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ABSTRACT

R&D Plans, Expectations, and Uncertainty: Evidence from the COVID-19 Shock in Italy*

This paper takes advantage of the COVID-19 outbreak to explore the determinants of firms' R&D choices around an exogenous shock. We make use of unique panel data on 7,800 Italian companies between January 2020 –right before the pandemic– and March of the same year –amid lockdown policies. We then exploit the revision in firms' research plans within this short-time window to test the impact of deteriorating expectations and uncertainty on firms' R&D choices. Our results show a dramatic effect of firms' expectations about future market conditions. In this regard, internationalized and innovative companies, which were particularly suffering the onset of the crisis, display a significantly higher probability of discontinuing research plans. Beyond the role played by expectations, innovative characteristics already in place are found to critically shape firms' reactions to the general uncertainty. Two main patterns emerge from our analysis. On the one hand, there is a strong degree of persistence in R&D choices for a small set of innovators with substantial past expenditure in in-house research activities. On the other, the COVID-19 shock especially jeopardized R&D plans of firms that recently started new research programs or newly innovative companies. We interpret such results as evidence that preexisting sunk costs increase the persistence of R&D choices after uncertainty shocks.

JEL Classification: O3, D22, D84
Keywords: firms, R&D, expectations, uncertainty, COVID-19

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1 Introduction

The COVID-19 outbreak brought a shock unprecedented in scale and speed. In a few weeks, the economic outlook changed dramatically and the introduction of lockdown policies increased substantially firms' uncertainty about the future.[1] Most importantly, the pandemic manifestly originated outside the business and banking sectors; as such, it can be regarded as largely orthogonal to firms' activities and fundamentals, including their growth opportunities, innovativeness, and financial conditions.

This paper exploits a short-window identification around the pandemic burst to provide new evidence on how companies revise their R&D plans in the aftermath of a truly exogenous shock. Our analysis explores two main dimensions that may affect R&D choices. The first one has to do with firms' own expectations about market conditions, whereby the heterogeneous revision in firms' expected sales at the onset of the turmoil may imply significantly different choices in terms of future R&D programs. The second component is, instead, related to past characteristics of the innovative process. In this regard, the sunk costs attached to preexisting investments in innovative activities can entail a differential sensitivity of R&D to the general uncertainty shock.

Our study 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 March-April of the same year –two weeks after the introduction of lockdown policies (on March 11). We enrich the large amount of information available in the 2019-wave of the MET survey with *ad hoc* interviews monitoring the effects of the pandemic on the same set of companies (7,800 in our final sample).

The empirical analysis compares research plans immediately before and after the COVID-19 event to identify firms that dismantled preexisting R&D projects or, instead, reacted to the crisis by scheduling new investments. Similarly, we proxy the magnitude of the perceived shock with the revision in firms' forward-looking expectations, computed as the difference between pre- and post-COVID expected sales on a one-year horizon. In essence, our econometric model relies on an event-study type of approach to explore heterogeneities in research patterns and expectations around the epidemic outbreak. We then account for the simultaneity in their revisions to distinguish effects on R&D that arise from idiosyncratic demand shocks from those linked with heterogeneous reactions to the general uncertainty.

Our findings suggest that the burst of the pandemic induced a substantial revision in firms' expected performances (-19% on a 12-month horizon), which, however, was far from being homogeneous. Results point at stronger perceived shocks for internationalized companies and firms that introduced product innovations

[1] Concerns regarded a broad array of dimensions: from epidemiological developments to the length of market lockdowns, the possibility of permanent shifts in consumer spending, as well as the very survival of firms. For the US, Baker et al. (2020) ranked the uncertainty of the COVID-19 event significantly above the 1933 Great Depression and the 2008 global financial crisis (and just below the 1929 stock market crash).

in the past, characterized by a substantially higher probability of a severe reduction in expected future sales. This evidence is crucially related to firms' information set in April 2020 and to the very characteristics of the first phases of the turmoil (we further discuss this in Section 5.1). Because expectations have been continuously revised throughout the evolution of the crisis, such a finding should not be interpreted as an accurate forecast on firms' realized performances, but rather as a sign of the greater shock perceived by more dynamic firms at the onset of the COVID-19 event. This is relevant because even transitory expectations based on temporary shocks may have long-run implications through managers' actual decisions, which are based on the current information set. 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.

In this regard, our descriptive evidence documents a substantial impact of the pandemic on firms' research plans, with the disruption of 44% of the R&D investments that were already scheduled before the crisis kicked in. Our analysis highlights two main dimensions driving this effect. The first one has to do with the direct role of expectations, whereby the severe demand shock perceived by internationalized and innovative companies significantly hampered their research activities. The second dimension goes over and beyond firms' beliefs and operates, instead, through a differential response to the increased uncertainty. In this regard, the very nature of the innovative investments already in place significantly shaped firms' reactions to the shock.

On the one side, there is a small set of persistent innovators whose sizable expenditure in in-house R&D implied a reduced sensitivity to uncertainty. Some of them, especially those that were heavily reliant on innovations for their business, even expanded their research plans in the aftermath of the shock. On the other side, the turmoil especially harmed projects of those firms that were transitioning to a new way of doing business. Companies that were in the process of upgrading toward more innovative strategies had a significantly higher probability of canceling 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 largest marginal gains from innovation.

More in general, our findings provide evidence that sunk costs attached to past innovative investments increase the persistence of R&D choices after uncertainty shocks. As we outline in Section 2, this is broadly consistent with the cautionary investment behavior in the literature on irreversible investments. However, we also provide results that go beyond standard predictions in the uncertainty-investment link. Companies with substantial past expenditure in R&D and highly innovative firms are found not only to have a less negative reaction but even to increase their research effort after an adverse shock. This finding signals their willingness to exploit potential growth opportunities in times of crisis as well as their innate propensity to invest in research activities. Because their competitive advantage is rooted in the generation and upgrading of new knowledge, they tend to invest continuously in innovation irrespectively of the business cycle.

The results of this paper also speak to the literature on firms' innovativeness in times of turmoil. Within this broad strand of research, we are more closely related to evidence in Paunov (2012), Archibugi et al. (2013), and Antonioli and Montresor (2019). On the financial crisis, Paunov (2012) shows a sizable disruption of innovative projects following export shocks, while 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) focus on the Great Recession and document a higher innovative effort for a small set of great innovators, together with a larger persistence of process innovations.

We differ from all these papers because we focus on a truly-exogenous event[2] and study plans and expectations rather than realized variables. Such measures have the great advantage of reacting immediately to a shock and allow for a short-window identification that bypasses endogeneity issues. Moreover, previous studies explored average dynamics, while neglecting the combined role of expectations and uncertainty in firms' choices. This novel emphasis allows highlighting differential behaviors that uncover important facts about firms' reactions to unexpected shocks.

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

2 Related literature

On top of a specific contribution to the literature on firms' innovativeness in times of crisis, the results of this paper also speak to the more general field of research on the real effects of expectations and uncertainty.

2.1 Effects of expectations

Expectations about future business conditions represent an important determinant of firms' capital accumulation, hiring, and strategic decisions and, as such, are regarded as essential factors in the propagation of shocks to the economy. The turmoil brought by the 2008-financial crisis gave new impulses to this field of research, with a number of studies connecting firms' economic outcomes with their forward-looking expec-

[2] Notice that this may not be true for previous crises triggered by fragilities of the real and financial sectors. In such cases, the feedback effects of firms' choices to the economy are likely to bring in the game third-parties unobserved factors driving both the severity of the crisis and firms' innovative dynamics.

tations. Most of this literature called attention to the role played by macroeconomic factors,[3] while only a few studies focused on firms' expectations on their own demand conditions in the future. Within the latter, Gennaioli et al. (2016) show that corporate investment plans and actual investments are well explained by expected sales of American companies. Along the same line, Boneva et al. (2020) focus on the UK to show substantial effects of expectations on pricing strategies and employment behavior. Finally, Enders et al. (2019a) study how changes in the outlook of German firms impact their real decisions, even if expectations turn out to be incorrect ex-post.

Our paper contributes to this strand of research by adopting a novel angle. First of all, we isolate firms' expectations revisions taking advantage of a truly-exogenous event and a short-window identification. Unlike the financial and sovereign-debt crises, the COVID-19 outbreak brought a shock that was totally unrelated to firms' fundamentals, including their level of productivity, financial conditions, and investment opportunities. This is a unique feature of the current crisis and assuages potential concerns about endogeneity issues. Moreover, the short-run perspective adopted in this analysis allows for isolating the effect of perceived demand shocks while ruling out any additional confounding factor that may mar the expectation-investment relationship.

Importantly, the existent literature has only focused on the accumulation of physical capital, labor, or pricing decisions, while there is still scant evidence on the effect of expectations on firms' R&D choices. This is an important issue as expectations play a critical role in the comparison of expected returns and the evaluation of the risks associated with the innovative process. As such, we expect R&D spending to be heavily influenced by shocks on firms' expected demand. We test this hypothesis by employing R&D plans that, unlike realized outcomes, respond immediately to external shocks and can be exploited in an event-study analysis around the pandemic outbreak.

2.2 Uncertainty and investments

In addition to the level of expectations, the overall degree of uncertainty plays a relevant role in firms' choices. For instance, in real options theories the unpredictability of future fundamentals leads to a postponement of investment plans because it increases the benefits from waiting for the uncertainty to resolve. The underlying idea is that, because companies have the right –but not the obligation– to purchase an asset, firms' investment at any point in time can be seen as the exercise of a "real" call option (Dixit and Pindyck, 1994). When firms choose to invest, they give up the chance to wait for new information that may affect the evaluation of their choice (about its desirability or optimal timing). Consistently with this intuition, the real options literature

[3] See, among others, Coibion et al. (2018), Enders et al. (2019b), Coibion et al. (2020), Coibion et al. (2020), and Tanaka et al. (2020).

predicts a negative relationship between uncertainty and investment, wherein uncertain information about future demand rises the option value of waiting and leads to a postponement of new investment decisions (Bernanke, 1983; Dixit, 1992).

While this induces a general slowdown in the investment dynamic (e.g., Bachmann et al., 2013 and Bloom et al., 2019), the effect of uncertainty is regarded to be especially severe in case of new projects that are irreversible, for which the value of waiting increases exponentially (Dixit and Pindyck, 1994; Guiso and Parigi, 1999). Yet, despite some studies point at a negative effect of an uncertain environment on irreversible investments (Pindyck and Solimano, 1993; Guiso and Parigi, 1999; Bachmann et al., 2013, among others), the relationship between R&D and uncertainty is still a matter of controversy. Some of the literature highlights a reduced sensitivity of R&D (Bloom et al., 2007), linked to mechanisms of "long times-to-build" (Bar-Ilan and Strange, 1996) or to the mitigating effect of patent protection (Bloom and Van Reenen, 2002; Czarnitzki and Toole, 2011). Other studies even predict a positive influence of uncertainty on research activities. This is the case, for instance, in markets with intense strategic competition wherein growth opportunities are increasing with the degree of uncertainty (Kulatilaka and Perotti, 1998). In such a framework, firms may choose to rise their investments in order to acquire greater capabilities and better exploit future possibilities of expansion. A similar relationship arises whenever strong competition is in place and a firm's ability to delay investment projects is undermined by its fear of preemption (i.e., competing companies may invest first and reduce the value of the research project; as in Weeds, 2002).

Our paper provides several contributions to this debate by exploring the revision in R&D plans around an exogenous shock. First of all, the existent literature has typically employed uncertainty measures recovered from historical data (past revenues volatility or the variance of daily stock returns, as in Czarnitzki and Toole, 2011 or Bloom and Van Reenen, 2002), with the underlying assumption that past experience is informative about firms' uncertainty in the future. Unlike previous studies, we deal with endogeneity issues in the uncertainty-R&D link by taking advantage of an unexpected shock and exploring firms' differential reactions in the very short run. As such, our empirical approach captures a more forward-looking component in the perception of uncertainty that should be factored in when firms make their current choices. We disentangle a differential reaction to the common uncertainty shock by taking advantage of a short-window identification and explicitly controlling for firms' expectations. As such, our analysis also provides a bridge between the literature on the real effects of expectations and the one on irreversible investments. This is a central issue when dealing with an event that simultaneously affects both dimensions.

Finally, we do not only focus on new investments but explore, instead, the revision of R&D plans that were already scheduled before the realization of the uncertainty shock. This emphasis allows us to test some predictions of real options theories from a novel perspective and to ask whether the probability of disruption of preexisting R&D projects is somewhat affected by the sunk costs attached to past investments. We do so by testing heterogeneities across firms with different levels of R&D expenditure, share of in-house R&D, and length of the innovative behavior (among other measures); all of which are correlated with the size of unrecoverable costs of the investments already made.

One of the main predictions of real options theory is that higher degrees of uncertainty increase a firm's value of waiting and that this is especially so in presence of large sunk costs. In our empirical framework, this translates into a general reduction of new R&D plans in the aftermath of the COVID-19 event. At the same time, firms should also be more reluctant to dismantle old projects if the loss from discontinuing previous research lines is high enough (a cautionary investment behavior as in Bloom et al., 2007). Therefore, one may expect a lower probability of R&D disruption for firms that are persistently involved in innovative activities or entered the pandemic with sizable investments already in place. On the other hand, a positive influence of uncertainty on R&D may even arise if some companies view the crisis as an opportunity to take advantage of future upswings (as in Kulatilaka and Perotti, 1998 or Weeds, 2002). The empirical approach outlined in Section 4 employs a rich set of characteristics of firms' innovative processes (pre-determined, as of January 2020) to explore possible heterogeneities and shed some light on this issue.

3 Data

3.1 Sources of data

Our analysis takes advantage of panel data on R&D plans and expectations 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.[4]

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 of the manufacturing sectors (60% of the sample) and the production-service industry (40%), which are stratified into 12 macro-sectors (ATECO sub-sections).[5] Unlike other recurring surveys, MET provides information on every size class including micro-sized companies with less than ten

[4] On the same dataset, Balduzzi et al. (2020) explore the effect of credit constraints on firms' expectations, investment, and pricing plans.

[5] 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.

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 answering our research question. The original questionnaire encompasses an extensive array of variables 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 COVID-19 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 pandemic.

We complement the information in the original questionnaire with a swift integration survey to the entire sample of the 2019-wave, so as to have full information on the pre-COVID condition of each company. To avoid excessive variation in the information set of the respondents, the timing of the survey has been restricted to 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 (on March 8 and 11), in order to leave firms enough time for updating their expectations and evaluating initial adjustments in their production processes 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.[6] The survey ended with 7,800 final interviews, which entails a sizable response rate given the time constraint. Importantly, the distribution of respondents across macro-sectors, geographical macro-regions, and size classes is in line with the original survey, as presented in Table 1. 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 size, productivity, or dummies for the macro-geographical location that capture the epidemiological severity of the shock (Table A1 in the online appendix). While this assuages concerns about the potential attrition in the COVID survey, there is still a possibility of distortion along unobservable characteristics. If this selection is somewhat simultaneously correlated with the revision in expectations/R&D plans and with the core measures of the analysis, then our results may suffer from selection bias (whose sign is a priori ambiguous). We take care of this issue by employing post-stratification weights that are specifically calibrated to reproduce known aggregates of the population. This approach aims at ruling out endogenous sampling selection as discussed in Solon et al. (2015).

[6] We further address this issue in a robustness check with day-of-the-interview fixed effects.

