The COVID-19 Shock and Firms' R&D Plans: Evidence from the Recent Italian Experience

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ABSTRACT

This paper contributes to the policy discussion on COVID-19 by presenting evidence on firms' perceived shock in the immediate aftermath of the pandemic outbreak, and exploring heterogeneities in the associated disruption of longer-run R&D choices. We take advantage of unique panel data on 7,800 Italian companies between January 2020 –right before the pandemic– and March of the same year –in the midst of lockdown policies. We then exploit the revision in firms' research plans and expectations within this short-time window to capture the idiosyncratic impact of the epidemic event.

Our analysis shows greater fragilities for internationalized companies and firms involved in (cutting-edge) product innovations. Their significantly-more pessimistic expectations in the short-run are also reflected into a sizable disruption of preexisting R&D plans, which will likely have a relevant impact on long-run growth. Beyond the role played by expectations, we show that the very characteristics of the innovative process critically shape firms' reaction to the general uncertainty induced by the pandemic outbreak. Two main patterns seem to emerge from our analysis. On the one hand, there is a strong degree of persistence in R&D choices for a small set of great innovators, with substantial past expenditure in in-house research activities. On the other, the COVID-19 shock especially jeopardized R&D plans of newly-innovative companies that were transitioning toward more-dynamic ways of doing business. Taken together, our results help the policy maker identifying ideal targets for interventions so to avoid the disruption of key segments of the market. This is of double importance in this stage of the crisis whereby a second pandemic wave may entail some regularities.

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1 Introduction

The COVID-19 outbreak brought about a shock that is unprecedented in both magnitude and timing. In a few weeks, the economic environment changed dramatically and the introduction of lockdown policies projected firms into a world of massive uncertainty. Concerns regarded a broad array of dimensions: from epidemiological developments, to the length of market lockdowns and the future of international trade, the possibility of permanent shifts in consumer spending, as well as the very survival of a firm's business. Within a short time period the economy experienced significant investment disruptions and job losses, with effects that will likely persist long after the end of the epidemic (Guerrieri et al., 2020). In this early stage of the crisis, and with a second wave of COVID-19 spreading across Europe, prompt measures in support of the economy are of paramount importance to limit adverse effects on key segments of the market and to help firms weathering the storm.

This paper contributes to the policy discussion by presenting evidence on the heterogeneity of firms' perceived shock in the immediate aftermath of the pandemic outbreak and, especially, by exploring the associated disruption of longer-run R&D choices. From a methodological perspective, we exploit the COVID-19 event as a shock that is truly exogenous to firms' financial position and innovative attitude. We then explore the impact on R&D plans, distinguishing effects that are merely due to expected demand shocks from those related to the very nature of a firm's innovativeness.

Our analysis takes advantage of unique panel data on firms' behavior and performance between (late) January 2020 –one month before the first official cases of COVID-19 in Italy– and (late) March of the same year –two weeks after the introduction of lockdown policies (March 11). We enrich the large amount of information available in the 2019-wave of the MET survey (24,000 observations) with *ad hoc* interviews monitoring the effects of the pandemic on the same set of companies (7,800 final estimating sample, see Section 3.1 for a discussion on selection issues).

Our approach is twofold. First, we proxy the short-run idiosyncratic shock for each firm with the *revision* in its forward-looking expectations, computed as the difference between pre- and post-COVID expected sales on a one-year horizon. In other words, we rely on an event-study type of exercise and compare firms' future prospects around the burst of the epidemic. We regard this measure to nicely synthesize the overall perceived demand shock for each company, which we allow to vary along several characteristics and dynamic strategies in the onset of the crisis (all reported in January 2020).

The second perspective focuses on longer-run components and explores the disruption of R&D plans induced by the pandemic. Symmetrically to the previous analysis, we compare firms' future research choices before and after the COVID-19 outbreak to identify companies that dropped preexisting R&D plans or that reacted to the crisis by scheduling new investments in research. We then allow the effect to depend on several firms' characteristics and types of innovative activity undertaken in the past. In doing so, we employ a simultaneous analysis of expected sales and R&D choices so to disentangle effects that are only due to worsening expectations, from those that are linked with the characteristics of the innovative process itself.

Although the focus on Italy is primarily driven by the unique characteristics of our dataset, it is also relevant in its own because of the severe exposure to the epidemic (in terms of cumulative mortality) and the early timing of the self-isolation policies adopted (the first Western country). Moreover, the structural features of the Italian economy make it an ideal laboratory to study heterogeneities in firms' reaction to a shock. Italy approached the COVID-19 pandemic after a long-lasting phase of declining productivity growth, mainly due to size issues and within-sector misallocation of resources (Calligaris et al., 2018). But despite the negative trend driven by many low-performing companies relying on market niches, there was a set of very-dynamic firms characterized by a high degree of innovativeness and projected toward international markets (a phenomenon called "neo-dualism", see for instance Dosi et al., 2012). Such a segmentation increased even further after the 2008-financial crisis, whereby the involvement in dynamic activities represented a successful strategy to overcome the drop in domestic demand. Importantly, this heterogeneity does not only reflect efficiency premia, but also entails a dissimilar way of doing business which can expose firms to higher or lower shocks depending on the very nature of the turmoil.

On average, the burst of the pandemic induced a substantial revision in firms' expected performance (-19% on a 12-month horizon), which, however, was far from being homogeneous. Our results point at stronger perceived shocks for internationalized companies and firms that introduced product innovations in the recent past, characterized by a substantially-higher probability of severe reduction in expected future sales. This evidence implies a drastic change of direction compared to the recent past, whereby international connections and innovations represented a significant engine for the performance of Italian firms. While this difference is likely coming from the short-run perspective adopted in this paper, it also emphasizes the dissimilar nature featuring the first phases of the current crisis, that jeopardized international trade and brought unprecedented uncertainty shocks casting doubts about possible returns from innovations, especially if cutting-edge.

Since firms will eventually revise their expectations throughout the evolution of the crisis, our analysis has not to be interpreted as a reliable estimation for the final effect of the pandemic (i.e., we do not regard expectations as accurate forecasts of future performances). Instead, our results have to be read as a warning about the greater difficulties perceived by more-dynamic companies in the onset of the COVID-19 event, which should be accounted for in a policy perspective. Indeed, even transitory expectations based on a temporary shock may have (independently of their accuracy) long-run implications through managers' actual decisions, which are based on the current information set (see Section 2 for a discussion of the relevant literature). This is the case for any input choice in presence of adjustment costs, but it is especially true for the disruption of R&D investments that are hardly revertible and entail relevant sunk-costs (especially if regarding projects already in place before the crisis; see Section 3.3 for a discussion).

In this regard, the revised R&D plans in March 2020 present a dramatic effect of pandemic, with the disruption of 44% of the R&D investments that were already scheduled before the crisis kicked in. Our simultaneous analysis highlights two main dimensions in this effect. The first one has to do with the direct role of expectations, whereby the severe perceived demand shock for internationalized and innovative companies significantly hampered their research choices. The second effect goes over and above firms' beliefs; instead, it is related to the very nature of the innovative process which shapes firms' reaction to the general increase in uncertainty after the COVID-19 outbreak. In this regard, two main patterns seem to emerge. On the one side, there is a small set of persistent great innovators whose sizable expenditure in in-house R&D implies a reduced sensitivity to adverse shocks. Some of them, especially those that were heavily-reliant on innovations for their business, even expanded their research plans in the aftermath of the pandemic. On the other, the turmoil especially harmed the innovativeness of those firms that were transitioning toward a new way of doing business. Companies that were in the process of upgrading toward more innovative strategies have a significantly-higher probability of cancelling their plans and downgrading to their previous non-innovative status. This may have significant consequences for long-run growth because such companies are also those with the highest potential gains from innovation (in terms of marginal benefits).

Our paper speaks to the empirical literature on the COVID-19 crisis. Within this field, we are more closely related to those papers analyzing the nature and consequences of the turmoil. Among others, Hassan et al. (2020) exploit textual analysis on earnings call transcripts to identify major fears related to demand components, increased uncertainty, and disruption in supply chains. With a different perspective, Baker et al. (2020) and Andersen et al. (2020) use households' transaction data to examine consumption behavior. The number of papers exploiting survey data is also sizable (see for instance Bartik et al., 2020; Baert et al., 2020; Coibion et al., 2020; Briscese et al., 2020).[1] We differ from all these papers in terms of research question and because we can exploit survey information on pre-COVID conditions in a short-window identification strategy. Most importantly, this is the first analysis documenting heterogeneities in the shock along firms' strategic choices and explicitly studying the effect on their research effort.

Our analysis also speaks to the broad literature on firms' innovativeness in times of trouble. Within this strand of research, Paunov (2012) exploits a sample of Latin-American firms in the financial crisis to show

[1] On the same dataset, Balduzzi et al. (2020) show the amplification effect of financial constraints on firms' expectations and investment plans. For other studies on financial issues in the pandemic see also Baker et al. (2020) and Jorda et al. (2020).

a sizable disruption of innovative projects following export shocks. Also on the Lehman crisis, Archibugi et al. (2013) highlight the polarization of innovative activities in the hands of companies that were already highly innovative before 2008. Importantly, they shed light on in-house R&D as a major factor underlying increases in innovation expenditure during the crisis. Finally, Antonioli and Montresor (2019) take advantage of the MET survey to document a significant reduction in firms' innovativeness during the Great Recession, together with a higher innovative effort for a small set of great innovators.

Because of the delay in data production, there is still scant evidence on the effect of COVID-19 on firms' innovative behavior. Within this field, Abi Younes et al. (2020) provide a general discussion on innovation economics in times of pandemic, while Donthu and Gustafsson (2020) review various effects of COVID-19 that are likely impacting innovative strategies.[2] Our paper informs on these issues by providing real-time information on firms' research attitude in the aftermath of the pandemic outbreak.

Importantly, this is the first analysis exploiting an exogenous (economy-wide) shock that is truly orthogonal to firms' financial position and innovative prospects before the turmoil. This is a unique feature of this crisis and of our dataset based on a short-time window around the pandemic outbreak.[3] Moreover, we adopt a dual perspective that simultaneously takes into account R&D choices and the size of firms' perceived shock. Our approach allows for disentangling the direct impact of expectations from effects that are instead linked to the characteristics of the innovative process. We do so by exploiting information on firms' extensive and intensive margins of R&D, the share of outsourced research, the type of past innovations introduced (product vs. process or radical vs. marginal), patent licensing, as well as the involvement in persistent or new R&D and innovative activities.

Overall, our findings may help the policy maker identifying ideal targets for interventions so to avoid the disruption of key segments of the market. This is of double importance in this stage of the crisis whereby a second pandemic wave may expose firms to similar shocks.

The reminder of the paper is as follows. Section 2 frames our analysis into the literature on firms' expectations and their real effects. Section 3 presents our dataset and the *ad-hoc* survey conceived to study the effect of the epidemic. Section 4 outlines the empirical methodology, while Section 5 discusses the main results. Finally, Section 6 concludes the paper.

[2] Sharma et al. (2020) and Kirk and Rifkin (2020) discuss change in consumer behavior and consumption habits which can, in turn, affect firms' incentives to innovate. Also informative to this paper, Lee and Trimi (2020) elaborate on the relevance of Convergence Innovations in the post-pandemic recovery, while Chesbrough (2020) specifically focus on Open Innovations.

[3] Since the existence and magnitude of the COVID-19 shock was totally unexpected in January 2020 and because the limited time interval is incompatible with feedback effects of firms' behavior onto the economy, our analysis is virtually immune from confounding factors or spurious relationships driving the innovative dynamic. Notice that this may not be the case for previous shocks arising from structural fragilities of the productive and financial systems.

2 Related literature

On the top of a specific contribution to the literatures on COVID-19 and firms' innovativeness, the results of this paper also speak to the more general field of research on expectations and their real effects.

Expectations about future business conditions represent an important determinant of firms' investment, hiring, and strategic decisions and, as such, are regarded as essential factors in the propagation of shocks (and policies) to the economy. Yet, empirical studies somewhat neglected expectations in the past (Bachmann, 2019), despite their widespread use in the construction of leading economic indicators (e.g., Ifo and the Tankan indexes). Because of the critical role in shaping the business cycle (Gennaioli et al., 2016), the recent financial crisis gave new impulses to this literature, with a growing number of studies linking firms' economic outcomes to their expectations about either macroeconomic factors or their own future earnings.

