	0.261	0.331
N obs.	5037	5037	5035	5036	5036	5033	5032	4993

Notes: WLS estimates. In column 1, $\mathbb{E}_{i,t}(\text{Sales}^g\text{1Y})$ denotes the post-COVID-19 expectations for sales growth over a 12-month horizon (ordinal). In columns 2-7, $\mathbb{E}_{i,t}(Y)$ 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. In column 8, $\mathbb{E}_{i,t}(P^g)$ denotes the post-COVID-19 plans for firm-level price over a 12-month horizon. In this table, we classify a firm to be credit constrained if the loan was granted but for an amount substantially lower than requested (or at very unfavorable conditions) or the loan was denied (i.e., we exclude discouraged borrowers in our benchmark classification). Additional controls (unreported) are listed in Table 1. Standard error (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C5: Alternative definition of credit constrained: only rejected loans

Dependent variable:	$\mathbb{E}_{i,t}$(Sales^{g}1Y)	$\mathbb{E}_{i,t}$(Sal^{g}3M)	$\mathbb{E}_{i,t}$(Sal^{g}1Y)	$\mathbb{E}_{i,t}$(Ord^g)	$\mathbb{E}_{i,t}$(Emp^g)	$\mathbb{E}_{i,t}$(Tan^g)	$\mathbb{E}_{i,t}$(Int^g)	$\mathbb{E}_{i,t}$(P^g)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit constrained	-0.473***	-5.171**	-4.435	-6.433*	3.629	0.355	-0.376	5.390***
	[0.0876]	[2.338]	[2.937]	[3.666]	[5.263]	[6.838]	[4.946]	[1.423]
Essential	0.413***	10.55***	9.235***	7.407***	1.930	7.209***	6.478***	-4.108***
	[0.0166]	[1.973]	[0.932]	[1.120]	[1.192]	[0.738]	[1.151]	[0.920]
Province (NUTS3) FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓	✓	✓	✓
Wide controls	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.334	0.375	0.405	0.335	0.332	0.290	0.259	0.223
N obs.	5037	5037	5035	5036	5036	5033	5032	4993

Notes: WLS estimates. In column 1, $\mathbb{E}_{i,t}$(Sales^{g}1Y) denotes the post-COVID-19 expectations for sales growth over a 12-month horizon (ordinal). In columns 2-7, $\mathbb{E}_{i,t}(Y)$ 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. In column 8, $\mathbb{E}_{i,t}(P^g)$ denotes the post-COVID-19 plans for firm-level price over a 12-month horizon. In this table, we classify a firm to be credit constrained only if the loan was was denied (i.e., we exclude both discouraged borrowers and partially constrained firms in our benchmark classification). Additional controls (unreported) are listed in Table 1. Standard error (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C6: Unweighted sample

Dependent variable:	$\mathbb{E}_{i,t}$(Sales^{g}1Y)	$\mathbb{E}_{i,t}$(Sal^{g}3M)	$\mathbb{E}_{i,t}$(Sal^{g}1Y)	$\mathbb{E}_{i,t}$(Ord^g)	$\mathbb{E}_{i,t}$(Emp^g)	$\mathbb{E}_{i,t}$(Tan^g)	$\mathbb{E}_{i,t}$(Int^g)	$\mathbb{E}_{i,t}$(P^g)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit constrained	-0.124***	-5.792***	-3.332***	-3.445***	-2.897***	-4.450***	-3.432***	0.849***
	[0.0161]	[0.566]	[0.489]	[0.508]	[0.412]	[0.655]	[0.435]	[0.315]
Essential	0.318***	10.47***	7.187***	6.889***	2.775***	8.502***	6.396***	-1.138***
	[0.0136]	[0.583]	[0.326]	[0.361]	[0.168]	[0.632]	[0.309]	[0.150]
Province (NUTS3) FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓	✓	✓	✓
Wide controls	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.152	0.127	0.140	0.123	0.105	0.097	0.089	0.071
N obs.	5037	5037	5035	5036	5036	5033	5032	4993