[Table 1 approximately here]

Finally, we match both surveys with balance-sheet data from CRIF-Cribis D&B; this information is needed to construct a wide set of controls employed to limit omitted-variable bias. Since balance sheets are not available for unincorporated firms (*società di persone*), the final size of the estimating sample is reduced to 5,000 observations.

3.2 Main measures

The empirical analysis outlined in Section 4 takes advantage of forward-looking measures on R&D plans and expected sales from the 2019-wave and COVID-19 MET surveys.

In both waves, the questionnaire asked the following: *"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(1)/No(0). The difference between the two dummy variables, Δ(R&D plans), represents an ordinal measure identifying the disruption of research plans that were already scheduled (value of -1), firms that were unaffected by the pandemic (0), and companies that reacted to the shock by planning new R&D investments (+1). We discuss the reliability of this measure in Section 3.3.

In a similar vein, we exploit the revision in firms' expectations to proxy for the expected demand shock in the short run. At 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%).[7] The difference between post- and pre-COVID answers gives raise to an ordinal measure ($\Delta\mathbb{E}$(Sales1Y)), in the discrete interval $[-4;+4]$) that captures the revision in firms' expectations induced by the pandemic. This variable proxies for a firm's idiosyncratic shock and is essential to disentangle the effects of expected demand on R&D choices from those associated with a differential reaction to the general increase in uncertainty. As alternative proxies for expectations, we also employ the revision in firms' expected sales growth for the following three and 12 months as provided by the COVID-19 survey alone (two continuous measures denoted $\Delta\mathbb{E}^R$(Sales3M) and $\Delta\mathbb{E}^R$(Sales12M), respectively).[8]

[7] The question asked the following: "*As for the sales growth in the 2019-2020 period, does your firm expect it to be: a) strongly decreasing (growth below -15%), b) decreasing (between -15% and -5%), c) roughly stable (between -5% and +5%), d) increasing (between +5% and +15%), or e) strongly increasing (above +15%).*"

[8] We use the superscript R to signal that the revision in sales expectation is reported directly in the COVID-19 survey rather than computed on panel data. In our robustness checks, we also exploit information on the managers' perception about the expected duration of the crisis and danger of the pandemic. This measure is contained in the COVID-19 survey and captures heterogeneous expectations on the possible extensions of lockdown policies and is employed in a series of robustness checks.

3.3 Validation and identification issues

Expectations represent a critical factor that drives firms' choices. In this regard, the existing literature has largely emphasized how firms' beliefs have effects on actual decisions even if expectations turn out to be inaccurate ex-post (Enders et al., 2019a) or are subsequently revised over time (Coibion et al., 2018, 2020). This is the case in our framework based on short-run revisions around the pandemic outbreak. Because expectations are likely to have been continuously updated along the subsequent stages of the crisis, our analysis is not designed to sell firms' beliefs as full effects of the epidemic in the longer run. Rather, we want to provide evidence on the magnitude of the perceived shock at the very onset of the crisis, which, independently of its accuracy, can have long-run effects through R&D choices that are based on the managers' current information set.

Nevertheless, while our analysis does not rely on the accuracy of firms' beliefs in the post-pandemic economy, understanding whether past expectations predict –to some extent– realized outcomes is important 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 set of validation exercises based on previous waves of the MET survey. 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 an 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). To better evaluate the accuracy of firms' expectations in times of uncertainty, we also repeat the analysis restricting the sample to the sovereign-debt crisis only, which represents the closest comparable scenario to the COVID-19 shock.[9] 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 A5 of the online appendix). Overall, our validation exercises 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 likely to be fundamental drivers of firms' choices.

As for future R&D choices, the formulation in the questionnaire 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. By construction, a negative value of Δ(R&D plans) captures both the intent of interrupting previously existent R&D activities

[9] 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).

–for companies with actual programs already in place– and a mere change in firms' strategies –for those that, in January, were willing to consider R&D investments but changed their minds after the COVID-19 outbreak (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 companies willing to consider the start of R&D only as a remote possibility. In this case, our measure of revision would not capture the disruption of R&D programs but just changes in firms' priors with no actual effect in practice. We tackle this concern in several ways.

First of all, as done for expected sales, we employ past surveys and show a strong degree of correlation between R&D plans and actual R&D investments in the following wave (Table A2 of the online appendix). This evidence is largely in line with Gennaioli et al. (2016), who show that ex-ante plans are deeply related to firms' ex-post behavior. Most importantly, if we repeat the analysis on split samples, the correlation is found to be significantly positive also for firms without preexisting R&D expenditures when reporting their plans (i.e., firms declaring their willingness to start research activities), although to a lower extent. This evidence allows us to conclude that also information on potential R&D disruption is relevant in our setup.

If a reader was not persuaded by this argument, it is worth noticing that the issue of potential disruptions (not linked with actual changes in firms' behavior) does not represent a critical concern in our framework because it is only related to companies with no R&D investments in January, which represent the vast minority of firms declaring R&D plans in the 2019-survey. As discussed in Section 5.3, we further tackle this concern by defining an alternative dependent variable that only accounts for the cancelation of preexisting R&D.[10]

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.[11]

[10] 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.

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

3.4 Descriptive evidence

Table 2 presents the main descriptive statistics of our dataset. As of April 2020, 80% of the companies forecast a sizable reduction in sales on a one-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, with more than 80% of firms predicting stable or positive trends (as shown in panel A of Figure 1).

[Table 2 approximately here]

[Figure 1 approximately here]

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 (44% in panel A of Figure 2). At the same time, only a few companies reacted to the crisis by planning new expenditures in research activities (roughly 7% in panel B).

[Figure 2 approximately here]

Notably, innovative and internationalized firms experienced particularly severe revisions. Not only do 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 Figures A4 and A5 of the online appendix). This is clearly reflected in their research plans characterized by a higher likelihood of R&D disruption and a lower propensity to start new research projects. Finally, Figure 3 also shows a 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 (i.e., with no actual effects). However, this issue is potentially affecting only a minority of firms, as 73% of the R&D plans in January were attached to research projects already in place.

[Figure 3 approximately here]

4 Empirical methodology

The empirical analysis exploits the unique features of our dataset centered around the COVID-19 outbreak. The aim is to explore the magnitude of the perceived shock in the short run and its effect on firms' R&D choices for the future. To this purpose, we start by setting some benchmark results about the overall effect of the pandemic on firms' revised expectations and R&D plans. We then move to a simultaneous-equation model that allows for disentangling effects on R&D that are due to worsening expectations about market demand, from those that are, instead, linked with a differential reaction to the general increase in uncertainty.

4.1 Benchmark

As a preliminary analysis, we explore heterogeneities in the magnitude of the shock and in the average dynamics of firms' R&D plans. Our baseline specification regresses firms' expectation revisions or changes in R&D plans between January and March 2020, on past internationalization, innovativeness, and (realized) R&D activity. We enrich the model with a broad set of controls capturing structural components and firms' conditions in entering the pandemic. The estimating equation reads as follows:

$$Y_{i,t} = \alpha + \gamma^{\top} X_{i,t-1} + \delta^{\top} Z_{i,t-1} + \lambda_S + \lambda_P + \varepsilon_{i,t} \tag{1}$$

where $Y_{i,t}$ is either $\Delta\mathbb{E}$(Sales1Y) or Δ(R&D plans), while $X_{i,t-1}$ 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 (labeled Internationalization, Innovation, and R&D, respectively), as of January 2020.

Notice that because both timing and magnitude of the COVID-19 shock, not to mention its very existence, were totally unexpected when firms chose their strategies, these measures are all predetermined variables and, thus, can be regarded as orthogonal to the error term $\varepsilon_{i,t}$. We also include an extensive set of fixed effects (λ_S and λ_P) for firms' belonging sector (88 2-digit classes) and geographical province (107 NUTS-3 areas) 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.[12] Note that granular controls for sectorial components also allow accounting for most of the variation in firms' capability of teleworking, which clearly affected the magnitude of the shock experienced (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. We also add the level of expectations reported in the 2019-wave ($\mathbb{E}_{t-1}$(Sales1Y)) to allow for path dependence in

[12] 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-digits level perfectly accounting for this issue. This last piece of data is from official registry (*Registro Imprese della Camera di Commercio*) and available in the AIDA Bureau van Dijk dataset.

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).

Depending on the specification, Equation 1 is estimated cross-sectionally via OLS, ordered logistic, or multinomial logistic models, with standard errors clustered at the province level to allow for correlation along the differential exposure to the pandemic. For R&D plans, we also make use of logit models on dummy measures that separately capture the disruption of R&D or the introduction of new plans (estimated with logistic models). To assuage concerns about possible endogenous selection issues in the COVID-survey, we estimate models by employing post-stratification weights that are specifically calibrated to reproduce known aggregates of the population (Solon et al., 2015). However, our results are qualitatively similar if we adopt unweighted regressions instead. Finally, notice that the use of a differenced dependent variable allows for purging our estimates from all factors that may persistently affect a firm's answer.[13] Other potential issues of the analysis are discussed in Section A5 of the online appendix and are tackled with a large set of robustness checks (in Section 5.5).

4.2 Simultaneous equations model

In order to disentangle the effect of deteriorating demand conditions from a differential reaction to uncertainty shocks, we move to an integrated framework that accounts for the simultaneity between R&D choices and firms' expectations. To this purpose, we rely on the following simultaneous-equation model:

$$\begin{cases} \text{eq2a}: \ \Delta(\text{R\&D plans}) = & \alpha_1 + \omega\Delta\mathbb{E}(\text{Sales1Y}) + \gamma_1^\top X_{i,t-1} + \delta_1^\top Z_{i,t-1} + \lambda_S + \lambda_P + \varepsilon_{i,t}^1 \\ \text{eq2b}: \ \Delta\mathbb{E}(\text{Sales1Y}) \ = & \alpha_2 + \beta\mathbb{E}(\text{Sales1Y})_{i,t-1} + \gamma_2^\top X_{i,t-1} + \delta_2^\top Z_{i,t-1} + \lambda_S + \lambda_P + \varepsilon_{i,t}^2 \end{cases} \quad (2)$$

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 expectations 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

[13] For instance, R&D plans may entail possible inaccuracies and respondents' biases. Since there is an exact correspondence of the questions in the 2019-wave and COVID-survey, any misinterpretation should be time-invariant so that taking first differences takes care of this 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.

affecting both dependent variables (see, for instance, Greene, 2012).[14]

Because we are interested in testing some predictions of real options theories, we also explore additional heterogeneities along specific features of the innovation process. We enrich System 2 with an extensive set of additional regressors that are somewhat correlated with the sunk costs already in place: R&D Expenditure (expenditure in R&D as a share of total turnover), In-house R&D (share of R&D that is internal to the company; i.e., not outsourced), New vs. Persistent R&D (dummies for companies that started R&D investments only in 2019 or have a long-lasting involvement in research activities), 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 and 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 $\Delta\mathbb{E}$(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 allegedly arise from a differential reaction to the general increase in uncertainty (common effects are absorbed by the constant).[15]

5 Results

This section presents the results of the paper. First, we discuss some general patterns in the perceived shock at the onset of the crisis and firms' disruption in future R&D investments. We then move to a joint analysis that allows for distinguishing effects on R&D plans that are driven by worsening expectations from those that arise from a differential sensitivity to uncertainty shocks. Finally, we explore heterogeneities along characteristics of past innovative investments and test some implications of real options theories.

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.

[14] 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.

[15] 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.

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 in the online appendix, or Frenz and Ietto-Gillies, 2009), the first phases of the COVID-19 turmoil seem to be characterized by stronger 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. When forming their expectations, internationalized firms were just experiencing the two largest export shocks in recent history (an aggregate fall of -17% in March, followed by an additional -35% in April), and there were substantial concerns about neo-protectionist policies, shipping costs, the possibility of re-shoring, as well as the very future of global networks. Note that the economic context is also very different from the one in the Great Recession, wherein the strong 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.[16] In Section A3 of the online appendix, we further discuss the information set available at the time of the survey and provide additional evidence on the experience of innovative and internationalized companies.

On the bright side, firms involved in R&D activities are found to be somewhat less pessimistic, possibly because their expectations internalize higher flexibility or superior ICT skills alleviating the short-run effects of the lockdown.[17] 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 (estimates of $\mathbb{E}_{t-1}$(Sales1Y) in columns 1 and 3), paired with a stronger worsening for companies that entered the pandemic with better prospects (in 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 in this first stage of the crisis.

Results are largely consistent if we employ continuous measures of revision based on the COVID-survey. The estimates in columns 5 and 6 confirm the 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.[18] The effect of past

[16] Consistently with this argumentation, Table A4 of the online appendix shows that innovative companies are mainly concerned about the need of product diversification, which can be seen as a strategy to edge against adverse demand shocks.

[17] 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.

[18] This result is not linked to specific classes of expectations. We tested conditional effects by interacting firms' innovativeness

R&D is, instead, muted in these specifications.

Before moving to the analysis of 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.

[Table 3 approximately here]

5.2 Revision in R&D plans

As a preliminary analysis, we disregard the role of expectations and explore average patterns in the persistence of R&D plans after the COVID-19 shock. Columns 1 and 2 of Table 4 report marginal effects of logit models on two dummies for the cancelation of preexisting projects or the start of new investments between January and March 2020. Columns 3-to-5 replicate the analysis employing multinomial logistic estimators on the raw differenced variable (Δ(R&D plans)).

The contraction of preexisting research plans (44%, as documented in Section 3.2) is found to be extremely heterogeneous across companies, with internationalized and innovative firms that display a significantly higher probability of canceling R&D projects that were already scheduled in January 2020 (-3.3% and -7.3%, respectively). Similarly, past R&D activities are associated with an 8.5%-higher likelihood of disruption.[19] As for firms' innovativeness, such effect is also paired with a greater probability of implementing new plans as a reaction to the crisis (+1.9%). These last two pieces of evidence hide significant heterogeneities in firms' innovative strategies that are carefully discussed in the following sections.[20]

[Table 4 approximately here]

Although these results are informative about some general patterns in the pandemic crisis, they combine two overlapping effects that are worth disentangling. On the one hand, companies have been exposed

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 A3 in the online appendix).

[19] Notice that the negative effect of past R&D on the cancellation of preexisting plans is not surprising, as it is mechanically induced by the correlation between existent R&D and future plans. Indeed, in order to dismantle R&D projects firms needed to enter the pandemic with active research plans that, as we showed in Section 3.4, are positively correlated with past R&D.

[20] Other estimates are in line with prior expectations, entailing a stronger disruption of R&D plans for smaller and younger companies, or firms with lower levels of human capital (as proxied by the share of graduated employees).

to heterogeneous shocks at the onset of the COVID-19 outbreak; these are likely to be reflected in their expected market conditions and to affect R&D choices through the expectation-investment channel. On the other hand, the very characteristics of firms' innovative process may entail a differential reaction to the uncertainty shock, which would uncover some testable implications for real options theories. In order to shed light on these issues, we move to a joint estimation of R&D and expectations through the SUR model outlined in Equation 2.

Column 2 of Table 5 presents the estimates for the revision in firms' expected sales, which largely confirm the significantly more pessimistic expectations for internationalized and innovative companies.[21] The associated results on R&D plans (Equation 2a) are reported in column 1. First of all, notice that the estimate for $\Delta\mathbb{E}$(Sales1Y) is very positive and significant, highlighting a detrimental effect of firms' short-run expectations on R&D plans. Such novel finding is largely consistent with the literature on firms' beliefs and physical investments. Most importantly, it emphasizes how even transitory shocks can have long-run effects through their impact on a company's current decisions. This channel explains a sizable component of the R&D disruption of innovative and internationalized firms documented in Table 4. The extent of this indirect effect (i.e., pass-through) is established in column 3, wherein we report the p-value of a non-linear multi-equation test, under the null hypothesis $[\text{eq2b}]\beta_X \times [\text{eq2a}]\beta_{\Delta\mathbb{E}(Sales1Y)} = 0$. We reject the null at the 5% and 1% levels for internationalization and innovation, respectively.