Contributing to the first strand of research, Coibion et al. (2020) identify the causal effect of inflation expectations on pricing strategies, demand for credit, employment, and capital accumulation of Italian firms. Similarly, Coibion et al. (2018) focus on New Zealand and show that exogenous shocks to inflation beliefs, despite being subsequently revised over time, have significant real effects on firms' decisions. About monetary policy surprises, Coibion et al. (2020), Bachmann (2019), and Enders et al. (2019b) study the reaction of firms' price and product expectations, while Tanaka et al. (2020) explore the role of expected GDP trends for employment, investment, and output growth of Japanese corporations.

As for the literature on firms' future expected outcome, Gennaioli et al. (2016) show that corporate investment plans as well as actual investments are well explained by sales expectations of American companies. Along the same line, Boneva et al. (2020) and Stevens (2003) focus on UK to show substantial effects of firms' beliefs on actual pricing strategies or employment behavior. With a specific focus on uncertainty, Bachmann et al. (2013) exploit German and American data to evaluate the impact of time-varying business uncertainty on economic activity, while Bloom et al. (2019) take advantage of the Brexit referendum to estimate its real effects on investments and productivity. Also instructive to our analysis, Koetse et al. (2006) show that expectations and uncertainty about domestic demand have sizable effects on firms' investment, especially for smaller companies. Finally, Enders et al. (2019a) study how changes in beliefs impact the real decisions of German firms, and find optimism or pessimism to matter even if expectations turn out to be incorrect ex-post.

In addition to these general patterns, several studies let expectations (and their effects) vary across the characteristics of the company under examination. Boneva et al. (2020) and Buchheim and Link (2017) explain such heterogeneities by highlighting the role of firm-specific factors in the formation of individual beliefs. Coibion et al. (2018) draw from models of costly information to show that inattention to macroeconomic conditions is related to firms' incentives to collect and process news. They demonstrate that firms facing higher competition and steeper profit functions are, on average, characterized by more precise information. Similarly, Bachmann and Elstner (2015) find that larger and exporting companies have more realistic expectations, while Tanaka et al. (2020) show that beliefs of productive and old firms are aligned with professional forecasters. Moreover, they document an amplified reaction for firms that are more sensitive to the state of the business cycle. Finally, Guiso and Parigi (1999) show that the negative effect of uncertainty onto investment is greatly magnified by the irreversibility of the project undertaken.

In this regard, the COVID-19 outbreak and the related lockdown policies generated a substantial shock to firms' expectations about future demand, which was paired with a significant increase in the overall uncertainty about the evolution of the crisis (see, for instance, Altig et al., 2020). As in Boneva et al. (2020), both dimensions are likely to display sizable heterogeneities across firms, depending on their structural and strategic characteristics when entering the pandemic. While this shock can potentially affect any dimension of a firm's business, it is likely to have detrimental effects especially on their investment decisions (see for instance Guiso and Parigi, 1999; Bontempi et al., 2010, Gennaioli et al., 2016, or Bachmann and Zorn, 2020). This is even more so for R&D spending, whereby firms' beliefs are essential in comparing expected returns and in evaluating risks of the innovative process (Paunov, 2012).[4] Moreover, R&D choices are also likely to display a stronger sensitivity to the general increase in uncertainty because their high-degree of irreversibility entails opportunity costs that may lead to the postponement of planned investments.[5]

Our paper tackles these issues by jointly taking into account the magnitude of the expected shock and firms' R&D choices. We provide a number of results that can be rationalized in light of the existing literature. As for firms' expectations, the stronger shock for innovative and internationalized companies clearly reflects the very characteristics of the crisis under examination, which exposed firms to heterogeneous shocks in the short-run. On the one hand, the spread of the virus induced an immediate freeze in international markets affecting both export sales and the purchase of imported inputs, hence inducing a higher perceived shock for internationalized companies. On the other, the great uncertainty associated with the pandemic outbreak may have raised doubts about the returns from innovations and about customers' behavior (see for instance, Bertola et al., 2005), feeding the fear of a permanent change in consumption habits. These argumentations are consistent with Buchheim and Link (2017) and Boneva et al. (2020), emphasizing the relevance of firm-specific factors in the formation of a company's beliefs. Note that such evidence is also compatible with a higher sensitivity to the business cycle (as in Coibion et al., 2018 or Tanaka et al., 2020), whereby the fiercer

[4] Indeed, Koga et al. (2017) shows that R&D spending is raised by optimism and severely hampered by pessimistic views on the future.

[5] As in Bernanke (1983), firms may rationally postpone some projects because of the potential difficulties in liquidating installed capital in case the ex-post demand proves to be lower than expected.

competition faced by internationalized and innovative firms can induce faster adjustments in their beliefs.[6]

Regarding R&D plans, we document a strong and significant impact of expectations onto future research choices, which is consistent with most of the aforementioned literature focusing on investment and input decisions. Importantly, we also show that firm characteristics, especially related to the innovative process, have effects that go over and beyond the role of expectations operating through a differential response to the general uncertainty shock.[7] The importance of the latter is widely emphasized by the literature on irreversibility predicting increasing effects in highly-competitive markets. In this regard, the very nature of firms' innovative attitude (e.g., persistent vs. new innovators) as well as the existence of already-relevant sunk costs (sizable expenditure in in-house R&D) seem to be associated with a reduced sensitivity to the overall increase in uncertainty.

3 Data

3.1 Sources of data

This paper takes advantage of panel data on the behavior and performance of Italian firms around the burst of the epidemic. We complement the large amount of information available in the 2019-wave of the MET survey with *ad hoc* interviews specifically designed to monitor the effects of the COVID-19 pandemic on the same set of companies.

MET is an Italian research center carrying on one of the most comprehensive surveys administrated in a single European country. The original sample is fully representative at the firm size (four classes), geographic region (20 areas at the NUTS-2 level), or industry levels and comprises seven waves – 2008, 2009, 2011, 2013, 2015, 2017, and 2019 – with roughly 24,000 observations in each cross section. The survey is fully representative for the manufacturing sectors (60% of the sample) and the production-service industry (40%), which are stratified into 12 2-Digit sectors.[8] Unlike other recurring surveys, MET provides information on every size class including micro-sized companies with less than ten employees. Because of their prominent role in the population (more than 90% of firms in Italy) and since they are more fragile and exposed to economic shocks, the inclusion of very small companies is a critical issue in understanding the (initial) effects of this pandemic. The original questionnaire encompasses an extensive array of variables

[6]Notice that Coibion et al. (2018) explain these adjustments with the role of inattention to macroeconomic conditions, which is strictly related to firms' incentives to collect and process information. While the COVID-19 shock induced such a generalized uncertainty that even expectations of more informed firms are likely to be inaccurate ex-post, it is still possible that their reaction in updating beliefs is faster than other companies, thus explaining part of the heterogeneity detected.

[7]We also test whether such characteristics affect the way firms react to the (same) expected shock (as in Tanaka et al., 2020). We show that, most of the times, this is not the case.

[8]Section A1 of the Online Appendix provides further details on the disproportionate sampling scheme, the post-stratification weights calibrated to reproduce the population of interest, and the full list of the sectors sampled.

related to firms' structure, behavior, and performance, including measures of innovativeness, R&D activities, and internationalization (Section A2 of the Online Appendix details the measures employed and the exact formulation of each question).

The administration of the 2019-survey ended in late-January of the following year, right before the outbreak of the pandemic in Italy (late February 2020). This characteristic makes the 2019-MET survey the only available data, to the best of our knowledge, providing a comprehensive snapshot of firms' conditions in entering the COVID-19 crisis.

We complement the information in the original questionnaire with a swift integration survey to the entire sample of the 2019-wave, so to have full information on the pre-COVID condition of each company. Because we wanted to avoid excessive variation in the information set of the respondents, we restricted the timing of the survey in a two-week window between March 24 and April 7, 2020. The administration started 13 days after the initial lockdown and the special measures imposed by the Italian government (March 8 and 11), so to leave firms enough time to update their beliefs and to evaluate initial adjustments in the production process and strategies. At the same time, not much additional information was revealed within this short-time window, guaranteeing that heterogeneous responses are neither due to changes in the measures imposed by the government, nor to updated beliefs on the severity of the pandemic (we further address this issue in robustness checks). The response rate was impressive given the time constraint (roughly 33%), and the survey ended with 7,800 final interviews. Importantly, Table 1 highlights that the distribution of respondents across macro sectors, geographical macro regions, and size classes is in line with the original survey, reassuring about potential selection issues. This is further taken care by the use of ex-post sampling weights that aim at ruling out endogenous sampling selections (see Section 5.1) and allows to realign the disproportionate sampling to the population of interest. Moreover, unreported regressions on the entire set of firms in the 2019-wave, show no correlation between firms' likelihood of being interviewed in the COVID-survey and the set of characteristics employed in our analysis, not even dummies for macro-geographical location that capture the severity of the pandemic (Table A1 in the Online Appendix). This assuages concerns about the potential attrition in the COVID survey compared to the representative sample of the 2019-wave.

Finally, we match both surveys with the last available official balance-sheet data (as of 2018) from CRIF-Cribis D&B; this information is needed to construct a wide set of controls employed to limit omitted-variable bias. As always, balance sheets are not available for unincorporated firms (*società di persone*), which implies a 35%-reduction in the estimating sample, with a final size of about 5,000 observations.[9]

[9] A few observations are also dropped to reduce the influence of outliers (balance-sheet variables are censored at the 1%) or because of unreasonable values due to measurement errors in pre-crisis variables (negative or nil assets, negative or nil sales).

3.2 Content of the COVID-19 MET survey

The COVID questionnaire is made of three main sections: i) a set of forward-looking questions on firms' future sales and R&D plans that replicates the exact same wording of the 2019-MET survey, ii) a block of questions directly asking the effect of the COVID-19 outbreak on the revision in firms' expected future earnings (at different horizons), and iii) a field about broader issues related to the pandemic.

Since the first block guarantees a perfect comparability between the two surveys, we exploit variations in a firm's answers to measure the short-run expected effects of the crisis. In each point in time, firms are asked to report their forward-looking expectations about sales growth on a 12-month horizon by choosing among five options: very negative (sales growth below -15%), negative (in the interval -15%/-5%), constant (-5%/+5%), positive (5%/15%), or very positive (>15%). The difference between post- and pre-COVID answers –$\Delta\mathbb{E}_t$(Sales1Y) in our notation– gives raise to an ordinal measure (in the discrete interval $[-4; +4]$) capturing the revision in firms' expectations induced by pandemic. This proxy for firms' idiosyncratic shock is then employed as a dependent variable in our preliminary analysis. In the same vein, we construct a measure for the change in planned R&D investments for the near future –$\Delta(\text{R\&D plans})_t$. In both waves we ask the following question: *"As of today, does your firm have any expenditure in Research and Development (R&D) scheduled for the next 12 months?"*, whereby a binary option was available: Yes/No. The difference between the two dummy variables (Yes=1) allows to construct an ordinal measure identifying the disruption of scheduled research plans (value of -1), firms that were unaffected by the pandemic (0), and the (few) companies that reacted to the shock by planning new R&D investments (+1). We will discuss the reliability of this measure in Section 3.3.

Because we were also interested in a more granular quantification, the second part of the COVID survey formulates questions so to rule out the need of pre-COVID observations. In particular, we ask about the *revision* in firms' expectations on sales growth for the following three and 12 months, which we allow to be continuous (denoted $\Delta\mathbb{E}_t^R$(Sales3M) and $\Delta\mathbb{E}_t^R$(Sales12M)). Finally, we ask about the managers' self-assessment on the perceived danger of the pandemic for the economy as a whole, as well as the expected duration of the crisis. This measure likely captures firms' heterogeneous expectations on the possible extensions of lockdown policies and is employed in our extensive set of robustness checks.

3.3 Validation and identification issues

While the absence of updated information does not allow us to assess the accuracy of firms' beliefs after the COVID-19 outbreak, understanding whether past expectations predict –to some extent– realized outcomes is of paramount importance for assessing the quality of the data. Indeed, if past beliefs turned out to be systematically wrong, the managers' reaction to changes in the information set (and expectations) would be substantially reduced. To assuage this concern, we perform a series of validation exercises based on past waves of the MET survey. First of all, we take advantage of the full dimension of our dataset (seven waves between 2008 and 2019) and match past (forward-looking) expected sales with the realized growth recorded in the following wave. Results clearly show a high predictive power of expected sales, with a R^2 that is four-times larger than the benchmark specification with province, sector, and year dummies (from 0.039 to 0.210 in Column 2 of Table A2 of the Online Appendix). In order to better evaluate the accuracy of firms' expectations in times of uncertainty, we repeat the analysis restricting the sample to the sovereign-debt crisis only, which represent the closest comparable scenario to the current shock.[10] Importantly, past expectations gain even more significance (the incremental R^2 reaches 0.333), possibly underlying firms' incentives to invest in information acquisition in a crisis. At the same time, forecast errors are found to be uncorrelated with firms' strategies reassuring about possible identification issues (as discussed in Section A4 of the Online Appendix).