Notes: OLS estimates. In column 1, $\mathbb{E}_{i,t}$(Sales^{g}1Y) denotes the post-COVID-19 expectations for sales growth over a 12-month horizon (ordinal). In columns 2-7, $\mathbb{E}_{i,t}(Y)$ 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. In column 8, $\mathbb{E}_{i,t}(P^g)$ denotes the post-COVID-19 plans for firm-level price over a 12-month horizon. Additional controls (unreported) are listed in Table 1. Standard error (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C7: Alternative clustering: NUTS-3 level (province)

Dependent variable:	$\mathbb{E}_{i,t}(\text{Sales}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{3M})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Ord}^g)$	$\mathbb{E}_{i,t}(\text{Emp}^g)$	$\mathbb{E}_{i,t}(\text{Tan}^g)$	$\mathbb{E}_{i,t}(\text{Int}^g)$	$\mathbb{E}_{i,t}(\text{P}^g)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit constrained	-0.302***	-14.05***	-9.149***	-10.61***	-9.004**	-8.425**	-7.369**	4.074**
	[0.0572]	[3.488]	[2.060]	[2.752]	[3.462]	[3.297]	[3.454]	[2.009]
Essential	0.410***	10.36***	9.113***	7.270***	1.786	7.084***	6.370***	-4.038**
	[0.0496]	[1.834]	[1.329]	[1.480]	[1.867]	[1.950]	[2.104]	[1.950]
Province (NUTS3) FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓	✓	✓	✓
Wide controls	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.342	0.402	0.422	0.356	0.351	0.298	0.266	0.230
N obs.	5037	5037	5035	5036	5036	5033	5032	4993

Notes: WLS estimates. In column 1, $\mathbb{E}_{i,t}(\text{Sales}^g\text{1Y})$ denotes the post-COVID-19 expectations for sales growth over a 12-month horizon (ordinal). In columns 2-7, $\mathbb{E}_{i,t}(Y)$ 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. In column 8, $\mathbb{E}_{i,t}(P^g)$ denotes the post-COVID-19 plans for firm-level price over a 12-month horizon. Additional controls (unreported) are listed in Table 1. Standard error (in square brackets) clustered at the province (NUTS-3) level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C8: Alternative clustering: 6-digits sector

Dependent variable:	$\mathbb{E}_{i,t}(\text{Sales}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{3M})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Ord}^g)$	$\mathbb{E}_{i,t}(\text{Emp}^g)$	$\mathbb{E}_{i,t}(\text{Tan}^g)$	$\mathbb{E}_{i,t}(\text{Int}^g)$	$\mathbb{E}_{i,t}(\text{P}^g)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit constrained	-0.302***	-14.05***	-9.149***	-10.61***	-9.004***	-8.425***	-7.369***	4.074***
	[0.0318]	[1.259]	[1.441]	[1.328]	[1.632]	[1.404]	[1.359]	[0.880]
Essential	0.410***	10.36***	9.113***	7.270***	1.786*	7.084***	6.370***	-4.038***
	[0.0175]	[1.755]	[0.842]	[0.971]	[1.055]	[0.599]	[1.066]	[0.881]
Province (NUTS3) FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓	✓	✓	✓
Wide controls	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.342	0.402	0.422	0.356	0.351	0.298	0.266	0.230
N obs.	5037	5037	5035	5036	5036	5033	5032	4993

Notes: WLS estimates. In column 1, $\mathbb{E}_{i,t}(\text{Sales}^g\text{1Y})$ denotes the post-COVID-19 expectations for sales growth over a 12-month horizon (ordinal). In columns 2-7, $\mathbb{E}_{i,t}(Y)$ 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. In column 8, $\mathbb{E}_{i,t}(P^g)$ denotes the post-COVID-19 plans for firm-level price over a 12-month horizon. Additional controls (unreported) are listed in Table 1. Standard error (in square brackets) clustered at the six-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C9: 6-digits sector dummies in place of Essential