As for the remaining regressors, internationalization strategies have no longer a role for firms' R&D choices once accounting for their revision in expected sales. As such, the overall negative effect seems to be entirely driven by the pass-through channel and their worse expectations about future performances.[22] 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 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. In the following sections, we discuss how this effect varies along characteristics of the innovation process and test some implications of real options theories.

[21]Notice that past (actual) R&D is no longer associated with better expectations if we account for third-party factors simultaneously affecting firms' beliefs and research plans.

[22]In Table A7 of the online appendix, we explored additional heterogeneities across the different modes of internationalization. Our results show that exporting firms experienced substantially worse expectation revisions on future sales, while import strategies are found to be largely insignificant. As for more complex forms of internationalization, we find negative and significant effects especially for foreign direct investments and commercial agreements. Consistently with our main finding, all of the effects are only operating through the revision in firms' expectations, while we find no significant reaction to the general uncertainty shock.

Notice that, an alternative explanation for our results may be linked with a larger sensitivity to the same shock on expected sales. Column 4 explicitly tests for this channel by introducing a set of interaction terms between each strategy and the revision in firms' expectations (only interaction terms are reported). The insignificance of the interacted coefficients suggests this is not the case.

[Table 5 approximately here]

5.3 Heterogeneity by R&D characteristics

The very features of the innovative process can underly significant heterogeneities in a company's reaction to unexpected shocks. In order to explore this issue, we enrich our baseline specifications with a set of measures capturing more granular characteristics of firms' past R&D activities, which are likely correlated with the sunk costs of the investments already in place. Columns 1 and 2 of Table 6 present their overall contribution to the disruption of R&D plans or the introduction of new projects (as done in Table 4), while columns 3-to-6 report SUR estimates to disentangle uncertainty shocks from pass-through effects of expectations (as in Table 5).[23]

In panel A, we allow the impact of past R&D to vary along its intensive margins. Results show that sizable past expenditures in research activities are associated with higher probabilities of introducing new R&D investments. This is despite the average negative effect of R&D documented in the previous section. 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).[24] Similarly, the share of R&D performed in-house (in panel B) entails a substantial increase in firms' future plans, impacting both the probability of canceling preexisting projects and of implementing new ones (respectively -5.7% and +3.9% at the 90th percentile). Importantly, SUR estimates indicate that such effects are not driven by heterogeneous demand shocks (as suggested by the insignificance in column 4), but are rather due to a differential response to the general uncertainty (significant in column 3).

Because unrecoverable costs of R&D are increasing with the knowledge accumulation process, the persistence of past activities may also have a sizable impact on firms' choices. While no precise information on the duration of the performed R&D is available, we can exploit previous waves of the MET survey to recover the existence of R&D programs in the past, which clearly correlates with it. Coherently with previous argumentations, firms that started R&D investments only in 2019 (New R&D), have a probability of

[23] For expositional purposes, we only present the main coefficients of interest (other estimates follow the baseline specifications in the original tables).

[24] Such estimates are derived by applying the marginal effect (0.96%) to the values of the specific percentiles (3.13 and 9.38 units of standard deviations, respectively).

abandoning preexisting projects that is significantly higher than companies with persistent involvement in research activities.[25] Compared to a long-lasting tradition of R&D, firms switching to innovative investments have a 5.7%-higher likelihood of canceling R&D plans, as shown in panel C. Once again, this effect is not driven by heterogeneous expectations about the future.

[Table 6 approximately here]

5.4 Heterogeneity by characteristics of the innovation process

Table 7 turns the attention to additional characteristics of the firms' innovation process. In panel A, we provide a breakdown by product and process innovations. While the former are found to increase the probability of R&D disruption by 3.7-percentage points, process innovations are not linked to any change in firms' research strategies. Noticeably, these effects are not due 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 to changes in expected sales, as emphasized by the positive interaction coefficient in column 5.

Notice, however, that the effect on product innovations is not increasing with the stream of sales generated by radical or imitative goods (in panel B). If any, firms whose overall turnover was mainly coming from truly innovative products seem to be more inclined to introduce new R&D plans.[26] Despite their worse expectations in column 4, such firms reacted to the general uncertainty by even increasing their research effort. This is, again, pointing at the very nature of some great innovators who are inherently projected towards such activities even in times of turmoil.

Finally, panels C and D 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.[27] While both types of firms experience a reduction in their planned research activities, new innovators have a 5.7%-higher probability of abandoning preexisting projects compared to firms that innovated persistently in the past. This is true despite their more favorable demand prospects in column 4. Persistent innovators also display a reduced sensitivity to expectations (column 5) and a somewhat higher probability of starting new

[25] 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.

[26] 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.

[27] Definitions are symmetric to "New R&D" and "Persistent R&D" in Footnote 25.

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 (an alternative proxy for firms' innovativeness; as in Geroski et al. 1997; Cefis and Orsenigo 2001) shows a 10%-lower probability of R&D disruption when strong appropriability conditions are in place.

[Table 7 approximately here]

5.5 Robustness

We performed a number of robustness checks to test the validity of our results on both expected sales and R&D plans. 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 at the 6-digits level according to the Italian government's decree on 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. We also have similar results when employing matching techniques (Nearest Neighbor and Coarsened Exact Matching) to further control for confounding factors.[28] Moreover, our main findings are qualitatively similar if we disregard endogenous sampling and use unweighted regressions instead of post-stratification weighted models. Finally, we find consistent results even if we employ a more restrictive definition of disruption and disregard companies with no actual investment in R&D (Table A8 of the online appendix).

6 Discussion and concluding remarks

This paper takes advantage of a unique dataset centered around the COVID-19 outbreak to explore the determinants of firms' R&D choices in the aftermath of an exogenous event. Differently from the existing literature, we focus on plans and expectations, rather than realized variables, because they react immediately to shocks and allow for a short-window identification that bypasses endogeneity issues. The analysis uncovers novel evidence about firms' research plans and tests implications of real options theories from a different angle.

Our results highlight two main dimensions driving R&D choices at the onset of the COVID-19 crisis. The first one has to do with firms' own expectations about market conditions, whereby the revised views on

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

future sales (i.e., worse/better expectations) are found to have a detrimental effect on research investments. This finding confirms their critical role in the comparison of expected returns and the evaluation of the risks associated with the innovative process. Even though this is not surprising per se, it represents an important contribution to the literature on expectations, which has mainly focused on physical capital and labor decisions, while largely neglecting the effect on R&D.

In this regard, the pandemic outbreak induced a substantial disruption of research plans of internationalized and innovative companies, which was linked with their significantly worse expectations in the short run. This evidence reflects the first stages of the current crisis, which reverberated through international linkages and raised doubts about the returns from preexisting innovations, possibly for the fear of a permanent change in consumption habits (Bertola et al., 2005).[29] Such effect was particularly severe for radical product innovations, confirming the importance of demand-side factors for innovation-related turnover (Piva and Vivarelli, 2007; Crespi and Pianta, 2008).

The second dimension goes over and beyond the role of expectations and operates, instead, through a differential response to the general uncertainty brought by the pandemic. In this respect, two broad patterns emerge. On the one hand, there is a small set of persistent innovators whose long-term commitment –based on sizable past expenditure in in-house R&D– makes them less sensitive to uncertain environments. These firms are inherently oriented to innovations and seem to display higher resilience and capacity of adaptation to major changes. Some of them even increased their innovative effort in the aftermath of the COVID-19 outbreak. On the extreme opposite, the pandemic particularly affected firms that were transitioning toward a more structured way of innovating. Companies that were in the process of upgrading to innovative strategies (i.e., new innovators) have a substantially higher probability of canceling 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 marginal gains from innovation.

Most of these results closely speak to the main argumentations in real options theories. The underlying idea is that, by increasing firms' incentives to wait for new information, uncertainty should lead to a postponement in investment decisions about irreversible capital. This is largely consistent with the general reduction of new R&D projects documented in the immediate aftermath of the COVID-19 event. However, predictions also entail a more general cautionary investment behavior, whereby large uncertainty about the near future should reduce the probability of dismantling old projects. As we focus on research plans that

[29] A thorough discussion on this is provided in Section A3 of the online appendix. Notice that this finding may also be consistent with the arguments in Coibion et al. (2018) and Tanaka et al. (2020), whereby the fiercer competition faced by internationalized and innovative firms can make them more sensitive to the business cycle and induce faster adjustments in their expectations.

may be linked to a broader preexisting stock of innovative capital, we test these theories from a novel angle and ask whether the sunk costs attached to past investments imply a reduced sensitivity of R&D to an uncertainty shock.

Overall, the higher persistence of R&D plans for companies with sizable and long-lasting in-house R&D is broadly in line with such a prediction. In fact, the existence of R&D departments within the firm represents a long-term commitment to innovation, which is increasing with the size of the investment already in place. In other words, the lower cumulativeness of technological change for external forms of research (Malerba and Orsenigo, 1995, Breschi et al., 2000) entails smaller sunk costs attached to R&D outsourcing, which make it easier to be cut in times of uncertainty. Taken together, our results show that firms with substantial involvement in innovative activities tend to postpone changes in their research strategies due to the irreversibility of preexisting investments. This is somewhat consistent with the general message of Ghosal and Loungani (2000) and Bloom et al. (2007) on tangible capital.[30]

Despite this broad coherence, our analysis also highlights effects that go beyond the main predictions of real options theories. Some features of the innovative process are found not only to reduce the sensitivity of R&D to uncertainty but even to increase a firm's research effort as a response to an adverse shock. This is the case for companies with substantial past investments in R&D and that heavily depend on cutting-edge (radical) innovations for their overall revenues. To the extent that such firms operate in markets with more intense strategic competition, this evidence reminds of the argumentation in Kulatilaka and Perotti (1998), whereby uncertainty not only increases risk but also has a positive effect on growth opportunities. The possibility to conquer a strategic advantage in the future may then explain the positive relationship between uncertainty and research investments.

More in general, both R&D expenditure and reliance on radical innovations are also likely to capture the very way firms envisage their own innovative propensity. For such companies, the competitive advantage is rooted in the generation and upgrading of new knowledge so that R&D is considered an innate mission. As such, they invest continuously in innovation irrespectively of the business cycle (Dosi, 1982; Nelson and Winter, 1982; Antonelli, 1997) and are inherently oriented towards R&D activities even in times of turmoil (Pavitt et al., 1989; Patel and Pavitt, 1994).

Finally, it is worth reminding that the strength of our approach based on short-run 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 regarded as accurate forecasts on the evolution of future performances. In other words, despite internationalized and innovative companies

[30] A similar dynamic is found if we employ patents as an alternative proxy for firms' innovativeness. This is, again, somewhat in line with the evidence in Czarnitzki and Toole (2011) who point at a mitigating effect in the uncertainty-investment relationships.

experienced the largest shocks at the onset of the crisis, they are also likely to be the ones that better adapt to the fast-evolving scenario. Based on past experience, this is likely to happen in the long run. However, in the meantime, we showed that transitory shocks on expectations can still have long-run implications through their effect on firms' current research choices. This issue should be central in a policy perspective because of its impact on the competitiveness of the entire industrial system and of the possible undesirable selection mechanisms at stake.

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, subsequent waves 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 period considered does not allow for fully capturing other potential entrants that may take advantage of new opportunities. The final shape of the industrial system and its overall competitiveness largely depend on such recomposition effects. These issues require information over a longer time span and are part of our research agenda, but they are left for future analyses.

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7 Figures

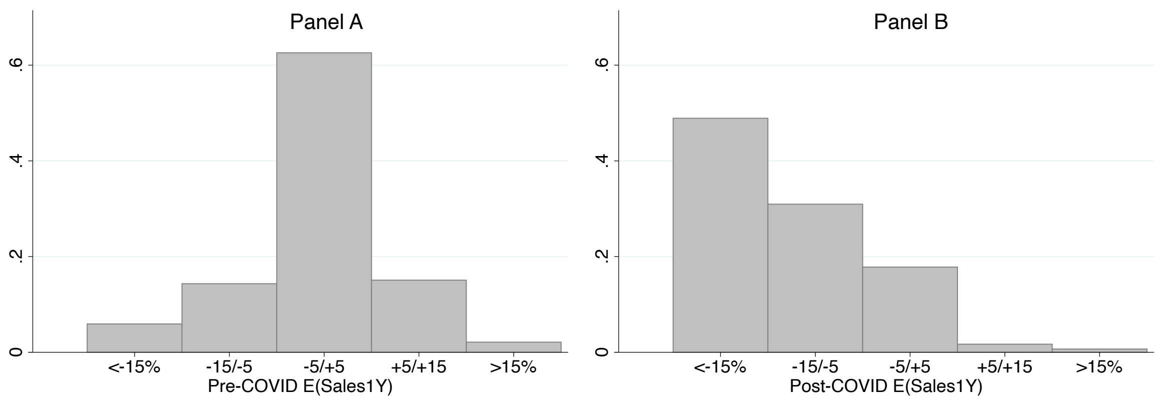

Figure 1: Revision in expected future sales.

Notes: distributions of pre- and post-COVID expectations on sales growth at a one-year horizon. Panel A displays firms' weighted forecasts as of January 2020, while panel B reports the updated expectations in the aftermath of the pandemic outbreak.

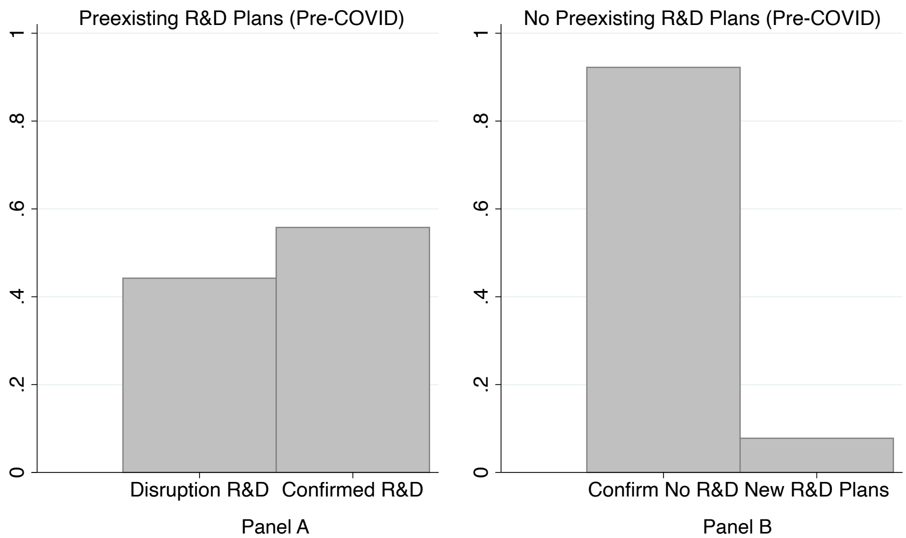

Figure 2: Revision in R&D plans.

Notes: change in R&D plans around the pandemic outbreak. Panel A focuses on companies that, in January 2020, declared expenditures in R&D scheduled for the following year. It presents the conditional distribution of firms confirming (Confirmed) or canceling (Disruption) preexisting R&D plans in April. Panel B focuses on companies without R&D plans in January. It displays the share of firms that confirmed their choices (No R&D) or scheduled new R&D expenditures (New R&D Plans).