While this evidence entails a certain reliability of expectations even in times of turmoil, our exercise is not meant to convince the reader about their ex-post accuracy in a period characterized by unprecedented uncertainty. In other words, our analysis is not designed to sell firms' beliefs as full effects of the epidemic in the longer run. Instead, its aim is to show the meaningfulness of firms' expectations, which are formed taking into account the available information at the time of the forecast and, as such, are fundamental drivers of firms' choices. In this regard, the existing literature has largely emphasized that expectations have substantial effects on firms' actual decisions even if turn out to be inaccurate ex-post (Enders et al., 2019a) or if they are subsequently revised over time Coibion et al. (2020, 2018).[11]

As for future R&D choices, we cannot perform a similar exercise since the question was introduced for the first time in the 2019-wave and there is still no realized counterpart available. Notice that the formulation of the questionnaire (provided in Section 3.2) refers to the overall expenditure in research activity scheduled for the following 12 months, which is comprising both projects that were already in place at the time of the survey and investments that were scheduled but not started yet. While there is wide evidence that ex-ante plans are strongly related to firms' ex-post behavior (see for instance Gennaioli et al., 2016), a reader may be concerned about whether a company switching answer between January and March 2020 actually entails a disruption of R&D projects.

[10] Indeed, the timing of the 2011-survey was only three months apart from the peak of the financial turmoil (in July 2011, with the administration in September).

[11] Similarly, Buchheim et al. (2020) and the theoretical contributions of Angeletos and La'O (2013) and Benhabib et al. (2015) highlight that shifts in expectations unrelated to fundamentals (i.e., sentiment) are an essential factors for firms' actual decisions. Finally, Gennaioli et al. (2016) shows that corporate investment (planned and realized) are better explained by expectations rather than traditional determinants employed in the literature.

By construction, a negative value of Δ(R&D plans) captures both the intent of interrupting previously-existent R&D activities –for companies with actual programs already in place– and the change in firms' strategic (future) strategies –for those that, in January, were willing to transition toward R&D activities but changed their minds after the abrupt worsening in market conditions induced by COVID-19 (i.e., actual vs. potential disruptions). Despite we regard both dimensions to be relevant in assessing the overall effect of the pandemic on firms' R&D choices, it is possible that within the second group there were some companies willing to consider the start of R&D only as a remote possibility. In this case, our measure of revision does not capture the disruption of R&D programs but just changes in firms' priors with no actual effect in practice. Notice that this issue does not represent a critical concern as it is only related to companies with no (actual) R&D investments in January, who represent the vast minority of firms declaring R&D plans in the 2019-survey (as we further elaborate in Section 3.4, 73% of R&D plans in January 2020 refer to companies with preexisting research activities). As we discuss in Section 5.3, we further assuage this concern showing that results are even stronger if we redefine R&D disruption ruling out this component.[12]

Finally, notice that the different nature of R&D choices makes them substantially less subject to high-frequency adjustments. While any change in firms' input choices can be seen as having persistent effects in models with adjustment costs, the specificity of R&D investments makes short-run choices harder to revert; even if they are only based on transitory expectations. Indeed, R&D projects are generally not flexible enough to be swiftly reinstated, and reestablishing original plans may take some time. In other words, choices based on short-run expectations can still affect firms' innovativeness through a delay in their investments. On the other hand, the disruption of preexisting R&D programs entails sizable unrecoverable costs, so that even if a company is capable of reverting its choices, the final investment in innovative activities will be lower than in the original plans.[13]

3.4 Descriptive evidence

Table 2 presents some weighted descriptive statistics for our dataset. As of April 2020, 80% of the companies forecast a sizable reduction in sales on a 1-year horizon (Negative or Very Negative), with 60% of them (48.9% of the sample) expecting an extremely-severe drop (below -15%). Importantly, the same expectations formed before the beginning of the pandemic portray a significantly-different picture (as shown in Figure 1), with more than 80% of firms predicting stable or positive trends (Constant, Positive, or Very Positive expectations). Regarding the magnitude of the effect, cross-sectional data highlight a 24%-reduction in

[12]Notice that our measure is likely underestimating the overall effect of the COVID-19 shock for companies with multiple projects before the burst of the pandemic. If such firms abandoned only some of their R&D projects but kept at least one of them, our comprehensive question would entail a positive answer in both surveys and miss to account for this effect.

[13]Again, this point does not apply to firms cancelling their plans before making any actual investment. This is an additional reason for the aforementioned robustness check.

expected sales on a three-month horizon, followed by a very small recovery at 12 months (-19%).

Concerning R&D choices, 10% of the overall sample declared a disruption in research plans, but this share turns to be substantial when conditioning to the set of firms with scheduled R&D investments in January 2020 (44% in the left plot of Figure 2). At the same time, only a few companies reacted to the crisis by planning new R&D investments (roughly 7% in the right plot).

As for the heterogeneity in these effects, innovative and internationalized firms display revisions that are particularly severe. Not only they have significantly worse post-COVID expected sales, but they also entered the pandemic with brighter prospects on their future earnings (conditional distributions are presented in the Online Appendix). This is also reflected in firms' revision of research plans for the near future, whereby innovative and internationalized companies display both a higher likelihood of R&D disruption and a lower probability of starting new research activities. This clearly translates into a decreased share of R&D plans carried on by the most dynamic segment of the market, as shown in Figure 3.

Finally, to further reassure about the relevance of our analysis, it is worth highlighting the strong correlation between research plans and actual R&D activity reported in January. As discussed in Section 3.3, our proxy for R&D disruption may generate some concerns if mainly related to mere changes in firms' plans with no actual effects. Figure 3 shows that this issue is potentially affecting only a minority of firms, as 73% of the R&D plans in January were coming from companies with preexisting research activities.

The next section outlines the empirical methodology aimed at digging deeper into these differential effects and explore additional heterogeneities along firms' innovative process.

4 Empirical methodology

The empirical analysis exploits the unique features of our dataset centered around the COVID-19 outbreak. The aim is to explore in the magnitude of the perceived shock in the short run and its effect on firms' R&D choices for the future, while allowing for heterogeneities in their *ex ante* characteristics and degree of innovativeness. For the sake of simplicity, we first present the specification for firms' revision in expectations on future sales at the 1-year horizon, as captured by the difference between pre- and post-COVID measures defined in Section 3.2. We later discuss variations in the econometric model for R&D plans and the integrated approach employed to jointly analyze the two phenomena.

In our baseline specification, we simply regress firms' beliefs on their internationalization, innovativeness, and R&D activity, all reported in January 2020, together with a rich set of controls capturing structural components and their condition in entering the pandemic. The model reads as follows:

$$Y_{i,t} = \alpha + \beta \mathbb{E}_{i,t-1}(\text{Sales1Y}) + \gamma^\top X_{i,t-1} + \delta^\top Z_{i,t-1} + \lambda_S + \lambda_P + \varepsilon_{i,t} \tag{1}$$

where $Y_{i,t}$ is the revision in a firm's expectations and $X_{i,t-1}$ is a vector of dummies identifying companies involved in relevant international connections (import, export, or more complex forms of internationalization), that introduced product or process innovations, or invested in R&D activities (labelled Internationalization, Innovation, and R&D, respectively).

Notice that because both timing and magnitude of the COVID-19 shock, not to mention its very existence, were totally unexpected when the firm chose its strategies, these measures are all predetermined variables and, thus, can be regarded as orthogonal to the error term ε_{it}. $\mathbb{E}_{i,t-1}(\text{Sales1Y})$ is the expectation on future sales reported in the 2019-wave and allows for path dependence in firms' revisions. Its inclusion aims at purging the model from past trends in firms' beliefs that may be correlated with $X_{i,t-1}$ (realized past sales growth is added as an additional control in $Z_{i,t-1}$ for a similar purpose). We also include an extensive set of fixed effects (λ_S and λ_P) for firms' belonging sector (2-Digit) and geographical province (NUTS-3 level) to account for the heterogeneous diffusion of the pandemic across the Italian territory and to capture differences between industries restricted by the shutdown and the "essential" sectors that stayed in business.[14] Note that granular controls for sectorial components also allow to account for most of the variation in firms' capability of teleworking, which clearly affected the magnitude of the shock and, thus, firms' expectation revision (see for instance Dingel and Neiman, 2020). Finally, $Z_{i,t-1}$ is a broad array of firm-specific characteristics from the 2019-MET survey or balance-sheet data. This set includes: size, age, realized past sales growth, share of graduated employees (further capturing ICT skills and teleworking capability), labor productivity, degree of vertical integration, a synthetic proxy for firms' financial conditions (the principal component of leverage, tangible assets, and rollover risk), and dummies for investment, corporate-group belonging, or family-managed firms.

Equation 1 is estimated cross-sectionally via OLS or ordered logistic models, with standard errors clustered at the province level (to allow for correlation along the differential exposure to the epidemic). However, in order not to rely on any parallel-line assumption (i.e., symmetry in the effect across each category of the dependent variable) we also test the robustness of our results to multinomial logistic models. To assuage concerns about possible endogenous selection issues in the COVID-survey, we estimate our models by employing

[14]The Italian Government regulated the economic activity with a progressive closure of sectors: the main decree in March 11 was later revised in March 22, two days before the beginning of the survey administration period. In order to account for such a heterogeneity (that can impact expectations and choices), we run a series of robustness tests controlling for industrial effects at the 6-Digit level perfectly accounting for this issue. Granular sectorial information is from the ASIA registry, *Archivio Statistico delle Imprese Attive*.

post-stratification weights that are specifically calibrated to reproduce known aggregates of the population (as discussed in Solon et al., 2015). However, our results are qualitatively similar if we adopt unweighted regressions instead. Other potential issues of our analysis are discussed in the Online Appendix (Section A4) and are tackled with a large set of robustness checks outlined in Section 5.[15]

Additional exercises are all variations upon our baseline specification. In a preliminary analysis we disregard the role of expectations and simply explore the overall effect on future R&D plans by means of logit or multinomial logistic models.[16] Notice that the use of a differenced dependent variable ($\Delta(\text{R\&D plans})_t$, as defined in Section 3.2) allows, also in this case, to purge the estimates from all characteristics that persistently affect a firm's answer.[17]

Armed with a quantification for the overall impact on R&D plans, we then set up a more integrated framework so to disentangle the effects of heterogeneous demand shocks from the ones driven by the very nature of a firm's innovativeness. To this purpose, we rely on the following simultaneous-equation model:

$$\begin{cases} \text{eq1}: \ \Delta(\text{R\&D plans})_t = & \alpha_1 + \omega \Delta \mathbb{E}_{i,t}(\text{Sales1Y}) + \gamma_1^\top X_{i,t-1} + \delta_1^\top Z_{i,t-1} + \lambda_S + \lambda_P + \varepsilon_{i,t}^1 \\ \text{eq2}: \ \Delta \mathbb{E}_{i,t}(\text{Sales1Y}) \ = & \alpha_2 + \beta \mathbb{E}_{i,t-1}(\text{Sales1Y}) + \gamma_2^\top X_{i,t-1} + \delta_2^\top Z_{i,t-1} + \lambda_S + \lambda_P + \varepsilon_{i,t}^2 \end{cases} \tag{2}$$

which consistently estimates the role of expectations for R&D plans (ω) and the additional effect of firms' characteristics (γ_1). Our choice is motivated by the clear simultaneity of the two dependent variables, whereby firms revised both their beliefs and R&D choices in the aftermath of the COVID-19 outbreak. We take advantage of seemingly-unrelated regressions (SUR) to jointly estimate the two dimensions and allow for a correlation between the error terms ($\varepsilon_{i,t}^1$ and $\varepsilon_{i,t}^2$ follow a bivariate normal distribution). This is extremely important in our context, as it perfectly controls for any third-party factor simultaneously affecting the dependent variables (see for instance, Greene, 2012). In all cases, the Breusch-Pagan test of independence between the two equations strongly rejects the null (the t-statistics is around 25, with an associated p-value that is essentially zero), thus motivating our choice of a simultaneous model.[18]

Because we are interested in testing specific features of the innovation process, we also explore further

[15] For the effect on expected sales growth at three and 12 months, we simply estimate OLS models by changing the dependent variable ($\Delta\mathbb{E}_t^R$(Sales3M) and $\Delta\mathbb{E}_t^R$(Sales12M), respectively), while keeping $\mathbb{E}_{t-1}$(Sales1Y) in the set of controls.