Dependent variable:	$\mathbb{E}_{i,t}(\text{Sales}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{3M})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Ord}^g)$	$\mathbb{E}_{i,t}(\text{Emp}^g)$	$\mathbb{E}_{i,t}(\text{Tan}^g)$	$\mathbb{E}_{i,t}(\text{Int}^g)$	$\mathbb{E}_{i,t}(\text{P}^g)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit constrained	-0.314***	-14.01***	-8.312***	-9.570***	-7.431***	-7.769***	-7.051***	5.751***
	[0.0397]	[0.811]	[0.707]	[1.415]	[1.076]	[1.323]	[1.334]	[1.358]
Province (NUTS3) FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry (6 Digit) FE	✓	✓	✓	✓	✓	✓	✓	✓
Wide controls	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.382	0.461	0.488	0.428	0.430	0.374	0.336	0.323
N obs.	5037	5037	5035	5036	5036	5033	5032	4993

Notes: WLS estimates. In column 1, $\mathbb{E}_{i,t}(\text{Sales}^g\text{1Y})$ denotes the post-COVID-19 expectations for sales growth over a 12-month horizon (ordinal). In columns 2-7, $\mathbb{E}_{i,t}(Y)$ 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. In column 8, $\mathbb{E}_{i,t}(P^g)$ denotes the post-COVID-19 plans for firm-level price over a 12-month horizon. In this table, we replace the dummy Essential with an extensive set of industry fixed effects at the 6-digits level. Additional controls (unreported) are listed in Table 1. Standard error (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C10: Controlling for observable proxies of relationship lending

Dependent variable:	$\mathbb{E}_{i,t}(\text{Sales}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{3M})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Ord}^g)$	$\mathbb{E}_{i,t}(\text{Emp}^g)$	$\mathbb{E}_{i,t}(\text{Tan}^g)$	$\mathbb{E}_{i,t}(\text{Int}^g)$	$\mathbb{E}_{i,t}(\text{P}^g)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit constrained	-0.297***	-14.07***	-9.123***	-10.61***	-9.066***	-8.480***	-7.360***	4.115***
	[0.0406]	[1.867]	[1.956]	[1.958]	[2.181]	[1.861]	[1.770]	[0.945]
Essential	0.410***	10.33***	9.131***	7.287***	1.808	7.136***	6.406***	-4.026***
	[0.0147]	[1.921]	[0.899]	[1.097]	[1.140]	[0.704]	[1.136]	[0.951]
N of Lender Banks	0.00497	4.989***	0.243	1.237	-0.0857	-1.799	-0.0493	-0.773
	[0.0552]	[0.923]	[0.991]	[1.099]	[1.123]	[1.530]	[1.382]	[1.259]
Lending Relationship (Years)	0.515***	2.585	3.224	3.604	0.156	1.859	6.134***	3.651
	[0.157]	[4.692]	[3.386]	[2.516]	[2.561]	[2.370]	[2.203]	[2.675]
Province (NUTS3) FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry (6 Digit) FE	✓	✓	✓	✓	✓	✓	✓	✓
Wide controls	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.346	0.405	0.423	0.356	0.351	0.299	0.267	0.231
N obs.	5011	5011	5009	5010	5010	5007	5006	4967

Notes: WLS estimates. In column 1, $\mathbb{E}_{i,t}(\text{Sales}^g\text{1Y})$ denotes the post-COVID-19 expectations for sales growth over a 12-month horizon (ordinal). In columns 2-7, $\mathbb{E}_{i,t}(Y)$ 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. In column 8, $\mathbb{E}_{i,t}(P^g)$ denotes the post-COVID-19 plans for firm-level price over a 12-month horizon. In this table, we control for two observable proxies for relationship lending: N of Lender Banks is the log number of lender banks, while Lending Relationship (Years) is the (log) number of years of the banking relationship (the simple average if the firm borrows from multiple banks). Additional controls (unreported) are listed in Table 1. Standard errors (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C11: Heterogeneity by firms' response date