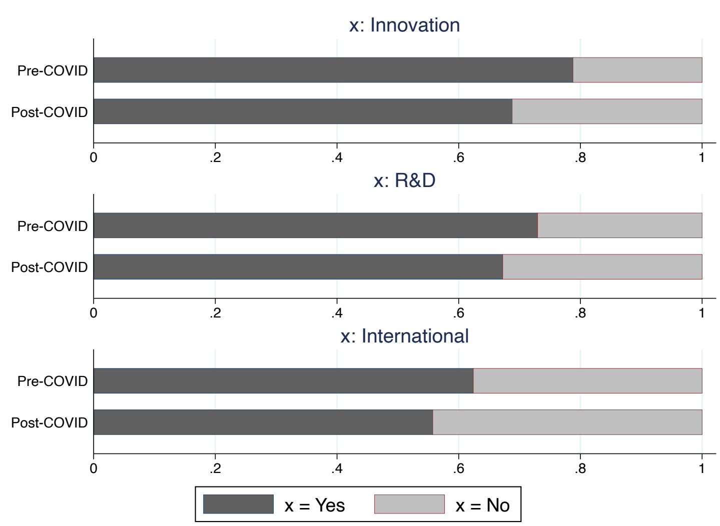

Figure 3: Composition of R&D plans by innovation, past R&D, and internationalization.

Notes: distribution of R&D plans by 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 all R&D plans within the period (pre- vs. post-COVID in the left axis).

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 by 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.
Δ(R&D plans)	Ordinal	-0.046	0.399	-1.000	1.000	7800
Disruption	Dummy	0.103	0.305	0.000	1.000	7800
New plans	Dummy	0.057	0.233	0.000	1.000	7800
$\Delta\mathbb{E}$(Sales1Y)	Ordinal	-1.189	1.046	-4.000	4.000	7800
$\mathbb{E}_{t-1}$(Sales1Y)	Ordinal	2.931	0.781	1.000	5.000	7800
$\Delta\mathbb{E}^R$(Sales3M)	Continuous	-0.240	0.290	-1.000	2.000	7800
$\Delta\mathbb{E}^R$(Sales12M)	Continuous	-0.193	0.235	-1.000	1.800	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
In-house R&D	Bounded	0.205	0.381	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)	$\Delta\mathbb{E}$(Sales1Y)	$\mathbb{E}_t$(Sales1Y)	$\Delta\mathbb{E}$(Sales1Y)	$\Delta\mathbb{E}^R$(Sales3M)	$\Delta\mathbb{E}^R$(Sales12M)
	(1)	(2)	(3)	(4)	(5)	(6)
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]
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]
$\mathbb{E}_{t-1}$(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 digits) 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 ($\Delta\mathbb{E}$(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 ($\Delta\mathbb{E}^R$(Sales3M) and $\Delta\mathbb{E}^R$(Sales12M), respectively). Unreported additional controls (mostly insignificant): PC Financial, Investment, Corporate Group, Group Headquarter, Family Firm, Past Sales Growth, 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) Δ(R&D plans) No change (0)	(5) New Plans (+1)
Innovation	0.0719***	0.0210**	0.0710***	-0.0913***	0.0203**
	[0.0148]	[0.00889]	[0.0150]	[0.0156]	[0.00883]
Internationalized	0.0379***	0.00945	0.0379**	-0.0472***	0.00938
	[0.0144]	[0.00897]	[0.0154]	[0.0163]	[0.00896]
R&D	0.0828***	0.00774	0.0835***	-0.0915***	0.00808
	[0.0147]	[0.00888]	[0.0155]	[0.0164]	[0.00884]
Size	-0.0228***	0.000366	-0.0229***	0.0224***	0.000487
	[0.00479]	[0.00262]	[0.00468]	[0.00489]	[0.00262]
Age	-0.0141*	-0.00827*	-0.0143*	0.0227***	-0.00839*
	[0.00735]	[0.00439]	[0.00772]	[0.00816]	[0.00438]
Province FE	yes	yes		yes	
Industry (2 digits) 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 in columns 3-to-5 is the variation in firms' R&D plans between January and March 2020 (see Section 3.2). Δ(R&D plans) takes 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 scheduled investments in R&D. Columns 1 and 2 employ dummy measures separately identifying the disruption or the start of R&D projects as alternative dependent variables. In this explorative set of results, we do not allow for a role of firms' expectation revisions, which will be later accounted for in a SUR framework (Tables 5, 6, and 7). Unreported additional controls (mostly insignificant): PC Financial, Investment, Corporate Group, Group Headquarter, Family Firm, Past Sales Growth, Labor Productivity, and Vertical Integration. 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 2a: Δ(R&D plans)	(2) Equation 2b: $\Delta\mathbb{E}$(Sales1Y)	(3) Pass-through (p-value)	(4) Interacted coeff. in Equation 2a
Innovation	-0.0458**	-0.151***	(0.001)	-0.0237
	[0.0185]	[0.0348]		[0.0168]
Internationalized	-0.0105	-0.113***	(0.006)	-0.00570
	[0.0195]	[0.0350]		[0.0161]
R&D	-0.0694***	-0.0460	(0.229)	0.00384
	[0.0198]	[0.0372]		[0.0177]
$\Delta\mathbb{E}$(Sales1Y)	0.0376***			
	[0.00741]			
Province FE	yes	yes		yes
Industry (2 digits) FE	yes	yes		yes
Estimator		SUR		SUR
R2	0.1331	0.1182		0.1336
N obs.		5070		5070

Notes: Seemingly-Unrelated Regression (SUR) models. The dependent variable in column 1 (Equation 2a) is the change in firms' R&D plans between January and March 2020 (Δ(R&D plans)), while in column 2 (Equation 2b) is the revision in firms' expectations as captured by the difference between post- and pre-COVID measures ($\Delta\mathbb{E}$(Sales1Y)). Column 3 tests the significance of the indirect effect of each regressor on R&D plans passing through the revision in firms' expectations. In parentheses, we report the p-values of a χ-test under the null hypothesis [eq2b]β_X × [eq2a]$\beta_{\Delta\mathbb{E}(Sales1Y)} = 0$. Column 4 explores differential sensitivities to expected demand shocks by enriching Equation 2a (of column 1) with a set of interaction terms $X_{t-1} \times \Delta\mathbb{E}$(Sales1Y) for each measure in X (R&D, Innovation, Internationalized). Only 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 4. Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table 6: Heterogeneity by R&D characteristics.

	(1) Disruption	(2) New Plans	(3) Equation 2a: Δ(R&D plans)	(4) Equation 2b: $\Delta\mathbb{E}$(Sales1Y)	(5) Pass-through (p-value)	(6) Interacted coeff. in Equation 2a
Panel A						
R&D Expenditure	-0.127	0.103**	0.251**	-0.274	(0.198)	0.157
	[0.0853]	[0.0413]	[0.109]	[0.206]		[0.158]
Panel B						
In-house R&D	-0.192*	0.0899**	0.359***	-0.287	(0.246)	-0.101
	[0.100]	[0.0449]	[0.129]	[0.243]		[0.097]
Panel C						
New R&D	0.123***	-0.000802	-0.135***	-0.00906	(0.879)	0.0192
	[0.0264]	[0.0154]	[0.0313]	[0.0598]		[0.0274]
Persistent R&D	0.0331*	0.000390	-0.0324	-0.0247	(0.585)	-0.0178
	[0.0183]	[0.0115]	[0.0238]	[0.0449]		[0.0186]
Province FE	yes	yes	yes	yes	–	yes
Industry (2 digits) FE	yes	yes	yes	yes	–	yes
Estimator	Logit	Logit		SUR		SUR
N obs.	5070	5070		5070		5070

Notes: Logistic marginal effects and Seemingly-Unrelated Regression (SUR) models. The dependent variables in columns 1 and 2 are dummy measures separately identifying the disruption or the start of R&D projects, as in Table 4. In column 3 (Equation 2a of the SUR), it is the raw change in firms' R&D plans (Δ(R&D plans)), while column 4 (Equation 2b of the SUR) concerns the revision in firms' expectations ($\Delta\mathbb{E}$(Sales1Y)). Column 5 tests the significance of the indirect effect of each regressor on R&D plans passing through the revision in firms' expectations. In parentheses, we report the p-values of a χ-test under the null hypothesis $[eq2b]\beta_X \times [eq2a]\beta_{\Delta\mathbb{E}(Sales1Y)} = 0$. As in Table 5, column 6 reports interaction coefficients testing differential sensitivities to expected demand shocks. 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.

Table 7: Heterogeneity by characteristics of past innovations.

	(1) Disruption	(2) New Plans	(3) Equation 2a: Δ(R&D plans)	(4) Equation 2b: $\Delta\mathbb{E}$(Sales1Y)	(5) Pass-through (p-value)	(6) Interacted coeff. in Equation 2a
Panel A						
Product Innovation	0.0456***	0.0230**	-0.0170	-0.194***	(0.000)	-0.053*
	[0.0151]	[0.00945]	[0.0190]	[0.0357]		[0.0272]
Process Innovation	0.0228	0.00427	-0.0170	0.00561	(0.875)	-0.00466
	[0.0145]	[0.00956]	[0.0189]	[0.0356]		[0.0165]
Panel B						
Sales Radical Inn.	-0.0108	0.0508***	0.0945*	-0.289***	(0.007)	0.0466
	[0.0390]	[0.0197]	[0.0489]	[0.0926]		[0.0754]
Sales Imitative Inn.	0.0446	-0.0179	-0.0441	-0.152	(0.119)	-0.0789
	[0.0367]	[0.0243]	[0.0492]	[0.0933]		[0.0744]
Panel C						
New Innovation	0.0994***	0.0159	-0.0815***	-0.136***	(0.007)	-0.0129
	[0.0190]	[0.0112]	[0.0228]	[0.0437]		[0.0201]
Persistent Innovation	0.0539***	0.0238**	-0.0220	-0.163***	(0.001)	-0.0231
	[0.0191]	[0.00932]	[0.0217]	[0.0413]		[0.0173]
Panel D						
Patents	-0.0934***	0.000152	0.0883**	0.0685	(0.318)	0.008185
	[0.0288]	[0.0147]	[0.0357]	[0.0672]		[0.0288]
Province FE	yes	yes	yes	yes		yes
Industry (2 digits) FE	yes	yes	yes	yes		yes
Estimator	Logit	Logit		SUR		SUR
N obs.	5070	5070		5070		5070

Notes: Logistic marginal effects and Seemingly-Unrelated Regression (SUR) models. The dependent variables in columns 1 and 2 are dummy measures separately identifying the disruption or the start of R&D projects, as in Table 4. In column 3 (Equation 2a of the SUR), it is the raw change in firms' R&D plans (Δ(R&D plans)), while column 4 (Equation 2b of the SUR) concerns the revision in firms' expectations ($\Delta\mathbb{E}$(Sales1Y)). Column 5 tests the significance of the indirect effect of each regressor on R&D plans passing through the revision in firms' expectations. In parentheses, we report the p-values of a χ-test under the null hypothesis $[eq2b]\beta_X \times [eq2a]\beta_{\Delta\mathbb{E}(Sales1Y)} = 0$. As in Table 5, column 6 reports interaction coefficients testing differential sensitivities to expected demand shocks. 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: Variables

Variable name	Description
Δ(R&D plans)	Difference between post- and pre-COVID-19 dummies for the existence of R&D expenditures scheduled for the next year.
Disruption	Dummy for firms reporting the existence of R&D plans in January 2020 and no scheduled R&D expenditure in March.
New plans	Dummy for firms reporting no R&D plan in January 2020 and with positive R&D expenditure scheduled in March.
$\mathbb{E}_t$(Sales1Y)	Post-COVID expected sales growth on a one-year horizon.
$\mathbb{E}_{t-1}$(Sales1Y)	Pre-COVID expected sales growth on a one-year horizon.
$\Delta\mathbb{E}$(Sales1Y)	Difference between firms' expected sales growth on a one-year horizon [$\mathbb{E}_t$(Sales1Y) $-$ $\mathbb{E}_{t-1}$(Sales1Y)].
R&D	Dummy for the existence of active R&D projects, as of January 2020.
R&D Expenditure	Overall expenditure in R&D activities as a share of total sales.
In-house R&D	Share of R&D that is performed internally to the firm (i.e., not outsourced to other firms, universities, labs, etc.).
New R&D	Dummy for companies that recently started (in the 2019-wave) R&D activities.
Persistent R&D	Dummy for companies persistently involved in R&D.
Innovation	Dummy for the introduction of any type of innovations, as of January 2020.
Product Innovation	Dummy for the introduction of product innovations, as of January 2020.
Process Innovation	Dummy for the introduction of process innovations, as of January 2020.
Sales Radical Inn.	Share of sales from product innovations that are new to the firm and to the market.
Sales Imitative Inn.	Share of sales from product innovations that are new to the firm but not to the market.
New Innovation	Dummy for newly innovative companies (in the 2019-wave).
Persistent Innovation	Dummy for companies that innovate continuously.
Patents	Dummy for patent-holding companies (independently of the number of patents).
Internationalization	Dummy for internationalized companies, as of January 2020.
Leverage	Total debts to equity ratio.
Tangible Assets	Fixed assets to total assets ratio.
Rollover Risk	Short-term debt to long-term debt ratio.
PC Financial	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 total variance.
Size	log of (total assets).
Age	log of (1 + age).
Group	Dummy for firms belonging to corporate groups, as of January 2020.
Headquarter	Dummy for the headquarter of to corporate group, as of January 2020.
Family Firm	Dummy for family-owned firms, as of January 2020.
Investment	Dummy for firms that undertook investments, as of January 2020.
% Graduated Empl.	Share of graduated employees, as of January 2020.
Labor Productivity	Log value added per worker.
Vertical Integration	Value-added to sales ratio.

Notes: Variable definitions and original questions are provided in Section A2 of the online appendix.

Online Appendix

A1 Sampling of the MET survey

The MET survey is the widest private survey administrated in a single European country and it is specifically conceived to study Italian firms' characteristics and strategies, with particular attention to their innovative behavior, internationalization processes, and performance. The original sample comprises seven waves – 2008, 2009, 2011, 2013, 2015, 2017, and 2019 – and roughly 24,000 firm-level observations in each cross-section. The sample follows a disproportionate Bayesian scheme and its large sample size allows for representativeness along three different dimensions: four size classes, 12 ATECO sectoral sub-sections, and 20 geographical regions (at the NUTS2 level). The population of interest of the MET survey refers to enterprises belonging to all the size classes (1-9 employees, 10-49, 50-249, 250 and above) operating within the manufacturing (construction excluded) and production services sectors.[31]

Starting from the 2009-wave, the disproportionate sampling scheme employs Bayesian techniques so as to increase the precision of the estimates regarding R&D, innovation, and internationalization strategies, which are the core of the survey. Exploiting information from the previous waves, these techniques draw on a tree-based classification model to detect those strata (intersection of 20 regions, 12 2-digits sectors, and four size classes) with the larger diffusion of such activities. This procedure allows for a better understanding of the phenomena under study but requires further constraints that lead to an oversampling of the targeted strata.