[16] Alternatively, we make use of logit models on dummy measures separately capturing the disruption of R&D or the introduction of new plans.

[17] For instance, R&D plans may entail possible inaccuracies and respondent's biases. Because there is an exact correspondence of the questions in the 2019-wave and COVID-survey, any misinterpretation should be time-invariant, so that taking the first differences allows to purge the model from such an issue. Even if misinterpretation in unlikely linked to a time-varying component (i.e., the COVID-19 crisis did not change the way a manager interprets the question), our extensive set of controls, as well as the simultaneous-equation model presented (which gets rid of any time-varying characteristic that jointly affects expected sales and R&D plans), should potentially account for any residual issue. Moreover, first differences also take care of permanent heterogeneities characterizing our estimating sample vis-à-vis companies that are excluded because of the unavailability of balance-sheet data.

[18] As a robustness check, we also employed bivariate probit on a binary variable for large revision in expectations (below median or 25th percentile of its distribution) together with a dummy for R&D disruption. Results are largely in line with the ones presented.

heterogeneities by enriching the system 2 with an extensive set of additional regressors (in both equations): R&D Expenditure (expenditure in R&D as a share of total turnover), R&D Outsourcing (share of R&D that is external to the company; i.e., not in-house), New vs. Persistent R&D (dummies for companies that started R&D investments only in 2020 –i.e., with no R&D program in the previous waves of the survey– or instead were already carrying on research in the past), Product and Process Innovation, Sales Radical Inn and Sales Imitative Inn (share of sales from product innovation that are radical –i.e., new to the market– or imitative –only new to the firm), New vs. Persistent Innovation (dummies for newly-innovative companies –i.e., with no innovation introduced in the previous waves of the survey– or instead for persistent innovators), and Patents (dummy for companies with patent licenses, independently of the number). Definitions are provided in the Appendix, together with the exact formulation of the questions they refer to. Note that, since we control for $\Delta\mathbb{E}_{i,t}(\text{Sales1Y})$ in the R&D equation, we are implicitly asking whether characteristics of the innovative process have effects that go over and beyond the role of expectations. Being unrelated to firm-specific demand factors, such heterogeneities are related to differential reactions to the general increase in uncertainty.[19]

5 Results

This section presents the results of the paper. First, we discuss the magnitude of the perceived shock by analyzing how the short-run revision in expected sales is shaped by firms' strategies. We then turn our attention to longer-run components and focus on the disruption in future R&D choices to explore potential heterogeneities along firms' degree of innovativeness.

5.1 Expected sales

The baseline results on expected future sales are presented in columns 1-to-4 of Table 3. Our findings highlight significant heterogeneities in the size of the perceived shock that followed the pandemic outbreak. Both OLS and ordered logistic models suggest a disproportionate impact on the sales expectations of internationalized and innovative companies, pointing at initial effects that are significantly-different from the recent Italian experience.

While during the financial and sovereign-debt crises such firms fared the downturn relatively better, both in terms of ex-ante expectations and ex-post realized performances (as shown in columns 7 and 5 of Table A2

[19]In principle, it is also possible for such characteristics to affect the way firms react to the same expected shock. We test for this channel with a wide set of interaction terms and find that this is not the case. We further discuss this issue in Section 5.2. In unreported regressions we also allowed for a feedback effect going from R&D plans to firms' expectations but, coherently with our priors, it turns out to be largely insignificant.

in the Online Appendix, or in Frenz and Ietto-Gillies, 2009), the first phases of the COVID-19 turmoil seem to be characterized by stronger perceived shocks for the most-dynamic segment of the market. This change of direction is likely driven by several interconnected issues related to the large uncertainty on international economic relationships and the concerns about the initial freeze of world trade: from the diffusion of neo-protectionist policies, to the rate of regionalization of the international commerce, and the very future of global networks (see Baldwin and Tomiura, 2020 for a review). Note that the economic context is very different from the one in the Great Recession, whereby the stronger drop in the Italian internal demand made international markets a tool to hedge adverse domestic conditions. On the other hand, the pandemic shock was so unexpected in its magnitude and unfolding, that dramatically raised the uncertainty of returns from risky innovative activities. This is especially true for product innovations that may no longer be suitable for the new environment and whose expected demand may further be worsened by the fear of a permanent change in consumption habits. Importantly, unreported regressions show that this effect is not linked to specific classes of expectations. We tested conditional effects by interacting firms' innovativeness with beliefs in January 2020 and show that, even compared to companies with similar pre-crisis expectations, innovative firms are characterized by stronger downward revisions (Table A4 in the Online Appendix).[20]

On the bright side, firms involved in R&D activities are found to be somewhat less pessimistic, possibly because their expectations internalize a higher flexibility or a superior ICT skills alleviating the short-run effects of the lockdown.[21] This result is, however, not consistent across alternative specifications and disappears once simultaneity is accounted for. Turning to the other coefficients, we document a certain degree of persistence in the level of firms' beliefs, paired with a stronger worsening for companies that entered the pandemic with better prospects (columns 2 and 4). Moreover, the expected shock is found to be especially detrimental for weaker companies, smaller and *a priori* financially fragile (PC financial is increasing in firms' creditworthiness). On the other hand, younger firms fared relatively better this first stage of the crisis.

After outlined the benchmark results on panel data (later exploited in a simultaneous-equation model), columns 5 and 6 turn to quantitive measures of revision based on the COVID-survey. The estimates on continuous measures confirm a stronger shock for internationalized and innovative companies, characterized by 2.9%- and 3.3%-lower expected sales in the very short-run (three months). The effect is slightly reduced on a one-year horizon (-1.9% and -1.7%) but still extremely significant, explaining a substantial share of the overall aggregate shock (17% and 13%, respectively).[22] Results on R&D are instead not significant in these

[20] This is somewhat less so for companies that entered the pandemic with already negative expectations (whose coefficient is negative but not statistically significant). On the other hand, the interaction effect for internationalization is substantially milder.

[21] These results are largely consistent if we employ multinomial logistic models that avoid assumptions on the symmetry in the effect of X_{t-1} across categories of the dependent variable.

[22] In this back-of-the-envelope exercise, we compare firms' revision in expectations with the counterfactual revision obtained by sequentially silencing the effect of the specific strategy (as estimated in Table 3). We then employ sampling weights to

specifications.

We performed a number of robustness checks to test the validity of our results. First of all, we controlled for direct measures from the COVID-survey about the manager's perception of danger, which allegedly capture also his/her expectations on possible extensions of lockdown policies. We interacted 107 province dummies with a binary measure for the essential sectors that kept producing during the lockdown (identified from the ASIA registry at the 6-Digit level on the basis of the Italian government's decree in March 22), together with controls for the exact day in which the company answered the survey. In all cases our findings prove to be extremely robust, independently of the chosen clustering of the standard errors –at the province level, 6-Digit sector level (766), or at the intersection of 2-Digit sector and geographic region (772). We have similar results even when employing matching techniques (Nearest Neighbor and Coarsened Exact Matching) on each strategy to further control for confounding factors. Finally, our main findings are qualitatively similar if we use unweighted regressions instead of employing post-stratification weights.

Before moving to the analysis on R&D plans, it is worth reminding that these effects do not necessarily imply lower realized performances for more-dynamic firms. Rather, our findings have to be interpreted as a signal of their larger perceived shock when the pandemic kicked in. Indeed, because of their higher efficiency (Melitz, 2003; Bernard et al., 2007), internationalized and innovative companies also display a better capacity of reaction to unexpected adverse conditions, which may even imply larger earnings ex-post. Based on past experience this is likely to happen in the longer run, but in the meantime we will show that even transitory shocks can have an impact with persistent effects operating through the disruption of hardly-revertible R&D investments.

5.2 Effect on R&D plans: baseline

Major economic downturns and periods of great uncertainty make companies less willing to invest in long-term activities with risky returns. While descriptive statistics already showed the overall negative impact of COVID-19 on R&D choices, this section formally explores heterogeneities in the persistence of R&D plans after an exogenous shock. First, we disregard the role of firms' beliefs and provide information on the average behavior of Italian companies. We later employ a more integrated framework to discuss whether such effects arise from heterogeneous demand shocks, or are instead driven by the very nature of firms' innovativeness.

Table 4 presents the baseline specification for firms' revision in R&D plans. The first two columns report marginal effects of logit models on two dummies for the disruption of preexisting plans or the start of new R&D investments between January and March 2020. Columns 3-to-5 present the associated probabilities

aggregate this counterfactual growth and compare it with the aggregate raw forecasts to recover the contribution of a strategy in terms of the overall shock.

from multinomial logistic models on the raw differenced variable. The pandemic brought about a strong contraction of scheduled investments in R&D (disruption of 44% of preexisting plans documented in Section 3.2), but this effect is significantly heterogeneous across companies. Coherently with the results in Table 3, internationalized and, especially, innovative firms display a significantly-higher probability of cancelling on R&D plans that were already programmed in January 2020 (-3.3% and -7.3%, respectively). The first evidence is somewhat consistent with Paunov (2012) who show that firms that are more exposed to adverse export shocks are also more likely to stop innovating activities. As for the average effect of firms' innovativeness, the higher likelihood of disruption in R&D programs is also paired with a greater probability of implementing new plans as a reaction to the crisis (+1.9%). This highlights the existence of significant heterogeneities in firms' innovative strategies that need to be carefully discussed.[23] Finally, despite the lower perceived shock documented in Table 3, pre-crisis R&D is found to imply a 8.5%-higher probability of disruption in future plans. While this is likely hiding differential effects that is worth exploring, it is also underlining how firms' behavior is not entirely driven by their expectations. To explore this issue, we transition to a joint analysis that allows for disentangling the role of firms' beliefs from effects that are, instead, linked to the very characteristics of the company.

Table 5 presents our baseline results for the SUR models. First of all, column 2 confirms a stronger perceived shock for innovative and internationalized companies, while past R&D is no longer associated with better expectations if we account for third-party factors simultaneously affecting firms' beliefs and R&D choices. Importantly, the positive coefficient of $\Delta\mathbb{E}_t(\text{Sales1Y})$ in column 1 suggests a detrimental effect of firms' short-run expectations on R&D plans. This is largely consistent with the broad literature on firms' beliefs and emphasizes how even transitory adverse shocks can have a significant impact on a company's current decisions.[24]

The other estimates in column 1 provide interesting insights as well. To begin with, the negative effect of internationalization on R&D choices (documented in Table 4) seems to be entirely driven by worse expectations about future performances, as suggested by the insignificance of its coefficient once we explicitly control for firms' beliefs. On the other hand, there is an effect of innovation and past R&D that goes over and beyond the role of expectations, providing a further negative contribution to firms' research plans. This effect entails an additional impact that is unrelated to firms' expected earnings (accounted for in the model, together with other simultaneous factors), but is rather driven by a differential reaction of such firms to the general uncertainty brought by the COVID-19 outbreak (common effects of uncertainty are captured

[23] As for the other regressors, less structured –smaller, younger, and more financially fragile– firms have a substantially-higher likelihood of cutting on preexisting R&D plans.

[24] Results are virtually identical if we model the level of expectations instead. We have also replaced expected sales with firms' expectations about future orders, which may be less driven by supply-side factors. Our findings are largely consistent with the ones presented.

by the constant term). This result is likely coming from the difficulties in evaluating the risks, in the new environment, associated with the innovative activities already in place. The sharp rise of uncertainty in the aftermath of the pandemic outbreak, paired with the irreversible nature of R&D investments, may have led some innovative companies to interrupt their research plans to wait for the uncertainty to be resolved. In Section 5.3, we will discuss how this effect may vary along specific characteristics of the innovation process.

Notice that, an alternative explanation for this finding may be linked to a heterogeneous sensitivity of such companies to the same change in expected sales. Column 3 explicitly tests for this channel by augmenting the model with a set of interaction terms between each strategy (R&D, Innovation, Internationalized) and the revision in firms' expectations (only interaction terms are reported). As it turns out, the insignificance of the interacted coefficients suggests this is not the case, thus pointing at a differential reaction to the common uncertainty shock.

5.3 Heterogeneity by characteristics of the innovation process

The very features of the innovative process can underly significant heterogeneities in company's reaction to unexpected shocks. In order to dig deeper into this issue, we enrich our baseline specifications with a wide set of measures capturing several characteristics of firms' past R&D and innovation activities. Columns 1 and 2 of Table 6 present their overall contribution to the disruption of R&D plans or the introduction of new projects (marginal effects from logistic models, as in Table 4). Columns 3-to-5, instead, focus on SUR estimates to disentangle the impact of firms' expectation revisions from the effect linked to specific features of firms' innovativeness (as in Table 5). For expositional purposes, we only report the coefficients of interest (other estimates follow the baseline specification in the original table).