Dependent variable:	$\mathbb{E}_{i,t}(\text{Sales}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{3M})$	$\mathbb{E}_{i,t}(\text{Sal}^g\text{1Y})$	$\mathbb{E}_{i,t}(\text{Ord}^g)$	$\mathbb{E}_{i,t}(\text{Emp}^g)$	$\mathbb{E}_{i,t}(\text{Tan}^g)$	$\mathbb{E}_{i,t}(\text{Int}^g)$	$\mathbb{E}_{i,t}(\text{P}^g)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Credit constrained	-0.327***	-14.48***	-7.161**	-7.041**	-12.00**	-7.814***	-8.495***	3.332**
	[0.0402]	[2.391]	[3.298]	[2.873]	[5.272]	[2.814]	[2.869]	[1.412]
Credit constrained × 2nd half	0.0478	0.845	-3.835	-6.885	5.776	-1.179	2.174	1.447
	[0.0489]	[2.695]	[4.081]	[4.275]	[7.219]	[4.129]	[4.009]	[1.878]
Essential	0.409***	10.34***	9.183***	7.395***	1.680	7.105***	6.330***	-4.060***
	[0.0156]	[1.893]	[0.826]	[1.022]	[1.028]	[0.657]	[1.064]	[0.916]
Province (NUTS3) FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry (2 Digit) FE	✓	✓	✓	✓	✓	✓	✓	✓
Wide controls	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.342	0.402	0.423	0.359	0.353	0.298	0.266	0.230
N obs.	5037	5037	5035	5036	5036	5033	5032	4993

Notes: WLS estimates. In column 1, $\mathbb{E}_{i,t}(\text{Sales}^g\text{1Y})$ denotes the post-COVID-19 expectations for sales growth over a 12-month horizon (ordinal). In columns 2-7, $\mathbb{E}_{i,t}(Y)$ 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. In column 8, $\mathbb{E}_{i,t}(P^g)$ denotes the post-COVID-19 plans for firm-level price over a 12-month horizon. In this table, we allow the effect of financial constraints to vary across dates by interacting Credit constrained with a dummy taking value of one if the firm answered in the second half of the interview period (*2nd half*). Additional controls (unreported) are listed in Table 1. Standard error (in square brackets) clustered at the two-digits industry level. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C12: Determinants of post-COVID-19 credit access concerns

Dependent Variable:	Post-COVID-19 credit access concerns	
	(1)	(2)
Credit constrained	0.227***	0.204***
	[0.0342]	[0.0272]
Essential	-0.0155	-0.0157
	[0.0248]	[0.0243]
Size	0.000842	-0.0208
	[0.0135]	[0.0187]
Age	0.0144	0.0181
	[0.0195]	[0.0180]
Group	-0.0619***	-0.0598***
	[0.0114]	[0.0118]
Family firm	-0.00321	0.00139
	[0.0202]	[0.0179]
Manager past exp.	-0.000120	-0.0000414
	[0.000145]	[0.000135]
Manager education	-0.000482*	-0.000402
	[0.000287]	[0.000282]
Z-score	-0.0173***	-0.559***
	[0.00372]	[0.168]
Liquidity		-0.0150
		[0.0577]
Leverage		-0.354***
		[0.122]
Cash flow		4.041***
		[1.235]
Tangible		-0.0146
		[0.0466]
Trade credit		-0.103**
		[0.0432]
Province (NUTS3) FE	✓	✓
Industry (2 Digit) FE	✓	✓
Pseudo R2	0.207	0.222
N obs.	5021	5021

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% levels, respectively.