The oversampling of unfrequent phenomena (larger and more innovative companies) is offset by the use of sampling weights that reproduce the population of interest. The weighting system is calibrated ex-post (by expert statisticians) to perfectly replicate the number of companies in the specific stratum and in the aggregate, as well as to reproduce total value-added, employment, and total sales.[32] Overall, the use of post-stratification weights re-proportionates the sample into the population of interest and allows to deal with the possible sample bias following from the (non-random) missing responses' distribution (both in the 2019-wave and in the COVID-19 survey).[33]

Throughout the paper, we make use of specific post-stratification weights calibrated on the set of re-

[31] The sampling design follows 12 aggregated 2-digits sectors: Food, Textile, Furniture, Printing and Publishing, Chemical, Machinery, Transportation, Engineering, Electric, and Mineral, for the manufacturing sector, and two production service sectors for distributive trades, transportation, and storage services, or information, communication services, administrative and support service activities.

[32] The set of auxiliary information is drawn from the population of interest and constitutes an additional binding constraint that the final sample has to reproduce. All the constraints are drawn from ISTAT Italian Statistical Business Register (ASIA) while the calibration procedure makes use of an ad-hoc iterative algorithm.

[33] For further information on the sampling methodology, see `https://www.met-economia.it/indagini-met/note-metodologiche/`

spondents to the COVID-19 survey. This allows dealing with endogenous sampling issues (as discussed in Sections 4 and 5) and is critical for presenting descriptive evidence that reflects the aggregate dynamics.[34]

A2 The MET questionnaire

Before moving to the extensive set of robustness checks performed, it is worth providing full details on the exact questions underlying the different measures employed in the analysis (part of the broader questionnaires of the COVID-19 survey and 2019-wave of the MET survey). For expositional purposes, we follow the order in Table 2.

1. $\mathbb{E}_t(\textbf{Sales1Y})$: post-COVID expected sales at a one-year horizon.

   Firms were asked the following question in the COVID-19 questionnaire (March-April 2020):
   "As for the sales growth in the 2019-2020 period, does your firm expect it to be:"

   a. strongly decreasing (growth below -15%);

   b. decreasing (growth between -15% and -5%);

   c. roughly stable (growth between -5% and +5%);

   d. increasing (growth between +5% and +15%);

   e. strongly increasing (growth above +15%).

   One choice only was allowed.

   Note: $\Delta\mathbb{E}(\textbf{Sales1Y})$, our proxy for firms' expectations revision, is simply obtained by taking the difference between post- and pre-COVID expectations ($\mathbb{E}_t(\text{Sales1Y}) - \mathbb{E}(\text{Sales1Y})_{it-1}$)

2. **Δ(R&D plans), Disruption**, and **New plans** are constructed from the following question:
   "As of today, does your firm have any expenditure in Research and Development (R&D) scheduled for the next 12 months?". The question was paired with a note for the interviewed specifying that *"R&D comprises creative and systematic activities undertaken in order to increase a firm's stock of knowledge that can be used to create new products or design new production processes, as well as to devise new applications of the already available knowledge"*.
   A binary option was available: Yes/No.
   Again, the same question was made in both the 2019-wave (January 2020) and the COVID-19 survey (March/April 2020), delivering two dummy variables taking the value of 1 if the company declared to

[34] We also employ sampling weights in the econometric estimations, although our econometric strategy based on first differences should already account for this issue. Indeed, as shown in our robustness checks, our econometric results are virtually identical if we use sampling weights or not in the estimations.

have scheduled R&D investments at the time of the interview (Yes=1).

The difference, **Δ(R&D plans),** is an ordinal measure in the interval [-1,+1] which is directly used as a dependent variable in a multinomial logistic framework (Table 3, columns 3, 4, and 5), or in the estimation of simultaneous equation models. **Disruption** and **New plans** are the different categories associated with values of -1 and +1, respectively.

3. **$\Delta\mathbb{E}^R$(Sales3M)** and **$\Delta\mathbb{E}^R$(Sales12M)** are continuous measures capturing the revision in firms' expectations on sales growth for the following three and 12 months. They are both inferred from the following question in the COVID-19 survey:

   "Compared to the situation in January 2020, what is the effect of the pandemic on your firm's:

   a. *sales growth in the next three months;*

   b. *sales growth in the next 12 months.*"

   Firms were asked to specify an exact percentage change for every single measure, labeled $\Delta\mathbb{E}^R$(Sales3M) and $\Delta\mathbb{E}^R$(Sales12M), respectively. They are employed in our extensive set of robustness exercises.

4. **Perception**: set of dummy variables in the COVID-19 survey providing information on the managers' self-assessment about the perceived danger of the pandemic (not firm-specific). The questionnaire asked, *"What is the perception of the firm on the danger for the overall economy of the COVID-19 pandemic?".* The following answers were available (only one choice allowed):

   a. *not dangerous at all;*

   b. *dangerous but inflated by social media;*

   c. *very dangerous but of short duration;*

   d. *very dangerous with effects that will last for up to 12 months;*

   e. *very dangerous with long-run effects that will last for more than 18 months.*

   We constructed dummy variables for each choice (labeled accordingly) and employed them in our robustness checks.

5. R&D variables: measures related to investments in Research and Development that were already in place before the pandemic outbreak.

   Firms were asked the following question in the questionnaire of the 2019-wave (January 2020): *"In the last years, did your firm undertake investments in Research and Development (R&D)".*

Again, the question was paired with a note for the interviewed specifying that *"R&D comprises creative and systematic activities undertaken in order to increase a firm's stock of knowledge that can be used to create new products or design new production processes, as well as to devise new applications of the already available knowledge".*

A binary option was available: Yes/No. **R&D** is a dummy variable taking the value of 1 for the existence of already implemented R&D projects (answer=Yes).

If R&D= 1, firms are also asked the following questions:

5a. *"What is the overall expenditure in R&D as a share of firms' turnover?"*

5b. *"What is the share of R&D that is performed in-house?".* Note for the interviewed: *"In-house R&D is defined as the activity that is performed within the firm (i.e., it is not outsourced to different firms, universities, labs, or other entities)."*

In both cases, firms are allowed to specify the exact percentage value associated with each question (that is allowed to be even greater than 100% in 5a, while it is bounded in between 0-100 in 5b). **R&D Expenditure** is simply the answer to 5a (after substituting 0 for firms answering "No" to question 6), while **In-house R&D** is related to answer 5b.

6. Innovation variables: measures related to innovations that were already introduced before the pandemic outbreak.

Firms were asked the following question in the questionnaire of the 2019-wave:

"In the last years, did your firm introduce the following innovations?:

6a. *Radical product innovations.*

6b. *Marginal product innovations.*

6c. *Radical process innovations.*

6d. *Marginal process innovations.*

In each case, a binary option was available: Yes/No.

The question was paired with a note for the interviewed specifying that *"Radical Product innovations involve the introduction of a totally new product or service (or a substantial restyling). Marginal Product innovations involve the introduction of a significantly improved product or service. Radical Process innovations entail a significant change in the production process (e.g., development and introduction* *of a new production process). Marginal Process innovations are related to a marginal change in the production process."*

Innovation is a dummy variable for the introduction of product or process innovations (i.e., 6a=Yes, or 6b=Yes, or 6c=Yes, or 6d=Yes). **Product Innovation** is a dummy variable for the introduction of product innovations (i.e., 6a=Yes or 6b=Yes). **Process Innovation** is a dummy variable for the introduction of process innovations (i.e., 6c=Yes or 6d=Yes). From this information, we also construct **New Innovation** and **Persistent Innovation** by comparing Innovation in the 2019-wave (equal to one in both cases) with the same variable in the 2017 (or 2015) survey (equal to zero or one, respectively).

The questionnaire also asks the following question:

"Indicate the share of the overall sales that are coming from:

6e. *product innovations that are new both to the firm and to the market (i.e., there are no similar products available);*

6f. *product innovations that are new to the firm but preexisting in the market (i.e., there are already similar products made by other firms);*

6g. *traditional products for the company (i.e., non-innovative)."*

Firms are allowed to specify the exact percentage value associated with each question, with the constraint that 6e+6f+6g=100%.

This additional piece of information is employed to define **Sales Radical Inn.** and **Sales Imitative Inn.** as the answers to 6e and 6f, respectively.

7. **Patents** is a dummy identifying patent-holding companies coming from the following question:

   "In the last years, was your firm involved in patent licensing?".

   Again, a binary option was available: Yes/No.

- Miscellanea: the other variables employed refer to the 2019 questionnaire only:

  8. *"In the last years, did your firm perform economic activities abroad?".*

     The questionnaire allowed for further details on the form of internationalization (Direct Export/Indirect Export/Import/Joint venture/. . . ., all in the same format).

     Internationalized is a dummy taking the value of 1 if 8=Yes.

9 *"In what year was your firm born?"*

Firms were asked to specify the exact year of birth.

Age is defined as ln[1+T-Year], where T is the year of the survey (2019) and Year is the answer to question 9.

10a. *"Does your firm belong to a corporate group?"*

A binary option was available: Yes/No.

Group is a dummy taking the value of 1 for firms belonging to corporate groups (10a=Yes).

10b. If 10a=Yes, *"Is your firm the parent company of the group?"*

A binary option was available: Yes/No.

Headquarter is a dummy taking the value of 1 for the parent company of the group (10b=Yes).

11. *"Is the control of the firm in the hands of one person/family?"*

Note for the interviewed: *"For control, we mean the dominant influence on strategic choices"*.

A binary option was available: Yes/No.

Family Firm is a dummy variable for family-owned firms (11=Yes).

12. *"In the last years, did your firm perform investments in tangible or intangible assets?"* (Yes/No)

A binary option was available: Yes/No.

Investment is a dummy taking the value of 1 if the firm undertook investments (12=Yes).

13a. *"How many employees does your firm have?"*

Firms are allowed to specify the exact number of employees.

13b. *"What is the share of employees with a bachelor or master's degree?"*

Firms are allowed to specify the exact share of graduated employees (which is used as it is in **% Graduated Empl**).

A3 More on the COVID-19 shock: internationalized and innovative firms

In this section, we provide additional insights on the shock experienced by internationalized and innovative companies and compare the relevance of the pandemic event with the recent Italian experience. In particular, a reader may notice that the crisis of 2008 depressed global trade significantly more than the COVID-19 event and wonder why we document such a detrimental effect for international firms in the recent crisis. First of all, it is worth reminding that our study focuses on the revision in firms' expectations around the very outburst of the epidemic and as such, the information set of the company does not extend beyond March-April 2020, the survey administration period. Back in those days, the COVID-19 pandemic was posing heavy threats to global trade, causing the confidence of international operators to drop in an unprecedented way. To provide an example, in April 2020 the World Trade Organization was predicting a fall in the volume of world trade between -13% and -32%. The magnitude of these forecasts is substantial, but the width of the confidence intervals (almost 20 percentage points) is even more informative about the large uncertainty surrounding the very evolution of international markets (higher than in 2008), mainly driven by the multi- faced and abrupt nature of the current shock. Differently from previous turmoils, the pandemic event dramatically changed the global environment in a few weeks and hit the real economy by simultaneously affecting demand and supply (forced to shut down or facing significant constraints on firms' provisions). Before discussing the actual information set available at the time of the survey, we provide a synthetic review of the major channels that could potentially impact the expectations of internationalized firms.

- First, the introduction of national lockdowns in response to the pandemic emergency led to a paralysis of a number of key players in supply chains. This domino effect contributed to a temporary disruption in the provision of intermediate goods (at least at the very beginning of the turmoil), which was particularly severe for deeply internationalized firms.

- While domestic companies were mainly concerned about national-specific idiosyncratic shocks, internationalized firms were also exposed to sequential lockdowns of foreign markets. Since the virus was proceeding in waves, hitting countries at different times, the shade of progressive lockdowns and demand shocks in exporting countries may have contributed to the perception of a cumulated (and prolonged) shock for such companies.

- Importantly, the beginning of the COVID-19 crisis caused significant shipping problems, increasing costs and times of delivery. This clearly had substantial effects both on the input and output sides of internationalized firms. Some of the causes were coming from:

    1. the cancellation of passenger flights (due to travel bans) that limited the availability of air cargo;
    2. the urgent shipping of essential goods that put pressure on the overall demand for shipping;
    3. the significant rise in freight cost (30% between China and the US, and more than 60% between Europe and North America), as well as a dramatic increase in delivery times;
    4. similar issues were affecting sea-shipping, wherein the changes in port protocols imposed further constraints (from closures to quarantine measures, examinations, and need for additional docu-

mentation), increased costs, and time of delivery. This was further worsened by the international shortage of shipping containers (many of them were stuck in Chinese ports when the virus hit China and experienced substantial restrictions on their movement).

- Furthermore, the outbreak of the pandemic pushed many countries to adopt trade restrictions aimed at protecting the supply of key items. According to the Global Trade Alert, 1863 new trade barriers were raised globally in 2020 (the highest value of the series), with the World Trade Organization reporting in April 2020 the introduction of export prohibitions or restrictions by 80 countries worldwide. While these measures were mainly related to food and health products, such an environment may have generated uncertainties and pessimism on the future dynamics of world trade also in other sectors.

- Moreover, after an initial stage of the crisis wherein there was concern about the possible spread of the virus through international commerce, appropriate biosecurity arrangements, and sanitary standards were introduced. This further increased the expected cost of exporting in the future.

- Finally, several major economies imposed restrictions to inbound travelers from (or transiting through) Italy (in addition to China and South Korea), further depressing the future prospects of those firms relying on face-to-face interactions for their international relationships.

All these issues (and many others) generated substantial concerns for internationalized companies and were doubly worrisome for firms involved in Global Value Chains. Such companies were effectively questioning the reliability of supply chains and evaluating the possibility of changing suppliers, altering logistics routes, and even re-shoring some phases of the production process. While, ex-post, this issue turned out to be only transitory, in April 2020 it represented a genuine and widespread concern.

In order to complete the available information set at the time of the interviews, we report the observed dynamics of import and export around the burst of the pandemic. Figure A6 clearly shows that the drop between February and April 2020 was dramatic. Compared to the previous month, exported values were hit by two consecutive drops of -17% and -35% in March and then in April (-17% and -19% for import). These jumps are substantial and significantly stronger than the largest drop in the Great Trade Collapse (-8.4% between November and December 2008).

It is within this framework of negative trends, pessimistic views on international trade, and huge uncertainty that firms formed their own expectations about future prospects. While ex-post we know that global trade recovered quickly in the following few months (with a lower cumulated shock than in the 2008-crisis), at the time of the forecast firms' information set was shocked by an unprecedented drop in global trade. Thus, it is not surprising that we observe significantly more pessimistic expectations attached to internationalized companies.

Additional evidence on this issue can also be recovered from external data. For instance, the periodical monitoring report of the Bank of Italy provides information on the expected export growth over the next 6 months.[35] 34% of the companies are expecting a fall in future exported sales, which is higher than the share observed in the great trade collapse of 2008 (25%). This difference becomes even wider if considering very negative expectations only: 25% vs 8% in 2008 (10% in 2009). Similar conclusions can be reached by looking at the IHS Markit Italy Manufacturing PMI index in April 2020, pointing at the steepest contraction in factory activity since the beginning of the series, confirming a perception of the pandemic shock that was significantly more severe than in the Great Recession. Importantly, expectations about export sales dropped to their lowest level on record and supplier delivery times lengthened to the greatest extent. Similar trends followed in May 2020.

Overall, there is quite compelling evidence to argue that, in terms of short-run expectations, the COVID-19 outbreak generated a shock that was even more severe than in the recent Italian experience.