First of all, Panel A shows that the average negative effect of R&D (in Tables 4 and 5) hides significant heterogeneities, whereby sizable past expenditures in research activities are instead associated with increasing probabilities of undertaking new R&D investments in the aftermath of the pandemic. A one-standard-deviation increase in R&D Expenditure induces a 0.96%-higher likelihood of new plans (in Column 2), which implies a substantial effect for the very right tail of the distribution (3% and 9% at the 90th and 95th percentiles of the conditional distribution for positive expenditures).[25] On the other hand, the share of outsourced R&D (Panel B) is linked with a severe reduction of firms' future plans in the aftermath of the COVID-19 crisis, with an adverse impact on the probability of both cancelling preexisting plans and implementing new ones (respectively +5.7% and -3.9% at the 90th percentile of its conditional distribution). Importantly, results from the SUR models suggest that such effects are not driven by heterogeneous demand

[25] In deriving such estimates, we simply applied the marginal effect (0.96%) to the values of the specific percentiles (3.13 and 9.38 units of standard deviations, respectively).

shocks (as indicated by the insignificance in Column 4), but are rather due to a differential response to the general uncertainty induced by the COVID-19 outbreak (significant in Column 3). Overall, our results point at sizable in-house R&D as a major factor affecting firms' reaction to uncertainty shocks; this is likely linked to the very way firms envisage their innovative propensity, as well as to the presence of unrecoverable costs. Indeed, the existence of R&D departments *within* the firm represents a long-term commitment to innovation (increasing with the size of the investment), which makes R&D plans less sensitive to adverse shocks. To frame this argument within the extant literature, our results may underly the existence of a set of "great innovators" for which R&D and innovation is an innate mission. Because their competitive advantage is rooted in the generation and upgrading of new knowledge, they invest continuously in innovation irrespectively of the business cycle (Dosi, 1982; Nelson and Winter, 1982; Antonelli, 1997) and, thus, display a reduced sensitivity to uncertainty shocks. On the other hand, the effect on R&D outsourcing can be rationalized in light of the lower cumulativeness of technological change for external forms of research (Malerba and Orsenigo, 1995, Breschi et al., 2000). This entails significantly-reduced sunk costs attached to R&D outsourcing, which make it more easy to be cut in times of great uncertainty.

Because unrecoverable costs of R&D are also increasing with the knowledge accumulation process, we expect the duration of the innovative activity to have sizable impact on firms' choices after a shock. While we have no precise information on the number of years of performed R&D, we can exploit previous waves of the MET survey to track down the existence of R&D programs in the past, which clearly correlates with it. Coherently with our expectations, firms that started R&D investments in the 2019-wave (New R&D) have a probability of abandoning preexisting projects in the aftermath of the COVID-19 crisis that is significantly-higher than companies with persistent involvement in R&D.[26] Compared to a long-lasting tradition of research, firms switching to innovative investments have a 5.7%-higher likelihood of cancelling on R&D plans, as shown in Panel C. This is, again, not linked to heterogeneous perceived shocks, as documented by the insignificance in Column 4, further confirming previous interpretations based on sunk costs.

Next, we move our attention to other dimensions of firms' innovativeness. First of all, product innovations are found to increase the probability of disruption by 3.7-percentage points, while process innovations are not linked to any change in firms' behavior (Panel D). Noticeably, this effect seems not to be linked to a differential reaction to the COVID-19 pandemic (Column 3), but rather to their significantly-worse expectations (in Column 4). Moreover, firms that introduced new products in the recent past also display higher sensitivity

[26] Unreported t-tests point at significantly-different coefficients. A firm with active R&D projects in the 2019-wave is defined to have "New R&D" in case of absence of R&D investments in the previous wave of the survey (2017). As the MET database is an unbalanced panel, we maximized the matched sample by also exploiting the 2015-wave for the subset of companies not interviewed in 2017. Overall, we are able to track the behavior of 65% of the companies in our cross-section, with a final estimating sample of about 3,300 observations. Results are similar but somewhat milder if we focus on the 2017-wave only. We define "Persistent R&D" in a symmetrical way.

to changes in expected sales, as emphasized by the positive interaction coefficient in Column 5. Overall, these results may point at the role of demand-side factors for innovation-related turnover (Piva and Vivarelli, 2007; Crespi and Pianta, 2008), which, in turn, reduce the self financing of R&D investments. Moreover, engaging in research activities may no longer be attractive for product innovators as the expected payoffs from successful R&D are dramatically-reduced in times of weak demand. On the other hand, process innovators, that are instead oriented toward efficiency and cost-reduction, display a stronger persistence even in times of crisis. This type of innovation is less risky to pursue, even in uncertain conditions, and is typically less financial demanding (Lee et al., 2015).

Notice, however, that the effect on product innovations is not increasing with the stream of sales generated by radical or imitative goods (in Panel E). If any, firms whose overall turnover was mainly coming from truly-innovative products seem to be more inclined to introduce new R&D plans.[27] Despite their worse expectations in Column 4 (consistent with the aforementioned role of demand factors), such firms reacted to the general uncertainty by increasing their effort in R&D (the magnitude is, however, somewhat small). This is, again, pointing at the very nature of great innovators who are inherently projected towards innovative activities even in times of turmoil (Pavitt et al., 1989; Patel and Pavitt, 1994). To confirm this interpretation, Panels F and G present results for two alternative measures capturing firms' degree of innovativeness. As done for R&D, New Innovation is a dummy identifying companies that introduced innovations for the first time in the 2019-wave, while Persistent Innovation refers to continuously-innovating companies.[28] Consistently with the proposed argumentation, while both firms are characterized by negative effects, new innovators have a 5.7%-higher probability of abandoning preexisting R&D plans compared to firms that innovated persistently in the past. This is true despite their more favorable demand prospects in Column 4. Persistent innovators are also displaying a reduced sensitivity to expectations (Column 5) and a somewhat higher probability of starting new R&D plans, possibly in the attempt of taking advantage of the upswing to come. Similarly, a binary variable for the existence of patent licensing (Geroski et al., 1997; Cefis and Orsenigo, 2001) shows a 10%-lower probability of R&D disruption when strong appropriability conditions are in place (allegedly capturing great innovators).

As in Section 5.1, the analysis is robust to a broad array of additional exercises controlling for the manager's perception of risk, heterogeneous sectorial shocks (6-Digit), time-varying information set, and to the use of matching techniques (which, however, do not allow for disentangling the overall effect).[29]

[27]The magnitude of the effect is somewhat small: 0.6% for a one-standard-deviation increase, translating into a 2.5%-increase at the 90th percentile of the conditional distribution of Sales Radical Inn.

[28]The definitions are symmetric to the ones for "New R&D" and "Persistent R&D" outlined in Footnote 26.

[29]We also experimented with an interaction term of the main variables of interest (Innovation, R&D, as well as the other innovative measures) with International, PC Financial (continuous or discretized), Size, macro-sector dummies, and Age. While direct effects are virtually unchanged, the interaction terms are, in most cases, largely insignificant.

Moreover, we find consistent, and even stronger, results if we employ a more restrictive definition of R&D disruption disregarding companies without actual R&D in January 2020 (Table A8 in the Online Appendix).

Taken together, our results show substantial effects of the pandemic along two main dimensions. The first one has to do with the drop of R&D plans associated with the higher perceived demand shock for internationalized and innovative companies. The second effect is more related to the nature of innovativeness itself and regards firms' reaction to the general increase in uncertainty after the COVID-19 outbreak. In this regard, the disruption of preexisting R&D plans has been particularly severe for firms that were in the process of upgrading toward more innovative ways of doing business, while companies with already sizable involvement in research and innovations displayed a reduced sensitivity to the uncertainty shock.

6 Concluding remarks

The COVID-19 pandemic is the most serious challenge the world has faced in recent times. In this early stage of the crisis, and with a second wave of the virus spreading across Europe, prompt policy interventions are critical to help firms managing the turmoil and avoid severe distress for the key segments of the economy. This paper contributes to the policy discussion by showing relevant heterogeneities in the shock experienced by Italian companies and analyzing their associated R&D choices. We investigate this issue by means of unique panel data allowing for an identification of the shock that is truly exogenous to firms' financial position and innovative attitude. Our results bear some relevant policy implications in two complementary directions.

The first one concerns significant heterogeneities in the size of the shock itself. In the onset of the pandemic, we highlight greater fragilities associated with firms' international openness and involvement in cutting-edge innovations, those same dynamic strategies that represented a factor of success in the recent past and that drove the performance of Italian firms during the Great Recession (Brancati et al., 2021). This evidence reflects the first stages of the current crisis, that reverberated through international linkages and increased the uncertainty about returns from innovations, possibly for the fear of a permanent change in consumption habits.

The second, and most interesting, direction goes beyond short-run revision in expectations and focuses on scheduled investments in R&D. The pandemic brought about a significant disruption of preexisting research plans that is hardly revertible and can potentially impact long-run growth. While deteriorating expectations are found to have a detrimental effect on firms' R&D choices (thus, especially for internationalized firms and product innovators), we show that the very characteristics of the innovative process play an even more important role in shaping firms' response to the increased uncertainty. In this regard, two broad patterns that emerge. On the one hand, there is a small set of great innovators whose long-term commitment –based on sizable past expenditure in in-house R&D– makes them less sensitive to adverse shocks. These firms are inherently oriented to innovations and seem to display higher resilience and capacity of adaption to major changes. On the extreme opposite, the pandemic particularly affected the innovativeness of those firms that were transitioning toward a new way of doing business. Companies that were in the process of upgrading to innovative strategies have a substantially-higher probability of cancelling their plans, thus downgrading to their previous status of non-innovative firms. This last piece of evidence can have severe implications for long-run dynamics since upgrading strategies are also associated with the highest potential gains from innovation.

Finally, it is worth reminding that the strength of our approach based on short-term revisions also calls for some caution in the interpretation of the results. First of all, earning expectations are likely to be further revised with the evolution of the pandemic and, as such, should not be considered as accurate forecasts on the evolution of future performances. Rather, our analysis points at short-run disproportionate shocks that call for a prompt heterogeneous response. This issue should be central in a policy perspective because the resulting effects on firms' strategic choices can impact the competitiveness of the entire industrial system and may translate into undesirable selection mechanisms. In addition to generalized policy interventions in support of the economy, tailoring policies so to target more exposed and competitive firms is of paramount importance in this early stage of the crisis.

As for R&D choices, they are less subject to this kind of critique since sunk costs make disruptions harder to revert, especially if related to preexisting research projects. However, the reliance on a short-time horizon prevents us from drawing conclusions on the full effects of the epidemic on firms' innovativeness. On the one hand, the second wave of COVID-19 and the prolonged market uncertainty likely depressed innovation investments even further, possibly also for the most innovative segment of the economy. On the other, the limited time-span considered does not allow us to capture potential entrants that may explore new opportunities. The final shape of the industrial system and the post-pandemic overall competitiveness largely depend on this kind of recomposition effects. While our paper sheds light on important dynamics in the aftermath of the pandemic outbreak, there is still much to learn about the effects of COVID-19 on firms' performance and innovativeness. These issues require updated information in the next few months and are part of our research agenda, but they are left for future analyses.

References

Abi Younes, G., C. Ayoubi, O. Ballester, G. Cristelli, G. de Rassenfosse, D. Foray, P. Gaulé, G. Pellegrino, M. van den Heuvel, E. Webster, and L. Zhou (2020). COVID-19: Insights from innovation economists. *Science and Public Policy*.

Altig, D., S. Baker, J. M. Barrero, N. Bloom, P. Bunn, S. Chen, S. J. Davis, J. Leather, B. Meyer, E. Mihaylov, P. Mizen, N. Parker, T. Renault, P. Smietanka, and G. Thwaites (2020). Economic uncertainty before and during the COVID-19 pandemic. *Journal of Public Economics 191*, 104274.

Andersen, A. L., E. T. Hansen, N. Johannesen, and A. Sheridan (2020). Consumer responses to the COVID-19 crisis: Evidence from bank account transaction data. *Mimeo*.

Angeletos, G.-M. and J. La'O (2013). Sentiments. *Econometrica 81*(2), 739–779.

Antonelli, C. (1997). The economics of path-dependence in industrial organization. *International Journal of Industrial Organization 15*(6), 643–675.

Antonioli, D. and S. Montresor (2019). Innovation persistence in times of crisis: An analysis of Italian firms. *Small Business Economics forthcoming*.