Table C13: Unweighted summary statistics

Variable	Type	Mean	Q1	Q2	Q3	Stdev
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Very Negative	Categorical	0.448	0.000	0.000	1.000	0.497
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Negative	Categorical	0.323	0.000	0.000	1.000	0.468
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Constant	Categorical	0.197	0.000	0.000	0.000	0.398
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Positive	Categorical	0.025	0.000	0.000	0.000	0.155
$\mathbb{E}_{i,t}$(Sales^{g}1Y): Very Positive	Categorical	0.008	0.000	0.000	0.000	0.090
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Very Negative	Categorical	0.047	0.000	0.000	0.000	0.211
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Negative	Categorical	0.134	0.000	0.000	0.000	0.340
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Constant	Categorical	0.581	0.000	1.000	1.000	0.493
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Positive	Categorical	0.208	0.000	0.000	0.000	0.406
$\mathbb{E}_{i,t-1}$(Sales^{g}1Y): Very Positive	Categorical	0.031	0.000	0.000	0.000	0.172
$\mathbb{E}_{i,t}$(P^g)	Continuous	4.447	0.000	0.000	8.800	11.846
$\mathbb{E}_{i,t-1}$(P^g)	Continuous	1.540	0.000	0.000	3.000	6.792
$\mathbb{E}_{i,t}$(Sal^{g}3M)	Continuous	-22.574	-30.000	-15.000	0.000	26.556
$\mathbb{E}_{i,t}$(Sal^{g}1Y)	Continuous	-16.981	-25.000	-10.000	0.000	20.790
$\mathbb{E}_{i,t}$(Ord^g)	Continuous	-15.620	-22.000	-10.000	0.000	22.092
$\mathbb{E}_{i,t}$(Emp^g)	Continuous	-6.953	0.000	0.000	0.000	19.155
$\mathbb{E}_{i,t}$(ITan^g)	Continuous	-13.883	-10.000	0.000	0.000	30.732
$\mathbb{E}_{i,t}$(IInt^g)	Continuous	-12.131	-6.000	0.000	0.000	29.268
Credit constrained	Categorical	0.163	0.000	0.000	0.000	0.370
Post-COVID-19 credit access concerns	Categorical	0.354	0.000	0.000	1.000	0.478
Deaths	Continuous	0.074	0.008	0.025	0.062	0.131
Population	Continuous	11.253	10.744	11.212	11.696	1.000
Essential	Categorical	0.595	0.000	1.000	1.000	0.491
Size	Continuous	7.835	6.659	7.711	8.874	1.745
Age	Continuous	3.011	2.639	3.178	3.555	0.823
Group	Categorical	0.125	0.000	0.000	0.000	0.330
Family firm	Categorical	0.707	0.000	1.000	1.000	0.455
Manager past exp.	Continuous	50.600	0.000	50.000	100.000	47.684
Manager education	Continuous	12.693	0.000	0.000	0.000	28.239
Z-score	Continuous	-0.000	-0.288	-0.041	0.344	1.312
Liquidity	Continuous	0.132	0.015	0.070	0.193	0.160
Leverage	Continuous	0.663	0.489	0.693	0.851	0.249
Cash flow	Continuous	0.024	0.002	0.017	0.057	0.138
Tangible	Continuous	0.214	0.039	0.150	0.339	0.209
Trade credit	Continuous	-0.121	-0.234	-0.063	0.000	0.161
Inventories	Continuous	0.034	0.000	0.000	0.030	0.077
Export	Categorical	0.299	0.000	0.000	1.000	0.458
Import	Categorical	0.246	0.000	0.000	0.000	0.431
R&D	Categorical	0.241	0.000	0.000	0.000	0.428
% graduated employment	Continuous	11.244	0.000	0.000	11.765	22.011
N of Lender Banks	Continuous	1.008	0.693	1.099	1.386	0.469
Lending Relationship (Years)	Continuous	0.598	0.251	0.470	0.775	0.535

Notes: Unweighted summary statistics.