As for firms' innovativeness, the size of the shock experienced during the sovereign debt crisis is, again, not directly comparable to the recent pandemic developments. As argued before, the turmoil that followed the first phases of the COVID-19 outbreak was significantly stronger in magnitude and especially way swifter in its timing. Indeed, the Great Recession came with a gradual worsening of the real economy while the COVID-19 pandemic, in a few weeks, projected firms into a world of massive uncertainty, thus destabilizing both sides of the market. To get a grasp of its magnitude, Baker et al. (2020) ranked the uncertainty of the COVID-19 outbreak in the US just below the 1929 stock market crash, but significantly above the 1933 Great Depression and even the 2008 global financial crisis. Within this framework of unparalleled uncertainty, the COVID-19 shock may have cast doubts about returns from innovations already in place and about the future dynamic of customers' behavior (see, for instance, Bertola et al., 2005), feeding the fear of a permanent change in consumption habits. This is also consistent with Sharma et al. (2020) and Kirk and Rifkin (2020) discussing how changes in consumers' attitudes affect firms' incentives to innovate.

To provide further insights on this issue, we exploit additional information from the COVID-19 survey regarding firms' opinions on the difficulties induced by the pandemic crisis. As a dependent variable, we employ a dummy measure for firms mentioning the need of *diversifying* the current array of products as a major concern for the near future.[36] Results in Table A4 suggest that innovative companies have an

[35] The original report (*Sondaggio congiunturale sulle imprese industriali e dei servizi*) in Italian can be downloaded here: `https://www.bancaditalia.it/pubblicazioni/sondaggio-imprese/2020-sondaggio-imprese/statistiche_SIS_20201109.pdf`.

[36] In the original survey, firms could select up to three major concerns associated with the COVID-19 event. Available options were about difficulties in (i) purchasing inputs/semifinished products, (ii) the relationship with usual suppliers, (iii) finding skilled workforce, (iv) accessing credit, (v) the availability of services (transportation and logistic), (vi) the reorganization

8%-higher probability of declaring concerns associated with the need of diversifying their production. Since the latter can be also seen as a strategy aimed at reducing firms' exposure to idiosyncratic demand shocks (see for instance Link and Long, 1981; Hoang et al., 2021), this evidence, together with the more pessimistic average expectations documented in Table 3, is again evocative of the adverse effects on future returns of the innovative products already in place. We have also experimented with alternative difficulties potentially affecting innovative firms and found no clear pattern (innovation was largely insignificant across the board), further reassuring about our interpretation.

A4 Additional analyses

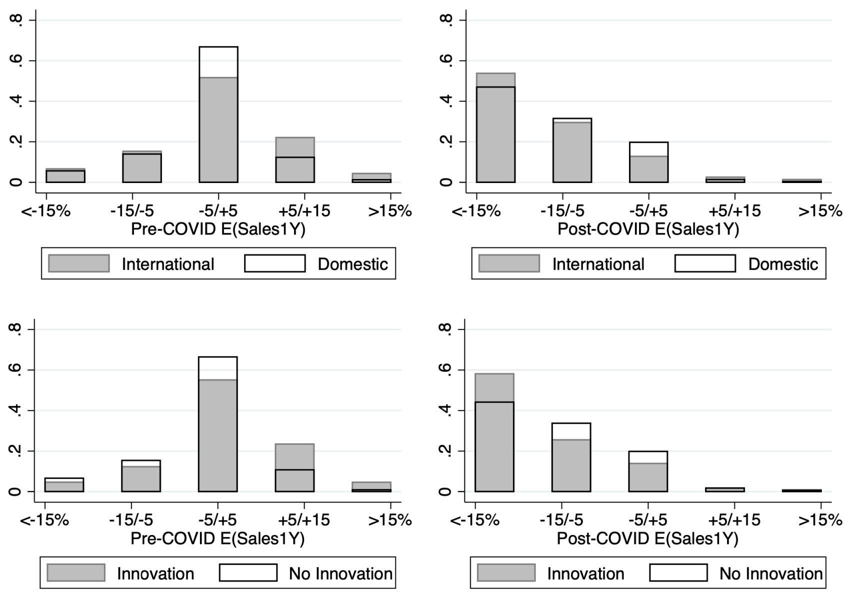

Figure A4: Sales expectation revisions by firms' internationalization and innovativeness.

Notes: Conditional distributions of pre- and post-COVID expectations on sales growth at a 1-year horizon. The top graphs distinguish between internationalized and domestic companies (in grey and white, respectively) while the bottom graphs provide a breakdown by firms' innovativeness (companies that introduced at least one type of innovation or not, in grey and white, respectively). Left graphs display firms' forecasts as of January 2020, while the right graphs report the updated expectations in March.

of work tasks and production, and (vii) the need of product diversification.

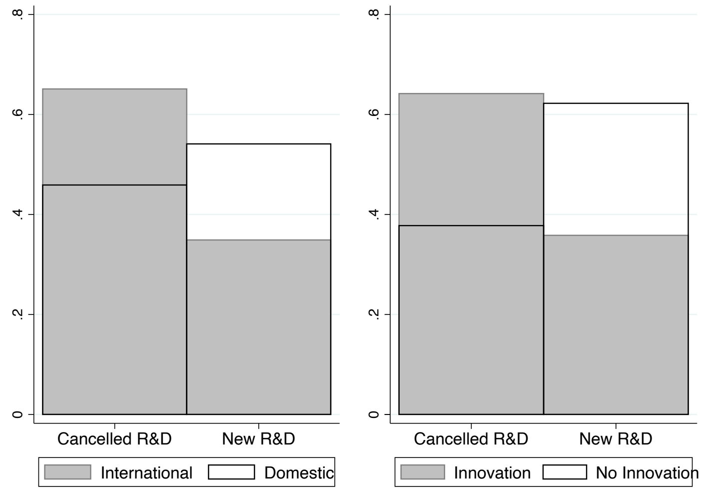

Figure A5: Revision in future R&D plans by firms' internationalization and innovativeness.
Notes: conditional distributions for companies that revised their R&D strategies around the pandemic outbreak (restricted to sum up to 100% by taking out the set of firms with stable plans). The left plot distinguishes between companies that were internationalized (International) or domestic (Domestic) in January 2020 –in grey and white bars, respectively. The right plot presents the same conditional distribution for firms that, as of January 2020, introduced at least one type of innovation (Innovation) or not (No Innovation) –in grey and white bars, respectively.

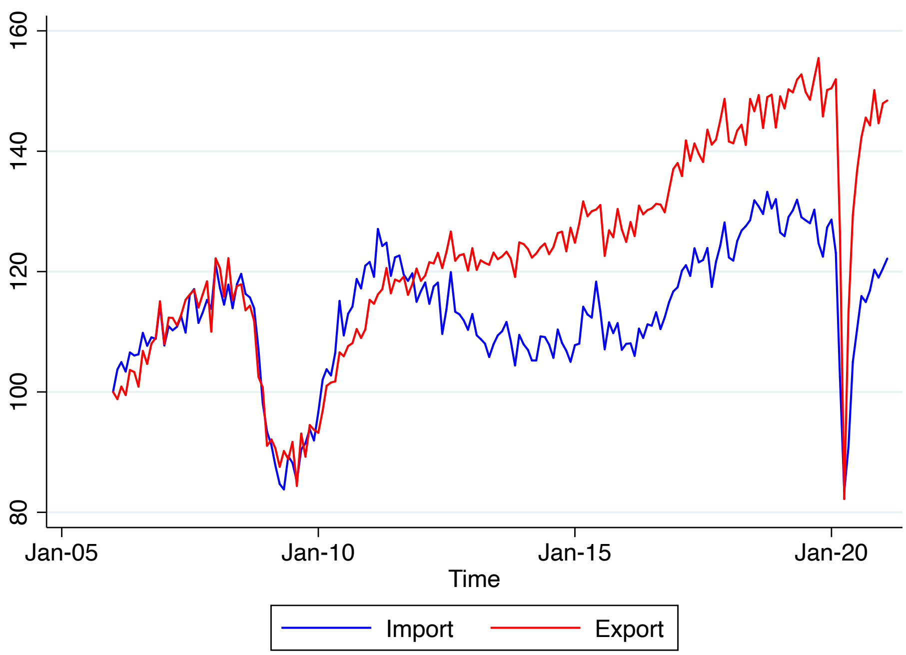

Figure A6: Italian import and export indices: seasonally-adjusted monthly values (January 2006 = 100).
Notes: source Italian National Institute of Statistics (ISTAT). Data are available at `http://dati.istat.it/`, following the path: "Commercio estero e internazionalizzazione/importazioni ed esportazioni/importazioni per paese e merce ATECO 2007/Importazioni ed esportazioni per paese e merce ATECO 2007 -valori destagionalizzati".

Table A1: Attrition.

Dependent variable	COVID survey interview (0-1)	
	(1)	(2)
Internationalized	-0.0240	-0.0201
	[0.0640]	[0.0641]
R&D	0.0487	0.0463
	[0.0655]	[0.0661]
Product Innovation	-0.00135	0.00473
	[0.0633]	[0.0638]
Process Innovation	0.100	0.100
	[0.0627]	[0.0627]
Labor Productivity	0.105	0.109
	[0.0976]	[0.0988]
Size	-0.132	-0.131
	[0.163]	[0.163]
North		0.0647
		[0.0702]
Center		0.0573
		[0.0718]
Manufacturing		0.0211
		[0.0510]
Obs.	24000	24000

Notes: Logit estimates for attrition. The estimating sample is the entire set of respondents in the 2019-wave of the MET survey (24,000 firms). The dependent variable is a dummy taking the value 1 if the company was interviewed in the COVID survey and 0 otherwise. No fixed effects are employed. The coefficients show no correlation between the probability of being interviewed a second time after the COVID outbreak and firms' past strategies, productivity, or size. Moreover, the insignificance of the North macro-regional dummy in column 2 suggests no correlation even with the severity of the pandemic. Finally, the insignificance of the macro-sectorial dummy suggests no oversampling (compared to the original sample design) of the manufacturing sector compared to production services.

Table A2: Validation on past waves.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Realized Sales		Realized Sales			R&D		Realized Sales	$\mathbb{E}$(Sales1Y)	Forecast Error
$\mathbb{E}$(Sales1Y): V.Neg		-7.024***		-10.13***						
		[0.0915]		[0.193]						
$\mathbb{E}$(Sales1Y): Neg		-2.347***		-2.179***						
		[0.0597]		[0.137]						
$\mathbb{E}$(Sales1Y): Pos		2.584***		2.744***						
		[0.0467]		[0.118]						
$\mathbb{E}_{t-1}$(Sales1Y): V.Pos		6.826***		5.088***						
		[0.113]		[0.432]						
R&D plans					0.325***	0.233***	0.103***			
					[0.00488]	[0.0149]	[0.00644]			
R&D								0.192	0.0221	0.0250
								[0.135]	[0.0176]	[0.0153]
Innovation								0.762***	0.0826***	0.0167
								[0.105]	[0.0138]	[0.0131]
International								0.275***	0.0315**	-0.0126
								[0.103]	[0.0134]	[0.0135]
Age								-0.142*	0.00276	0.0261***
								[0.0742]	[0.00970]	[0.00966]
Size								0.224***	0.0314***	-0.0136***
								[0.0340]	[0.00445]	[0.00482]
Sample	All	All	2011-13	2011-13	All	R&D$_{t-1}$ =1	R&D$_{t-1}$ =0	2011-13	2011-13	All
Year FE	yes	yes	–	–	yes	yes	yes	yes	yes	yes
Province FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Industry (2 digits)	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
N obs.	89820	89820	12462	12462	40020	6510	33510	14270	14270	14270
R-squared	0.032	0.178	0.012	0.250	0.304	0.271	0.118	0.029	0.027	0.061

Notes: OLS estimates. This table exploits past waves of the MET survey to perform validation tests on the accuracy of forward-looking expectations and R&D plans. It also explores performance and forecast errors in times of crisis, as well as the relationship between firms' strategies and expectations outside the COVID-19 pandemic. All regressors are lagged once. Column 2 exploits the full set of available waves (2008–2019) to show the positive and significant correlation between forward-looking expectations on sales over one-year horizon with and their realized levels (as recorded in the following wave of the survey, which are coded coherently). Column 1 is the benchmark regression of fixed effects only, needed to derive the incremental R^2 (variation in R^2 once past expectations are added, in Column 2). Results show a strong predictive power of forward-looking expectations, with an incremental R^2 of about 0.146. Columns 3 and 4 present the same analyses focusing only on expectations formed at the onset of the sovereign debt crisis (2011, then matched with realized sales of the following wave). This is a benchmark on the accuracy of firms' expectations in times of crisis, which is useful to interpret firms' expectations at the onset of the COVID-19 pandemic. Also in this case, the predictive power of firms' expectations for realized sales is extremely significant. Interestingly, the magnitude of the incremental R^2 almost doubles if we focus on the sovereign debt crisis only (column 2). Overall, our results suggest that firms' expectations are informative about the future dynamics of the actual variables, and that this is especially true in times of crisis. This last piece of evidence may underly firms' incentives to invest in information acquisition in times of crisis. In Columns 5 to 7, we show the strong correlation between firms' research plans and the actual R&D investment in the following wave. Once again, the majority of firms confirm their plans at the beginning of the period, providing support about the informativeness of R&D plans in our analysis. As expected, the correlation is stronger in case of preexisting R&D investments already in place, but it is still extremely significant also for companies that were transitioning toward the start of new R&D activities (in Columns 6 and 7, respectively). Column 8 shows the correlation between actual performance in the sovereign debt crisis and firms' characteristics. Our dataset provides results that are consistent with the existing literature and suggests that internationalized and innovative companies fared relatively better the first stages of the sovereign debt crisis (on the top of positive effects of investment and size). Column 9 explores firms' expectations outside the COVID-19 crisis. Our results show that firms' expectations behave roughly in line with realized sales, whereby innovative and internationalized companies are significantly-more optimistic, even controlling for the beginning-of-period level of expectations. This result is indeed opposite to the evidence emerged in the pandemic. Finally, Column 10 shows the correlation between the forecast error and such firm-level variables. Forecast Error is defined as the simple difference between Realized Sales and (past) forward looking expectations $\mathbb{E}(\text{Sales1Y})_{it-1}$. We focus again on the sovereign debt crisis only as it represents the best available benchmark for our analysis on the COVID-19 crisis (however, main findings are not sensitive to alternative choices of the estimation period). Our results show that larger firms are characterized by a significantly-higher forecast error, implying an over-optimistic attitude that does not match actual superior performances. On the other hand, our main variables of interest are not correlated with the forecast error reassuring about identification issues and the average reliability of their post-COVID-19 expectations.

Table A3: Expected future sales: conditional effects of innovation by pre-crisis expectations.