Archibugi, D., A. Filippetti, and M. Frenz (2013). Economic crisis and innovation: Is destruction prevailing over accumulation? *Research Policy 42*(2), 303–314.

Bachmann, R. (2019). Comments on "Monetary policy announcements and expectations: Evidence from German firms". *Journal of Monetary Economics 108*, 64–68.

Bachmann, R. and S. Elstner (2015). Firm optimism and pessimism. *European Economic Review 79*, 297–325.

Bachmann, R., S. Elstner, and E. R. Sims (2013). Uncertainty and economic activity: Evidence from business survey data. *American Economic Journal: Macroeconomics 5*(2), 217–49.

Bachmann, R. and P. Zorn (2020). What drives aggregate investment? Evidence from German survey data. *Journal of Economic Dynamics and Control 115*, 103873.

Baert, S., L. Lippens, E. Moens, P. Sterkens, and J. Weytjens (2020). How do we think the COVID-19 crisis will affect our careers (if any remain)? *IZA Discussion Paper 13164*.

Baker, S. R., N. Bloom, S. J. Davis, K. J. Kost, M. C. Sammon, and T. Viratyosin (2020). The unprecedented stock market impact of COVID-19. *NBER Working Paper 26945*.

Baker, S. R., R. A. Farrokhnia, S. Meyer, M. Pagel, and C. Yannelis (2020). How does household spending respond to an epidemic? Consumption during the 2020 COVID-19 pandemic. *NBER Working Paper 26949.*

Balduzzi, P., E. Brancati, M. Brianti, and F. Schiantarelli (2020). The economic effects of COVID-19 and credit constraints: Evidence from Italian firms' expectations and plans. *IZA Discussion Paper 13629.*

Baldwin, R. and E. Tomiura (2020). Thinking ahead about the trade impact of COVID-19. *Economics in the Time of COVID-19 59.*

Bartik, A. W., M. Bertrand, Z. B. Cullen, E. L. Glaeser, M. Luca, and C. T. Stanton (2020). How are small businesses adjusting to COVID-19? Early evidence from a survey. *NBER Working Paper 26989.*

Benhabib, J., P. Wang, and Y. Wen (2015). Sentiments and aggregate demand fluctuations. *Econometrica 83*(2), 549–585.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *Quarterly Journal of Economics 98*(1), 85–106.

Bernard, A. B., J. B. Jensen, S. J. Redding, and P. K. Schott (2007). Firms in international trade. *Journal of Economic Perspectives 21*(3), 105–130.

Bertola, G., L. Guiso, and L. Pistaferri (2005). Uncertainty and consumer durables adjustment. *Review of Economic Studies 72*(4), 973–1007.

Bloom, N., P. Bunn, S. Chen, P. Mizen, P. Smietanka, and G. Thwaites (2019). The impact of Brexit on UK firms. *NBER Working Paper 26218.*

Boneva, L., J. Cloyne, M. Weale, and T. Wieladek (2020). Firms' price, cost and activity expectations: Evidence from micro data. *Economic Journal 130*(627), 555–586.

Bontempi, M. E., R. Golinelli, and G. Parigi (2010). Why demand uncertainty curbs investment: Evidence from a panel of Italian manufacturing firms. *Journal of Macroeconomics 32*(1), 218–238.

Brancati, E., R. Brancati, D. Guarascio, and A. Zanfei (2021). Innovation drivers of external competitiveness in the great recession. *Small Business Economics forthcoming.*

Breschi, S., F. Malerba, and L. Orsenigo (2000). Technological regimes and Schumpeterian patterns of innovation. *Economic Journal 110*(463), 388–410.

Briscese, G., N. Lacetera, M. Macis, and M. Tonin (2020). Compliance with COVID-19 social-distancing measures in Italy: The role of expectations and duration. *NBER Working Paper 26916.*

Buchheim, L., J. Dovern, C. Krolage, and S. Link (2020). Firm-level expectations and behavior in response to the COVID-19 crisis. *CESifo Working Paper 8304*.

Buchheim, L. and S. Link (2017). The effect of disaggregate information on the expectation formation of firms. *CESifo Working Paper 6768*.

Calligaris, S., M. Del Gatto, F. Hassan, G. I. Ottaviano, and F. Schivardi (2018). The productivity puzzle and misallocation: An Italian perspective. *Economic Policy 33*(96), 635–684.

Cefis, E. and L. Orsenigo (2001). The persistence of innovative activities: A cross-countries and cross-sectors comparative analysis. *Research Policy 30*(7), 1139–1158.

Chesbrough, H. (2020). To recover faster from COVID-19, open up: Managerial implications from an open innovation perspective. *Industrial Marketing Management 88*, 410–413.

Coibion, O., Y. Gorodnichenko, and S. Kumar (2018). How do firms form their expectations? New survey evidence. *American Economic Review 108*(9), 2671–2713.

Coibion, O., Y. Gorodnichenko, S. Kumar, and M. Pedemonte (2020). Inflation expectations as a policy tool? *Journal of International Economics 124*, 103297.

Coibion, O., Y. Gorodnichenko, and T. Ropele (2020). Inflation expectations and firm decisions: New causal evidence. *Quarterly Journal of Economics 135*(1), 165–219.

Coibion, O., Y. Gorodnichenko, and M. Weber (2020). Labor markets during the COVID-19 crisis: A preliminary view. *NBER Working Paper 27017*.

Crespi, F. and M. Pianta (2008). Demand and innovation in productivity growth. *International Review of Applied Economics 22*(6), 655–672.

Dingel, J. I. and B. Neiman (2020). How many jobs can be done at home? *NBER Working Paper 26948*.

Donthu, N. and A. Gustafsson (2020). Effects of COVID-19 on business and research. *Journal of Business Research 117*, 284.

Dosi, G. (1982). Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. *Research Policy 11*(3), 147–162.

Dosi, G., M. Grazzi, C. Tomasi, and A. Zeli (2012). Turbulence underneath the big calm? The micro-evidence behind Italian productivity dynamics. *Small Business Economics 39*(4), 1043–1067.

Enders, Z., F. Hünnekes, and G. J. Müller (2019a). Firm expectations and economic activity. *CESifo Working Paper 7623*.

Enders, Z., F. Hünnekes, and G. J. Müller (2019b). Monetary policy announcements and expectations: Evidence from German firms. *Journal of Monetary Economics 108*, 45–63.

Frenz, M. and G. Ietto-Gillies (2009). The impact on innovation performance of different sources of knowledge: Evidence from the UK Community Innovation Survey. *Research Policy 38*(7), 1125–1135.

Gennaioli, N., Y. Ma, and A. Shleifer (2016). Expectations and investment. *NBER Macroeconomics Annual 30*(1), 379–431.

Geroski, P. A., J. Van Reenen, and C. F. Walters (1997). How persistently do firms innovate? *Research Policy 26*(1), 33–48.

Greene, W. H. (2012). *Econometric analysis, 7th edition.* Pearson.

Guerrieri, V., G. Lorenzoni, L. Straub, and I. Werning (2020). Macroeconomic implications of COVID-19: Can negative supply shocks cause demand shortages? *NBER Working Paper 26918*.

Guiso, L. and G. Parigi (1999). Investment and demand uncertainty. *Quarterly Journal of Economics 114*(1), 185–227.

Hassan, T. A., S. Hollander, L. van Lent, and A. Tahoun (2020). Firm-level exposure to epidemic diseases: COVID-19, SARS, and H1N1. *NBER Working Paper 26971*.

Jorda, O., S. R. Singh, and A. M. Taylor (2020). Longer-run economic consequences of pandemics. *NBER Working Paper 26934*.

Kirk, C. P. and L. S. Rifkin (2020). I'll trade you diamonds for toilet paper: Consumer reacting, coping and adapting behaviors in the COVID-19 pandemic. *Journal of Business Research 117*, 124–131.

Koetse, M. J., A. J. Van der Vlist, and H. L. De Groot (2006). The impact of perceived expectations and uncertainty on firm investment. *Small Business Economics 26*(4), 365–376.

Koga, M., H. Kato, et al. (2017). Behavioral biases in firms' growth expectations. *Bank of Japan Working Paper 17-E-9*.

Lee, N., H. Sameen, and M. Cowling (2015). Access to finance for innovative SMEs since the financial crisis. *Research Policy 44*(2), 370–380.

Lee, S. M. and S. Trimi (2020). Convergence innovation in the digital age and in the COVID-19 pandemic crisis. *Journal of Business Research 123*, 14–22.

Malerba, F. and L. Orsenigo (1995). Schumpeterian patterns of innovation. *Cambridge Journal of Economics 19*(1), 47–65.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica 71*(6), 1695–1725.

Nelson, R. R. and S. G. Winter (1982). *An evolutionary theory of economic change*. Cambridge, Mass. and London, Belknap Harvard.

Patel, P. and K. Pavitt (1994). Uneven (and divergent) technological accumulation among advanced countries: Evidence and a framework of explanation. *Industrial and Corporate Change 3*(3), 759–787.

Paunov, C. (2012). The global crisis and firms' investments in innovation. *Research Policy 41*(1), 24–35.

Pavitt, K., M. Robson, and J. Townsend (1989). Technological accumulation, diversification and organisation in UK companies, 1945–1983. *Management Science 35*(1), 81–99.

Piva, M. and M. Vivarelli (2007). Is demand-pulled innovation equally important in different groups of firms? *Cambridge Journal of Economics 31*(5), 691–710.

Sharma, P., T. Y. Leung, R. P. Kingshott, N. S. Davcik, and S. Cardinali (2020). Managing uncertainty during a global pandemic: An international business perspective. *Journal of Business Research 116*, 188–192.

Solon, G., S. J. Haider, and J. M. Wooldridge (2015). What are we weighting for? *Journal of Human Resources 50*(2), 301–316.

Stevens, P. A. (2003). Firms' expectations and employment behaviour: evidence from a panel of UK manufacturing firms. *Economics Letters 81*(3), 305–308.

Tanaka, M., N. Bloom, J. M. David, and M. Koga (2020). Firm performance and macro forecast accuracy. *Journal of Monetary Economics 114*, 26–41.

7 Figures

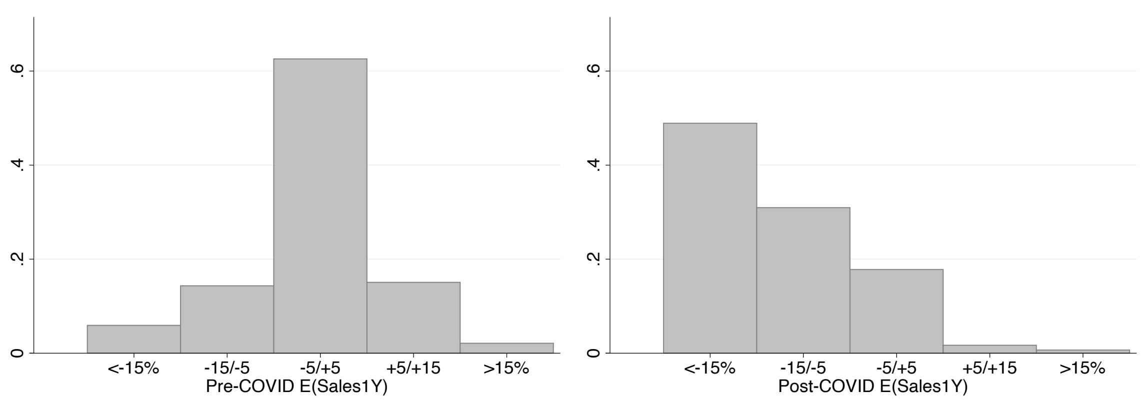

Figure 1: Revision in expected future sales.

Notes: Distributions of pre- and post-COVID expectations on sales growth at a 1-year horizon. The left graph displays firms' weighted forecasts as of January 2020, while the right graph reports the updated expectations in the aftermath of the pandemic outbreak.

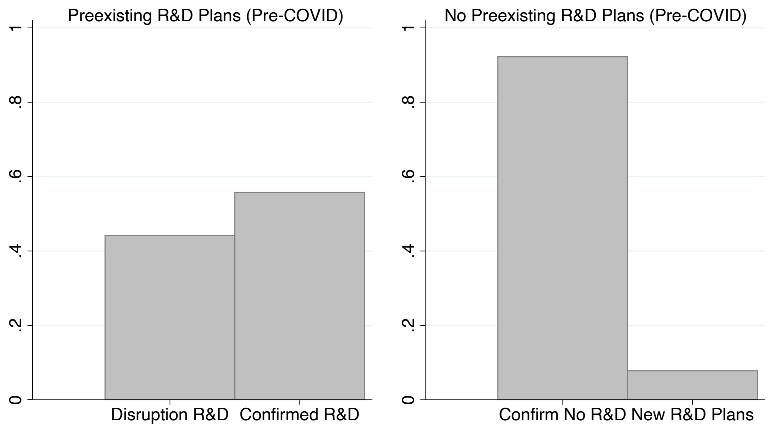

Figure 2: Revision in R&D plans.