	(1) $\Delta\mathbb{E}$(Sales1Y)	(2) $\Delta\mathbb{E}^R$(Sales3M)	(3) $\Delta\mathbb{E}^R$(Sales12M)
	Coefficient t-test: (Innovation=1 – Innovation=0)		
(γ_1): γ(Innovation $\times$ V.Neg/Neg)$-\gamma$(V.Neg/Neg)	-0.880	-1.626	0.020
	[0.521]	[1.776]	[1.737]
(γ_2): γ(Innovation $\times$ Const)$-\gamma$(Const)	-0.688**	-2.912***	-1.783**
	[0.304]	[0.903]	[0.737]
(γ_3): γ(Innovation $\times$ Pos/V.Pos)$-\gamma$(Pos/V.Pos)	-1.253***	-3.341**	-1.601**
	[0.338]	[1.479]	[0.770]
Province FE	yes	yes	yes
Industry (2 digits) FE	yes	yes	yes
N obs.	5071	5071	5104
R2	0.431	0.111	0.121
	t-tests for heterogeneity		
($\gamma_3 - \gamma_1$)	-0.373	-1.715	-1.621
	[0.622]	[2.079]	[2.182]
($\gamma_3 - \gamma_2$)	-0.565	-0.429	0.182
	[0.369]	[1.511]	[0.895]
($\gamma_2 - \gamma_1$)	0.192	-1.285	-1.803
	[0.603]	[2.016]	[2.019]

Notes: OLS estimates. This table replicates the specification of Table 3 while allowing the effect of Innovation to vary along different levels of pre-crisis expectations on 1-year sales growth. In essence, we interact Innovation with the set of dummy variables identifying sales expectations in the 2019-wave [$\mathbb{E}$(Sales1Y)$_{it-1}$ in our notation] and compare the resulting coefficients with the ones for non-innovative companies within the same expectation class. The estimates reported in the table already refer to this difference. Notice that to overcome issues related to the low number of firms with pre-COVID extreme expectations (V.Neg or V.Pos, as shown in Figure 1), we re-grouped firms into three broader classes: (1) V.Neg or Neg prospects, (2) Const, and (3) Pos or V.Pos. Both in our main ordinal measure and in the continuous variables at the 3-month and 1-year horizons, innovative firms are characterized by significantly stronger downward revisions in their expectations. This is somewhat less true for companies that entered the pandemic with already negative expectations on future sales (whose coefficient is still negative, albeit not statistically significant). In the bottom panel, we formally check for heterogeneity by testing the significance of the difference in the groups of coefficients. As an illustrative example, ($\gamma_3 - \gamma_1$), reports the estimated difference (and its standard error) between the impact of innovation in the third expectation class (Pos and V.Pos) and the same impact within the first expectation class (V.Neg and Neg). The significance of this difference represents a formal test for heterogeneity in the effect of innovation across different levels of pre-crisis expectations. As it turns out, the heterogeneities documented In the top panel, are not sufficient to reject the null of equality in the effects, thus suggesting that the expectation revision of innovative firms was quite homogeneous across starting expectation classes. Unreported regressors follow the specification in Table 3. Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table A4: Difficulties in the aftermath of the COVID-19 crisis.

Difficulty:	(1) Product diversification	(2)	(3) Financial constraints	(4)
Innovation	0.0769***	0.0768***	0.0112	0.0106
	[0.0163]	[0.0161]	[0.0156]	[0.0154]
Internationalized	0.0258	0.0254	-0.0225	-0.0212
	[0.0168]	[0.0167]	[0.0162]	[0.0159]
R&D	-0.0123	-0.0121	-0.00758	-0.00850
	[0.0176]	[0.0175]	[0.0168]	[0.0168]
Province FE	yes	yes	yes	yes
Industry (2 digits) FE	yes	yes	yes	yes
Estimator	OLS	Logit	OLS	Logit
R2 (Pseudo Rs)	0.049	(0.037)	0.040	(0.031)
N obs.	5105	5105	5105	5090

Notes: OLS estimates and *marginal effects* from Logit models. The dependent variable in Columns 1 and 2 are dummy measures (from the COVID-19 survey) taking the value of one if the firm mentions the need of *diversifying* the current array of products as a major concern and critical factor for the near future. In Columns 3 and 4, we report the same measure associated with financial constraints (*access to credit*). In the original questionnaire, firms could select up to three major concerns associated with the pandemic event. Available options were about difficulties in (i) purchasing inputs/semifinished products, (ii) the relationship with usual suppliers, (iii) finding skilled workforce, (iv) accessing credit, (v) the availability of services (transportation and logistic), (vi) the reorganization of work tasks and production, and (vii) the need for product diversification. Results in Columns 1 and 2 point at an 8%-higher probability for innovative companies in the need of diversifying their array of products in the near future. To the extent that diversification is an effective strategy in reducing the exposure to idiosyncratic risks, this evidence, together with the more pessimistic average expectations documented in Table 3, is again evocative of the effect of increased uncertainty in casting doubts about future returns from innovations already in place. On the other hand, access to finance does not seem to display a significant correlation with our main measures and, as such, is unlikely to drive the results. We have also experimented with the other available choices for possible difficulties (i-vii) and found no clear pattern (they were largely insignificant). 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 A5: Simultaneity of firms' R&D plans and expectations: controlling for log of employees.

	(1) Equation 1: Δ(R&D plans)	(2) Equation 2: $\Delta\mathbb{E}$(Sales1Y)	(3) Pass-through (p-value)	(4) Interacted coeff. in Equation 1
R&D	-0.0726***	0.0357	(0.271)	-0.003
	[0.0199]	[0.0376]		[0.017]
Innovation	-0.0416**	-0.143***	(0.000)	-0.025
	[0.0185]	[0.0351]		[0.017]
Internationalized	-0.0157	-0.0850**	(0.085)	-0.006
	[0.0191]	[0.0361]		[0.016]
Log-Employees	0.0164**	0.0219*	(0.093)	0.0051
	[0.00661]	[0.0126]		[0.00533]
$\Delta\mathbb{E}$(Sales1Y)	0.0451***	–		
	[0.00741]	–		
Province FE	yes	yes		yes
Industry (2 digits) FE	yes	yes		yes
Estimator		SUR		SUR
R2	0.074	0.362		0.075
N obs.		5070		5070

Notes: Seemingly-Unrelated (SUR) regression models. This table replicates the results in Table 5 by adopting the log (1+) number of employees as an alternative measure of firms' size. 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 (Δ(R&D plans)). The dependent variable in Column 2 (Equation 2 of the SUR) is the revision in firms' expectations as captured by the difference between post- and pre-COVID beliefs ($\Delta\mathbb{E}$(Sales1Y)). In Column 3, we test the significance of the indirect effect of each regressor onto R&D plans passing through the revision in firms' expectations by performing a χ-test under the null hypothesis $[eq2]\beta_X \times [eq1]\beta_{\Delta E(Sales1Y)} = 0$ (p-values are reported in parentheses). In Column 4, we test for differential sensitivities to expected demand shocks by enriching Equation 1 (of Column 1) with a set of interaction terms $X_{t-1} \times \Delta\mathbb{E}_t$(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, except for log of assets (Size) that has been replaced by Log-Employees. Main results are virtually identical if we control for both measures of size. Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table A6: Change in R&D future plans: additional heterogeneities.

	(1)	(2)	(3)	(4)	(5)
Estimator:	Logit	Logit		Multinomial Logit	
Change in future R&D plan:	Disruption	New Plans	Disruption (-1)	Unaffected (0)	New Plans (+1)
Panel A					
R&D Expenditure	-0.00983	0.00964**	-0.00771	-0.00114	0.00885**
	[0.00853]	[0.00457]	[0.00877]	[0.00908]	[0.00424]
Panel B					
R&D Outsourcing	0.0102***	-0.00694**	0.0100***	-0.00375	-0.00624**
	[0.00285]	[0.00338]	[0.00277]	[0.00378]	[0.00318]
Panel C					
New R&D	0.130***	-0.00438	0.129***	-0.128***	-0.00135
	[0.0266]	[0.0156]	[0.0266]	[0.0310]	[0.0144]
Persistent R&D	0.0315*	-0.00199	0.0313*	-0.0297	-0.00169
	[0.0182]	[0.00964]	[0.0181]	[0.0195]	[0.00881]
Panel D					
Product Innovation	0.0367**	0.0173**	0.0365**	-0.0522***	0.0158**
	[0.0156]	[0.00787]	[0.0154]	[0.0168]	[0.00722]
Process Innovation	0.0166	0.00616	0.0169	-0.0226	0.00573
	[0.0147]	[0.00956]	[0.0145]	[0.0165]	[0.00883]
Panel E					
Sales Radical Inn.	0.00104	0.00404**	0.00169	-0.00541	0.00373**
	[0.00375]	[0.00199]	[0.00370]	[0.00382]	[0.00184]
Sales Imitative Inn.	0.00433	-0.00172	0.00430	-0.00280	-0.00149
	[0.00357]	[0.00236]	[0.00353]	[0.00382]	[0.00218]
Panel F					
New Innovation	0.110***	0.0145	0.108***	-0.121***	0.0130
	[0.0175]	[0.0114]	[0.0172]	[0.0201]	[0.0103]
Persistent Innovation	0.0532***	0.0180*	0.0525***	-0.0683***	0.0158*
	[0.0181]	[0.00951]	[0.0178]	[0.0181]	[0.00861]
Panel G					
Patents	-0.104***	-0.00254	-0.104***	0.106***	-0.00209
	[0.0283]	[0.0149]	[0.0281]	[0.0303]	[0.0136]
Province FE	yes	yes		yes	
Industry (2 digits) FE	yes	yes		yes	
N obs.	5070	5070		5070	

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 (dummy measure). The difference between planned R&D expenditure in the COVID-19 survey and the same measure in January 2020 identifies a variable (Δ(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. The dependent variables (listed in the top row) are continuous measures from the COVID-19 survey. The questionnaire was formulated so as to directly capture revisions in expectations due to the pandemic. Specifically, we asked about the effect, compared to the pre-COVID situation, on the future evolution of sales growth in the following three and 12 months. We control for past expectations on future sales to correct for misreporting. Because all Panels employ the same baseline specification of Table 4, each coefficient represents the *additional* impact with respect to the estimate of the baseline connected variable. R&D Expenditure is the overall expenditure in R&D project as a share of total sales. R&D Outsourcing is the share of R&D that is outsourced (to firms, universities, labs, etc.). Persistent R&D and New R&D are, respectively, dummy variables identifying companies that persistently invested in R&D or that just started reporting research activities in the 2019-survey (to compute such measures we took advantage of the reported R&D in the 2017 and 2015-waves of the MET survey so as to maximize the observations matched). Product Innovation and Process Innovation are dummy variables identifying product and process innovations, respectively. Sales Radical Inn. and Sales Imitative Inn. are, respectively, the shares of total sales attributable to product innovations that are new to the market or new to the firm only. Persistent Innovation and New Innovation are dummy variables identifying companies that are persistent or new innovators (again identified by the matching with the 2017 and 2015-waves of the MET survey). Patents is a dummy variable taking the value of one for patent-holding companies and zero otherwise. Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively. Additional controls (not reported) follow the specifications in Table 4. Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table A7: Heterogeneities across different forms of internationalization.

	(1) Equation 1: Δ(R&D plans)	(2) Equation 2: $\Delta\mathbb{E}$(Sales1Y)	(3) Pass-through (p-value)
Import	0.00557	0.0223	(0.611)
	[0.0231]	[0.0437]	
Export	-0.0207	-0.0942**	(0.029)
	[0.0213]	[0.0404]	
Delocalization	-0.0295	-0.0621	(0.369)
	[0.0361]	[0.0683]	
FDI	0.0556	-0.224***	(0.0152)
	[0.0449]	[0.0847]	
Commercial international agreement	-0.00730	-0.157***	(0.004)
	[0.0256]	[0.0482]	
International agreement R&D	0.0152	0.142	(0.119)
	[0.0466]	[0.0879]	
Province FE	yes	yes	
Industry (2 digits) FE	yes	yes	
Estimator		SUR	
R2	0.076	0.364	
N obs.		5070	

Notes: Seemingly-Unrelated (SUR) regression models. This table explores heterogeneities across the different forms of internationalization. Starting from the same specification of Table 5, we replace the general dummy for internationalized companies with an extensive set of firms' foreign strategies: import, export, delocalization activities, foreign direct investments, commercial foreign agreements, as well as foreign agreements oriented to R&D activities. 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 (Δ(R&D plans)). The dependent variable in Column 2 (Equation 2 of the SUR) is the revision in firms' expectations as captured by the difference between post- and pre-COVID beliefs ($\Delta\mathbb{E}$(Sales1Y)). In Column 3, we test the significance of the indirect effect of each regressor onto R&D plans passing through the revision in firms' expectations by performing a χ-test under the null hypothesis $[eq2]\beta_X \times [eq1]\beta_{\Delta E(Sales1Y)} = 0$ (p-values are reported in parentheses). Unreported Breusch-Pagan tests strongly reject the null of independence between the two equations. Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table A8: Alternative definition of disruption: conditioning to the existence of R&D activity in January 2020.

Dependent Variable:	(1) Disruption_2	(2) Equation 1: Δ(R&D plans_2)	(3) Equation 2: $\Delta\mathbb{E}$(Sales1Y)
R&D	–	-0.378***	-0.0738
	–	[0.0142]	[0.0565]
Innovation	0.133***	-0.0836***	-0.141***
	[0.0111]	[0.0134]	[0.0351]
Internationalized	0.0548***	-0.0356**	-0.0839**
	[0.0117]	[0.0144]	[0.0361]
$\Delta\mathbb{E}$(Sales1Y)		0.0210***	
		[0.00565]	
Province FE	yes	yes	
Industry (2 digits) FE	yes	yes	
N obs.	5070	5070	

Notes: Logistic marginal effects and Seemingly-Unrelated (SUR) regression models. The dependent variable in Columns 1 is a dummy measure identifying the disruption of R&D projects. Compared to the one used in the paper (as in Table 4) we conditioned the disruption in R&D to the existence of R&D projects already in place in January 2020. Similarly, the dependent variable in Column 2 cannot take negative values if the firm did not have preexisting actual R&D. We do not display the effect on new R&D investments as they are unaffected with respect to Table 4. Additional controls (not reported) follow the specifications in Table 4 for Columns 1 and 2, and in Table 3 for Column 3. Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table A9: Average treatment effects from matching techniques.

	Outcome variable:		
	(1)	(2)	(3)
Treatment variable below:	$\Delta\mathbb{E}^R$(Sales3M)	$\Delta\mathbb{E}^R$(Sales12M)	Δ(R&D plans)
Internationalized	-20.17***	-14.55***	-0.091*
Innovation	-20.58***	-14.75*	-0.107***
R&D	-19.13	-13.78	-0.185***
R&D Outsourcing (Dummy)	-18.67	-13.34	-0.172***
New R&D	-19.70	-14.51	-0.242***
Product Innovation	-20.87***	-14.97***	-0.109***
Process Innovation	-19.69	-14.13	-0.106
New Innovation	-19.73	-14.56	-0.111***
Patent	-17.52	-11.74	-0.107

Notes: Average Treatment Effect from Nearest Neighbor Matching. The treatment variable is shown in the first column. The matched sample is selected so as to compare firms with identical characteristics and similar probability of being treated, but that differ for the actual treatment variable in time $t-1$. The statistical matching is performed via Nearest Neighbor Matching, imposing a maximum of matched firms in the control group of 3 and a maximum distance of the 0.25 stdev in the propensity score between treated and control companies. The matching variables used for the estimation of the propensity score (via a logistic model) are: Investment, Group, Headquarter, Family Firm, Leverage, Tangible Assets, Rollover Risk, Size, Age, % Graduated Empl., Labor Productivity, Vertical Integration, sector dummies (2-Digit ATECO2007), region dummies (20 regions). The statistical matching also accounts for Internationalized, Innovation, and R&D (clearly sequentially excluding the variable employed as a treatment effect). Because of the nature of matching techniques, we do not perform exercises on continuous measures used in the main text. The only exception is R&D outsourcing which, in this framework, is discretized in a dummy variable taking the value of one in case of R&D outsourcing (independently of the intensity). Unreported analyses show good balancing properties of the treatment and control groups, accepting the null of equivalent distributions along all the dimensions taken into account. The choice of alternative thresholds for the caliper (0.1 or 0.5 stdev) or the maximum number of control companies matched (1 or 5) provide quantitatively and qualitatively similar results. Results are even robust to the use of alternative matching techniques such as CEM (Coarsened Exact Matching; Iacus, King, and Porro, 2012). *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

A5 Other Identification Issues

One potential issue of our analysis has to do with the possible correlation of forecast errors with X_{t-1}. Indeed, if firms update their beliefs based on past forecast errors (as in a Bayesian learning type of model, Brancati and Macchiavelli, 2019), any persistent over- or under-estimation in realized growth would induce an in-built correlation in Equation 1 that would interfere with the interpretation of $\delta < 0$ as evidence of a stronger shock. The insignificance of the coefficients in Table A2 (based on past waves) reassures about this possibility.[37]

A further identification issue is related to the possibility of endogenous selection of the respondents along unobserved factors. This may be induced by the very administration of the COVID-19 survey –concentrated in a short-time window during the lockdown– which may lead to inconsistent estimates.[38] To overcome this potential problem our analysis is performed by means of weighted regressions employing ex-post stratification weights for the COVID-19 survey. The latter were calibrated ex-post to reproduce the aggregate population starting from the full set of 7,800 firms interviewed in the COVID-19 survey (see Section A1). The use of weighted regressions should restore the consistency of the estimates (see the discussion in Solon et al., 2015). Overall, results are virtually identical if we employ unweighted regressions instead, thus reassuring about the importance of possible endogenous sampling selection (as emphasized in Section 5).