Notes: change in future R&D plans around the pandemic outbreak. The left plot focuses on companies that, as of January 2020, declared to have scheduled expenditures in R&D for the following year. It presents the conditional distribution of firms that confirmed (Confirmed) or came back (Disruption) on preexisting R&D plans in April 2020. The right plot focuses on companies with no future R&D plans in January 2020 and shows the conditional distribution of firms that, in April 2020, confirmed their decision of not investing in R&D (No R&D) or reacted to the crisis by programming new R&D expenditures (New R&D Plans).

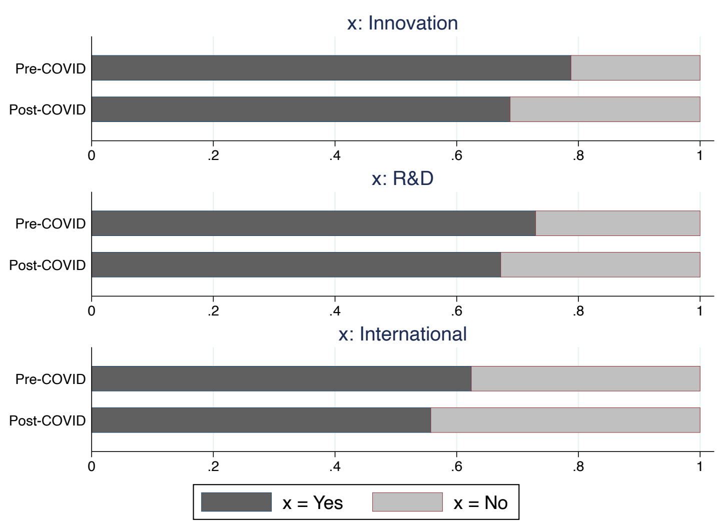

Figure 3: Composition of R&D plans by innovation, past R&D, and internationalization.

Notes: In each point in time (pre-COVID or post-COVID, listed on the y-axis), we report the distribution of overall R&D plans between firms with or without a specific strategy "x" (in dark and light grey, respectively). In the top, middle, and bottom panel, we compare innovative vs. non-innovative companies, firms with or without actual R&D projects, or internationalized vs. domestic companies, all as of January 2020. Each bar accounts for the entire set of R&D plans in the period (overall decreasing in the aftermath of the COVID-19 pandemic, as shown in Table 2) and sums to 100.

8 Tables

Table 1: Composition of the COVID and MET-2019-surveys.

	COVID-survey (1)	MET-2019 (2)
Size Class		
1-9 employees	51.1%	48.1%
10-49 employees	33.0%	34.8%
50-249 employees	12.8%	12.5%
$\geq$ 250 employees	3.20%	4.60%
Macro Industry		
Manufacturing	63.2%	66.7%
Production services	36.8%	33.3%
Macro Region		
North-West	25.1%	24.8%
North-East	26.6%	24.8%
Center	24.1%	25.4%
South	24.2%	25.0%
Overall size	7,800	24,000

Notes: sample composition of the COVID and MET-2019-surveys along macro-sector, size class, and macro-geographical region. Section A1 of the Online Appendix provides detailed information on the disproportionate sampling scheme, the construction of ex-post sampling weights employed to reproduce the population, as well as the list of the sectors that are sampled in the survey.

Table 2: Descriptive statistics.

Variable	Type	Mean	Stdev	Min	Max	Obs.
$\mathbb{E}_t$(Sales1Y): Original	Ordinal	1.742	0.854	1.000	5.000	7800
$\mathbb{E}_t$(Sales1Y): V.Neg	Dummy	0.489	0.499	0.000	1.000	7800
$\mathbb{E}_t$(Sales1Y): Neg	Dummy	0.310	0.462	0.000	1.000	7800
$\mathbb{E}_t$(Sales1Y): Const	Dummy	0.178	0.382	0.000	1.000	7800
$\mathbb{E}_t$(Sales1Y): Pos	Dummy	0.017	0.129	0.000	1.000	7800
$\mathbb{E}_t$(Sales1Y): V.Pos	Dummy	0.007	0.082	0.000	1.000	7800
$\mathbb{E}_{t-1}$(Sales1Y): Original	Ordinal	2.931	0.781	1.000	5.000	7800
$\mathbb{E}_{t-1}$(Sales1Y): V.Neg	Dummy	0.059	0.236	0.000	1.000	7800
$\mathbb{E}_{t-1}$(Sales1Y): Neg	Dummy	0.143	0.350	0.000	1.000	7800
$\mathbb{E}_{t-1}$(Sales1Y): Const	Dummy	0.626	0.484	0.000	1.000	7800
$\mathbb{E}_{t-1}$(Sales1Y): Pos	Dummy	0.151	0.358	0.000	1.000	7800
$\mathbb{E}_{t-1}$(Sales1Y): V.Pos	Dummy	0.021	0.144	0.000	1.000	7800
$\Delta\mathbb{E}_t^R$(Sales3M)	Continuous	-0.240	0.290	-1.000	2.000	7800
$\Delta\mathbb{E}_t^R$(Sales1Y)	Continuous	-0.193	0.235	-1.000	1.800	7800
Δ(R&D plans)	Ordinal	-0.046	0.399	-1.000	1.000	7800
Cancelled R&D plans	Dummy	0.103	0.305	0.000	1.000	7800
New R&D plans	Dummy	0.057	0.233	0.000	1.000	7800
Internationalization	Dummy	0.280	0.449	0.000	1.000	7800
R&D	Dummy	0.154	0.154	0.000	1.000	7800
R&D Expenditure	Bounded	0.023	0.078	0.000	1.000	7800
R&D Outsourcing	Bounded	0.029	0.130	0.000	1.000	7800
Persistent R&D	Dummy	0.116	0.321	0.000	1.000	3345
New R&D	Dummy	0.040	0.196	0.000	1.000	3345
Innovation	Dummy	0.340	0.474	0.000	1.000	7800
Product Innovation	Dummy	0.288	0.453	0.000	1.000	7800
Process Innovation	Dummy	0.206	0.404	0.000	1.000	7800
Sales Radical Inn.	Bounded	0.051	0.166	0.000	1.000	7800
Sales Imitative Inn.	Bounded	0.065	0.176	0.000	1.000	7800
Persistent Innovation	Dummy	0.217	0.412	0.000	1.000	3345
New Innovation	Dummy	0.131	0.338	0.000	1.000	3345
Patents	Dummy	0.013	0.114	0.000	1.000	7800
PC Financial	Continuous	0.052	1.505	-1.631	4.802	5071
Leverage	Continuous	0.762	1.522	0.001	22.27	5071
Tangible Assets	Bounded	0.211	0.244	0.001	0.840	5071
Rollover Risk	Continuous	0.798	0.287	0.000	2.061	5071
Size	Continuous	13.55	1.672	9.348	21.80	5071
Age	Continuous	2.935	0.777	0.000	6.203	7800
Group	Dummy	0.068	0.252	0.000	1.000	7800
Headquarter	Dummy	0.015	0.120	0.000	1.000	7800
Family Firm	Dummy	0.769	0.421	0.000	1.000	7800
Investment	Dummy	0.458	0.498	0.000	1.000	7800
% Graduated Empl.	Bounded	0.154	0.315	0.000	1.000	7800
Labor Productivity	Continuous	9.000	1.835	0.693	15.99	5071
Vertical Integration	Continuous	0.126	0.162	0.000	0.945	5071

Notes: Descriptive statistics for the main variables employed.

Table 3: Revision in expected future sales.

	$\mathbb{E}_t$(Sales1Y) (1)	$\Delta\mathbb{E}_t$(Sales1Y) (2)	$\mathbb{E}_t$(Sales1Y) (3)	$\Delta\mathbb{E}_t$(Sales1Y) (4)	$\Delta\mathbb{E}_t^R$(Sales3M) (5)	$\Delta\mathbb{E}_t^R$(Sales12M) (6)
R&D	0.981*	0.138**	0.361**	0.364**	0.0800	-0.253
	[0.507]	[0.0688]	[0.179]	[0.181]	[0.730]	[0.525]
Innovation	-1.190**	-0.166***	-0.425***	-0.474***	-3.251***	-1.698***
	[0.462]	[0.0572]	[0.150]	[0.160]	[0.875]	[0.549]
Internationalized	-1.129***	-0.165***	-0.520***	-0.465***	-2.857***	-1.952***
	[0.403]	[0.0551]	[0.154]	[0.150]	[0.690]	[0.583]
$\mathbb{E}_{t-1}$(Sales1Y): V.Neg	-3.585***	1.425***	-2.464***	3.834***	-9.299***	-7.948***
	[0.771]	[0.111]	[0.485]	[0.305]	[1.707]	[1.287]
$\mathbb{E}_{t-1}$(Sales1Y): Neg	-1.970***	0.698***	-0.982***	1.659***	-4.412***	-4.105***
	[0.460]	[0.0608]	[0.193]	[0.182]	[1.031]	[0.8081]
$\mathbb{E}_{t-1}$(Sales1Y): Pos	1.196*	-0.855***	0.368*	-2.319***	1.559***	1.701***
	[0.622]	[0.0768]	[0.199]	[0.252]	[0.681]	[0.468]
$\mathbb{E}_{t-1}$(Sales1Y): V.Pos	4.165***	-1.503***	1.067***	-4.367***	1.396***	2.443***
	[1.297]	[0.159]	[0.367]	[0.502]	[1.438]	[1.117]
PC Financial	1.298**	0.204**	0.696**	0.583**	-5.789***	-3.308***
	[0.583]	[0.0830]	[0.294]	[0.227]	[0.993]	[0.747]
Size	1.169***	0.148***	0.391***	0.400***	1.989***	1.839***
	[0.162]	[0.0190]	[0.0501]	[0.0536]	[0.226]	[0.169]
Age	-0.797***	-0.101***	-0.265***	-0.267***	-0.470	-0.271
	[0.289]	[0.0340]	[0.0906]	[0.0948]	[0.436]	[0.294]
Province FE	yes	yes	yes	yes	yes	yes
Industry (2 Digit) FE	yes	yes	yes	yes	yes	yes
Estimator	OLS		Ordered Logistic		OLS	
N obs.	5071	5071	5071	5071	5071	5104
R2 (Pseudo R2)	0.217	0.362	0.129	0.207	0.101	0.118

Notes: OLS and Ordered Logistic *estimates*. This table reports the effect on the change in firms' expected future sales. In columns 1 and 3, the dependent variable is an ordinal measure identifying a company's expectations on future sales as reported in the COVID-19 survey. The variable can take five values: V.Neg (sales growth below -15%), Neg (in the interval -15%/-5%), Const (-5%/+5%), Pos (5%/15%), or V.Pos (>15%). The same answer, as reported in the 2019-wave of the MET survey (January 2020), is used as a control to capture variations in expectations due to the COVID-19 pandemic (Const is the benchmark). In columns 2 and 4, the dependent variable is the difference between post- and pre-COVID expectations ($\Delta\mathbb{E}_t$(Sales1Y) in our notation). In columns 5 and 6, we directly employ the revision in expectations on sales at the three- and 12-month horizons, as reported in the COVID-19 survey ($\Delta\mathbb{E}_t^R$(Sales3M) and $\Delta\mathbb{E}_t^R$(Sales12M), respectively). Additional controls (not reported) are: past sales growth (realized), dummies for investments, corporate group belonging, whether the company is the headquarter of the group, or a family-managed firm, the share of graduated employees, labor productivity, and vertical integration. All variables are defined in Appendix. Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 4: Change in R&D plans.

	(1) Disruption	(2) New Plans	(3) Disruption (-1)	(4) Unaffected (0)	(5) New Plans (+1)
R&D	0.0851***	0.00398	0.0852***	-0.0894***	0.00418
	[0.0152]	[0.00902]	[0.0149]	[0.0158]	[0.00834]
Innovation	0.0728***	0.0190**	0.0717***	-0.0887***	0.0170**
	[0.0151]	[0.00809]	[0.0147]	[0.0158]	[0.00739]
Internationalized	0.0331**	0.0111	0.0328**	-0.0430***	0.0102
	[0.0145]	[0.00880]	[0.0144]	[0.0145]	[0.00813]
% Graduated Empl.	-0.0339***	0.00997***	-0.0329***	0.0233***	0.00964***
	[0.00761]	[0.00367]	[0.00747]	[0.00741]	[0.00340]
PC Financial	0.0693***	0.00591	0.0688***	-0.0756***	0.00677
	[0.0158]	[0.0103]	[0.0157]	[0.0166]	[0.00952]
Size	-0.0218***	0.000373	-0.0219***	0.0215***	0.000446
	[0.00480]	[0.00275]	[0.00475]	[0.00551]	[0.00254]
Age	-0.0202***	-0.00535	-0.0200***	0.0251***	-0.00502
	[0.00755]	[0.00457]	[0.00743]	[0.00772]	[0.00424]
Province FE	yes	yes		yes	
Industry (2 Digit) FE	yes	yes		yes	
Estimator	Logit	Logit		Multinomial Logit	
N obs.	5070	5070		5070	
Pseudo R2	0.112	0.074		0.107	

Notes: Logistic and Multinomial Logistic marginal effects. The dependent variable is the variation in firms' future R&D plans between January and March 2020. This measure is based on the same question posed in the 2019-wave and COVID-19 MET surveys, asking for the existence of planned investment in R&D for the next year (see Section 3.2). The difference between planned R&D expenditure in the COVID-19 survey and the same measure in January 2020 identifies $\Delta(\text{R\&D plans})_t$ taking values: -1 in case of disruption of planned R&D investments, 0 in case of no change (confirming previous strategies), and +1 in case of new planned R&D investment as a result of the COVID-19 pandemic. This measure is employed as a dependent variable in columns 3-to-5. Columns 1 and 2 employ the dummy measures identifying the disruption or increase of R&D projects as alternative dependent variables. Additional controls (not reported) follow the specifications in Table 3. Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 5: Simultaneity of firms' R&D plans and expectations.

	(1) Equation 1: $\Delta(\text{R\&D plans})_t$	(2) Equation 2: $\Delta\mathbb{E}_{i,t}(\text{Sales1Y})$	(3) Interacted coeff. in Equation 1
R&D	-0.0726***	0.0357	-0.003
	[0.0199]	[0.0376]	[0.017]
Innovation	-0.0416**	-0.143***	-0.025
	[0.0185]	[0.0351]	[0.017]
Internationalized	-0.0157	-0.0850**	-0.006
	[0.0191]	[0.0361]	[0.016]
$\Delta\mathbb{E}_{i,t}(\text{Sales1Y})$	0.0451***	–	
	[0.00741]	–	
Province FE	yes	yes	yes
Industry (2 Digit) FE	yes	yes	yes
R2	0.074	0.362	0.075
N obs.	5070		5070

Notes: Seemingly-Unrelated (SUR) regression models. The dependent variable in Column 1 (Equation 1 of the SUR) is the change in firms' future R&D plans between January and March 2020 ($\Delta(\text{R\&D plans})_t$). The dependent variable in Column 2 (Equation 2 of the SUR) is the revision in firms' expectations as captured by difference between post- and pre-COVID beliefs ($\Delta\mathbb{E}_t(\text{Sales1Y})$). In Column 3 we test for differential sensitivities to expected demand shocks by enriching Equation 1 (of Column 1) with a set of interaction terms $X_{t-1} \times \Delta\mathbb{E}_t(\text{Sales1Y})$ for each measure in X (R&D, Innovation, Internationalized). Only the estimated interactions are reported (other estimates are virtually identical to the ones in Column 1). Unreported Breusch-Pagan tests strongly reject the null of independence between the two equations. Additional controls (not reported) follow the specification in Table 3. Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 6: Simultaneity in firms' R&D plans and expectations: additional heterogeneities.

	(1) Disruption	(2) New Plans	(3) Equation 1: Δ(R&D plans)$_t$	(4) Equation 2: $\Delta\mathbb{E}_{i,t}$(Sales1Y)	(5) Interacted coeff. in Equation 1
Panel A					
R&D Expenditure	-0.00983	0.00964**	0.0303***	0.0215	-0.0112
	[0.00853]	[0.00457]	[0.0109]	[0.0207]	[0.0082]
Panel B					
R&D Outsourcing	0.0102***	-0.00694**	-0.0193***	-0.00682	0.0041
	[0.00285]	[0.00338]	[0.00365]	[0.00930]	[0.00297]
Panel C					
New R&D	0.130***	-0.00438	-0.143***	-0.0320	0.0046
	[0.0266]	[0.0156]	[0.0316]	[0.0604]	[0.0278]
Persistent R&D	0.0315*	-0.00199	-0.0270	-0.0334	-0.0232
	[0.0182]	[0.00964]	[0.0240]	[0.0458]	0.0187
Panel D					
Product Innovation	0.0367**	0.0173**	-0.00929	-0.188***	0.0268*
	[0.0156]	[0.00787]	[0.0191]	[0.0360]	[0.0163]
Process Innovation	0.0166	0.00616	-0.0146	0.00614	-0.006
	[0.0147]	[0.00956]	[0.0190]	[0.0360]	[0.0165]
Panel E					
Sales Radical Inn.	0.00104	0.00404**	0.00819*	-0.0281***	-0.00304
	[0.00375]	[0.00199]	[0.00493]	[0.00930]	[0.00421]
Sales Imitative Inn.	0.00433	-0.00172	-0.00511	-0.0197**	-0.00174
	[0.00357]	[0.00236]	[0.00495]	[0.00936]	[0.00429]
Panel F					
New Innovation	0.110***	0.0145	-0.0891***	-0.125***	-0.0118
	[0.0175]	[0.0114]	[0.0229]	[0.0441]	[0.0202]
Persistent Innovation	0.0532***	0.0180*	-0.0228	-0.151***	-0.0311*
	[0.0181]	[0.00951]	[0.0216]	[0.0415]	[0.0172]
Panel G					
Patents	-0.104***	-0.00254	0.0978***	0.0847	0.005
	[0.0283]	[0.0149]	[0.0360]	[0.0682]	[0.0286]
Province FE	yes	yes	yes	yes	yes
Industry (2 Digit) FE	yes	yes	yes	yes	yes
Estimator	Logit	Logit	SUR		SUR
N obs.	5070	5070	5070		5070

Notes: Logistic marginal effects and Seemingly-Unrelated (SUR) regression models. The dependent variables in Columns 1 and 2 are dummy measures identifying the disruption or increase of R&D projects as in Table 4. The dependent variable in Column 3 (Equation 1 of the SUR) is the raw change in firms' future R&D plans between January and March 2020 (Δ(R&D plans)$_t$), while in in Column 4 (Equation 2 of the SUR) is the revision in firms' expectations as captured by difference between post- and pre-COVID beliefs ($\Delta\mathbb{E}_t$(Sales1Y)). As in Table 5, In Column 5 we test for differential sensitivities to expected demand shocks by enriching Equation 1 (of Column 3) with a set of interaction terms $X_{t-1} \times \Delta\mathbb{E}_t$(Sales1Y) for each measure in X. Only the estimated interactions are reported (other estimates are virtually identical to the ones in Column 3). Unreported Breusch-Pagan tests strongly reject the null of independence between the two equations. Additional controls (not reported) follow the specifications in Table 5 . Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Appendix: Variable Definition

Variable name	Definition
$\mathbb{E}_t$(Sales1Y): V.Neg	Dummy =1 for firms forecasting, in March 2020, sales growth on a 1-year horizon below -15%.
$\mathbb{E}_t$(Sales1Y): Neg	Dummy =1 for firms forecasting, in March 2020, sales growth on a 1-year horizon in the interval (-15%,-5%).
$\mathbb{E}_t$(Sales1Y): Const	Dummy =1 for firms forecasting, in March 2020, sales growth on a 1-year horizon in the interval [-5%,+5%].
$\mathbb{E}_t$(Sales1Y): Pos	Dummy =1 for firms forecasting, in March 2020, sales growth on a 1-year horizon in the interval (+5%,+15%).
$\mathbb{E}_t$(Sales1Y): V.Pos	Dummy =1 for firms forecasting, in March 2020, sales growth on a 1-year horizon above +15%.
$\mathbb{E}_{t-1}$(Sales1Y): V.Neg	Dummy =1 for firms forecasting, in January 2020, sales growth on a 1-year horizon below -15%.
$\mathbb{E}_{t-1}$(Sales1Y): Neg	Dummy =1 for firms forecasting, in January 2020, sales growth on a 1-year horizon in the interval (-15%,-5%).
$\mathbb{E}_{t-1}$(Sales1Y): Const	Dummy =1 for firms forecasting, in January 2020, sales growth on a 1-year horizon in the interval [-5%,+5%].
$\mathbb{E}_{t-1}$(Sales1Y): Pos	Dummy =1 for firms forecasting, in January 2020, sales growth on a 1-year horizon in the interval (+5%,+15%).
$\mathbb{E}_{t-1}$(Sales1Y): V.Pos	Dummy =1 for firms forecasting, in January 2020, sales growth on a 1-year horizon above +15%.
Δ(R&D plans)$_t$	Difference between the dummy for firms reporting planned expenditure in R&D for the next year in the COVID-19 survey and the same measure in the 2019-wave (January 2020).
Disruption	Dummy =1 for firms that reported planned expenditure in R&D for the next year in January 2020, and declared no R&D expenditure (for the same horizon) in March.
Unaffected	Dummy =1 for firms that reported consistent answers on R&D planned expenditures in the two surveys (dummies in January and March are either both equal to 1 or to 0).
New plans	Dummy =1 for firms that reported no planned investment in R&D for the next year in January 2020, and introduced new R&D plans (for the same horizon) in March.
$\Delta\mathbb{E}_t^R$(Sales3M)	Continuous measure for the change in expected future sales on a three-month horizon (as reported in March 2020).
$\Delta\mathbb{E}_t^R$(Sales12M)	Continuous measure for the change in expected future sales on a 12-month horizon (as reported in March 2020).

Variable name	Definition
R&D	Dummy =1 for the existence of R&D projects, as of January 2020.
R&D Expenditure	Overall expenditure in R&D project as a share of total sales.
R&D Outsourcing	Share of R&D that is external to the firm (i.e., outsourced to firms, universities, labs, etc.).
New R&D	Dummy =1 for R&D companies in the 2019-wave of the MET survey but that did not have active R&D programs in the previous available wave (either 2017 or 2015 to maximize the size of the sample).
Persistent R&D	Dummy =1 for R&D companies in the 2019-wave of the MET survey that not have active R&D programs also in the previous available wave (either 2017 or 2015 to maximize the size of the sample).
Innovation	Dummy =1 for the introduction of any type of innovations, as of January 2020.
Product Innovation	Dummy =1 for the introduction of product innovations, as of January 2020.
Process Innovation	Dummy =1 for the introduction of process innovations, as of January 2020.
Sales Radical Inn.	Share of total sales linked to product innovations that are new both to the firm and to the market.
Sales Imitative Inn.	Share of total sales linked to product innovations that new to the firm but preexisting in the market.
New Innovation	Dummy =1 for companies that introduced innovation in the 2019-wave of the MET survey but were not innovators in the previous available wave (either 2017 or 2015 to maximize the size of the sample).
Persistent Innovation	Dummy =1 for companies that introduced innovation in the 2019-wave of the MET survey and were innovators also in the previous available wave (either 2017 or 2015 to maximize the size of the sample).
Patents	Dummy =1 for patent-holding companies (independently of the number of patents).
Internationalization	Dummy =1 for internationalized companies (import, export, or more complex forms of international relationship), as of January 2020.
Leverage	Total debts to equity ratio.
Tangible Assets	Stock of fixed assets to total assets ratio
Rollover Risk	Short-term debt to long-term debt ratio.
PC Financial	The first principal component of Tangible Assets, Leverage, and Rollover Risk. It is increasing with firms' creditworthiness as it loads positively on the availability of collateral (Tangible Assets) and negatively on Leverage and Rollover Risk. It explains 48% of the overall variance.
Size	log of (total assets).
Age	log of (1 + age).
Group	Dummy =1 for firms belonging to corporate groups, as of January 2020.
Headquarter	Dummy =1 if the firm is the headquarter of to corporate group, as of January 2020.
Family Firm	Dummy =1 for family-owned firms, as of January 2020.
Investment	Dummy =1 for firms that undertook investments (independently of the type), as of January 2020.
% Graduated Empl.	Share of graduated employees (bachelor at minimum), as of January 2020.
Labor Productivity	Log value added per worker.
Vertical Integration	Value added to sales ratio.