The last issue that is worth discussing is related to firms' information set and beliefs. In particular, it is possible that expectations on future outcomes reflect differential priors on the extension of lockdown policies (see, for instance, Briscese et al., 2020). Notice that, to the extent that firms' perception is correlated with the health crisis, we already control for most of it with the inclusion of 107 provincial effects capturing the local severity of the pandemic (such as the provincial number of deaths, positive cases, hospitalized patients, etc.). However, we perform a number of robustness tests to further assuage this concern. First of all, we explicitly control for the manager's expectation on the length and severity of the crisis, which is likely incorporating beliefs on the duration of the lockdown. Moreover, we account for a heterogenous information set of the respondents along the survey administration period by including a full set of controls for the exact day of the manager's answer (i.e., 14 time dummies, one for each day). This captures common changes in the expected length of the crisis and any effect related to announcements or planned interventions by the Italian government (as well as ECB policies). We even allow time effects to depend on broader geographical and industrial characteristics (four macro-areas and 12 sectors) so as to deal with time-varying correlated shocks. Finally, we interact province dummies with a binary variable for essential sectors that were not

[37] On the other hand, results show that larger firms are characterized by higher forecast errors, implying an over-optimistic attitude that does not match actual superior performances.

[38] For instance, if firms that are less affected by the pandemic also have a higher probability of being sampled, and if this selection is somewhat correlated with the error terms.

directly affected by the lockdown (identified at the 6-digits level) to further account for firms' unobserved heterogeneity.

A5.1 Controlling for the perception of risk

Table A10: Revision in expected future sales: controlling for the perception of risk.

Model:	OLS		Ordered Logistic		OLS	
Dependent Variable:	$\mathbb{E}_t$(Sales1Y)	$\Delta\mathbb{E}$(Sales1Y)	$\mathbb{E}_t$(Sales1Y)	$\Delta\mathbb{E}$(Sales1Y)	$\Delta\mathbb{E}^R$(Sales3M)	$\Delta\mathbb{E}^R$(Sales12M)
	(1)	(2)	(3)	(4)	(5)	(6)
Perception: Dangerous but Inflated	2.520*	0.360**	0.930**	1.003**	0.138	-0.00116
	[1.319]	[0.146]	[0.389]	[0.425]	[2.684]	[2.004]
Perception: Very Dangerous ($\leq$ 12 months)	-0.646	-0.122	-0.295	-0.290	-8.493***	-6.238***
	[0.650]	[0.0798]	[0.199]	[0.228]	[2.440]	[1.746]
Perception: Very Dangerous ($\leq$ 18 months)	-2.007***	-0.356***	-1.120***	-1.023***	-15.96***	-12.87***
	[0.756]	[0.0932]	[0.243]	[0.263]	[2.413]	[1.706]
Internationalized	-1.264***	-0.178***	-0.606***	-0.538***	-2.736***	-1.877***
	[0.436]	[0.0589]	[0.178]	[0.171]	[0.681]	[0.580]
R&D	0.971*	0.137*	0.381*	0.373*	0.0935	-0.205
	[0.540]	[0.0726]	[0.197]	[0.202]	[0.705]	[0.493]
Innovation	-1.169***	-0.173***	-0.443***	-0.471***	-3.152***	-1.604***
	[0.445]	[0.0554]	[0.155]	[0.166]	[0.858]	[0.549]
Province FE	yes	yes	yes	yes	yes	yes
Industry (2 digits) FE	yes	yes	yes	yes	yes	yes
N obs.	4974	4974	4974	4974	4974	4974
R2 (Pseudo R2)	0.233	0.454	0.151	0.228	0.140	0.176

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 question 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 ($\Delta\mathbb{E}$(Sales1Y) $\in [-4, +4]$). Columns 5 and 6 use expected sales at the 3-month and one-year horizon as alternative dependent variables. We explicitly control for self-assessment about the manager's perception of danger related to the pandemic, as reported in the COVID-19 survey. The questionnaire allowed one answer among five options: i) not dangerous at all (never chosen and thus dropped), ii) dangerous but inflated by social media, iii) very dangerous but of short duration (chosen as a benchmark), iv) very dangerous with effects that will persist up to 12 months, and v) very dangerous with long-run effects that will persist for more than 18 months. Additional controls (not reported) are: past sales growth (realized), dummies for 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 (see the variable definition in the online appendix). Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table A11: Change in R&D future plans: controlling for the perception of risk.

	(1)	(2)	(3)	(4)	(5)
Change in future R&D plan:	Disruption	New Plans	Disruption (-1)	Unaffected (0)	New Plans (+1)
R&D	0.0847***	0.00415	0.0848***	-0.0891***	0.00432
	[0.0148]	[0.00897]	[0.0145]	[0.0156]	[0.00830]
Innovation	0.0718***	0.0188**	0.0706***	-0.0875***	0.0168**
	[0.0151]	[0.00807]	[0.0146]	[0.0157]	[0.00737]
Internationalized	0.0320**	0.0108	0.0319**	-0.0417***	0.00987
	[0.0142]	[0.00872]	[0.0141]	[0.0144]	[0.00805]
Perception: Dangerous but Inflated	-0.0279	0.0410	-0.0303	-0.00657	0.0369
	[0.0713]	[0.0562]	[0.0718]	[0.0747]	[0.0520]
Perception: Very Dangerous ($\leq$ 12 months)	0.0553	0.0236	0.0520	-0.0707	0.0187
	[0.0665]	[0.0522]	[0.0672]	[0.0691]	[0.0483]
Perception: Very Dangerous ($\leq$ 18 months)	0.139**	0.0216	0.136**	-0.154**	0.0179
	[0.0655]	[0.0534]	[0.0662]	[0.0678]	[0.0495]
Province FE	yes	yes		yes	
Industry (2 digits) 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 (dummy measure). The difference between planned R&D expenditure in the COVID-19 survey and the same measure in January 2020 identifies a variable (Δ(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. We explicitly control for self-assessment about the manager's perception of danger related to the pandemic, as reported in the COVID-19 survey. The questionnaire allowed one answer among five options: i) not dangerous at all (never chosen and thus dropped), ii) dangerous but inflated by social media, iii) very dangerous but of short duration (chosen as a benchmark), iv) very dangerous with effects that will persist up to 12 months, and v) very dangerous with long-run effects that will persist for more than 18 months. 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 A12: Change in R&D future plans: controlling for the perception of risk.

	(1)	(2)	(3)	(4)	(5)
Estimator:	Logit	Logit		Multinomial Logit	
Change in future R&D plan:	Disruption	New Plans	Disruption (-1)	Unaffected (0)	New Plans (+1)
Panel A					
R&D Expenditure	-0.00883	0.00779**	-0.00700	-0.000245	0.00724**
	[0.00688]	[0.00381]	[0.00707]	[0.00733]	[0.00354]
Panel B					
R&D Outsourcing	0.0166***	-0.0115**	0.0163***	-0.00594	-0.0104**
	[0.00465]	[0.00558]	[0.00451]	[0.00621]	[0.00526]
Panel C					
New R&D	0.0960***	-0.00265	0.0955***	-0.0956***	0.000176
	[0.0296]	[0.0178]	[0.0296]	[0.0353]	[0.0164]
Panel D					
Product Innovation	0.0356**	0.0173**	0.0354**	-0.0512***	0.0158**
	[0.0156]	[0.00796]	[0.0153]	[0.0168]	[0.00730]
Process Innovation	0.0178	0.00617	0.0182	-0.0239	0.00579
	[0.0150]	[0.00956]	[0.0148]	[0.0168]	[0.00881]
Panel E					
Sales Radical Inn.	0.00123	0.00642**	0.00231	-0.00823	0.00591**
	[0.00579]	[0.00315]	[0.00568]	[0.00585]	[0.00290]
Sales Imitative Inn.	0.00670	-0.00288	0.00662	-0.00419	-0.00243
	[0.00655]	[0.00420]	[0.00648]	[0.00693]	[0.00389]
Panel F					
New Innovation	0.0560***	-0.00326	0.0549***	-0.0524**	-0.00251
	[0.0191]	[0.0118]	[0.0189]	[0.0205]	[0.0108]
Panel G					
Patents	-0.101***	-0.00266	-0.100***	0.102***	-0.00213
	[0.0289]	[0.0147]	[0.0287]	[0.0309]	[0.0135]
Province FE	yes	yes		yes	
Industry (2 digits) FE	yes	yes		yes	
N obs.	5070	5070		5070	

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 (dummy measure). The difference between planned R&D expenditure in the COVID-19 survey and the same measure in January 2020 identifies a variable (Δ(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. We explicitly control for self-assessment about the manager's perception of danger related to the pandemic, as reported in the COVID-19 survey. The questionnaire allowed one answer among five options: i) not dangerous at all (never chosen and thus dropped), ii) dangerous but inflated by social media, iii) very dangerous but of short duration (chosen as a benchmark), iv) very dangerous with effects that will persist up to 12 months, and v) very dangerous with long-run effects that will persist for more than 18 months. 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.

A5.2 Controlling for 6-digits fixed effects

Table A13: Revision in expected future sales: controlling for 6-digits sector fixed effects.

Model:	OLS		Ordered Logistic		OLS	
Dependent Variable:	$\mathbb{E}_t$(Sales1Y)	$\Delta\mathbb{E}$(Sales1Y)	$\mathbb{E}_t$(Sales1Y)	$\Delta\mathbb{E}$(Sales1Y)	$\Delta\mathbb{E}^R$(Sales3M)	$\Delta\mathbb{E}^R$(Sales12M)
	(1)	(2)	(3)	(4)	(5)	(6)
Internationalized	-2.100***	-0.278***	-0.748***	-0.702***	-2.763***	-1.988***
	[0.499]	[0.0674]	[0.186]	[0.186]	[0.720]	[0.579]
R&D	1.328**	0.184**	0.379*	0.364*	-0.0748	-0.299
	[0.519]	[0.0723]	[0.218]	[0.214]	[0.730]	[0.556]
Innovation	-1.097**	-0.162**	-0.432**	-0.439**	-3.496***	-1.806***
	[0.516]	[0.0659]	[0.194]	[0.187]	[0.925]	[0.567]
Province FE	yes	yes	yes	yes	yes	yes
Industry (6 digits) FE	yes	yes	yes	yes	yes	yes
N obs.	5071	5071	5071	5071	5071	5104
R2 (Pseudo R2)	0.345	0.521	0.155	0.229	0.154	0.171

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 question 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 ($\Delta\mathbb{E}$(Sales1Y) $\in [-4, +4]$). Columns 5 and 6 use expected sales at the 3-month and one-year horizon as alternative dependent variables. We control for 6-digits sector fixed effects to further account for the difference between industries restricted by the shutdown and the "essential" ones that stayed in business. Additional controls (not reported) are: past sales growth (realized), dummies for 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 (see the variable definition in the online appendix). Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table A14: Change in R&D future plans: controlling for 6-digits FE.

	(1)	(2)	(3)	(4)	(5)
Change in future R&D plan:	Disruption	New Plans	Disruption (-1)	Unaffected (0)	New Plans (+1)
R&D	0.0830***	0.00512	0.0848***	-0.0891***	0.00432
	[0.0157]	[0.0106]	[0.0145]	[0.0156]	[0.00830]
Innovation	0.0729***	0.0175*	0.0706***	-0.0875***	0.0168**
	[0.0156]	[0.00970]	[0.0146]	[0.0157]	[0.00737]
Internationalized	0.0250*	0.0157*	0.0319**	-0.0417***	0.00987
	[0.0149]	[0.00924]	[0.0141]	[0.0144]	[0.00805]
Province FE	yes	yes		yes	
Industry (6 digits) FE	yes	yes		yes	
Estimator	Logit	Logit		Multinomial Logit	
N obs.	5070	5070		5070	
Pseudo R2	0.123	0.100		0.121	

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 (dummy measure). The difference between planned R&D expenditure in the COVID-19 survey and the same measure in January 2020 identifies a variable (Δ(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. We control for 6-digits sector fixed effects to further account for the difference between industries restricted by the shutdown and the "essential" ones that stayed in business. Additional controls (not reported) are: past sales growth (realized), dummies for 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 (see the variable definition in the online appendix). Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table A15: Change in R&D future plans: controlling for 6-digits FE.

	(1)	(2)	(3)	(4)	(5)
Estimator:	Logit	Logit		Multinomial Logit	
Change in future R&D plan:	Disruption	New Plans	Disruption (-1)	Unaffected (0)	New Plans (+1)
			Panel A		
R&D Expenditure	-0.00883	0.00779**	-0.00700	-0.000245	0.00724**
	[0.00688]	[0.00381]	[0.00707]	[0.00733]	[0.00354]
			Panel B		
R&D Outsourcing	0.0166***	-0.0115**	0.0163***	-0.00594	-0.0104**
	[0.00465]	[0.00558]	[0.00451]	[0.00621]	[0.00526]
			Panel C		
New R&D	0.128***	-0.00455	0.128***	-0.126***	-0.00149
	[0.0263]	[0.0157]	[0.0263]	[0.0306]	[0.0143]
Long-lasting R&D	0.0325*	-0.00191	0.0323*	-0.0306	-0.00167
	[0.0180]	[0.00969]	[0.0179]	[0.0194]	[0.00884]
			Panel D		
Product Innovation	0.0356**	0.0173**	0.0354**	-0.0512***	0.0158**
	[0.0156]	[0.00796]	[0.0153]	[0.0168]	[0.00730]
Process Innovation	0.0178	0.00617	0.0182	-0.0239	0.00579
	[0.0150]	[0.00956]	[0.0148]	[0.0168]	[0.00881]
			Panel E		
Sales Radical Inn.	0.00123	0.00642**	0.00231	-0.00823	0.00591**
	[0.00579]	[0.00315]	[0.00568]	[0.00585]	[0.00290]
Sales Imitative Inn.	0.00670	-0.00288	0.00662	-0.00419	-0.00243
	[0.00655]	[0.00420]	[0.00648]	[0.00693]	[0.00389]
			Panel F		
New Innovation	0.0547***	-0.00514	0.0544***	-0.0581***	-0.00502
	[0.0203]	[0.0129]	[0.0200]	[0.0201]	[0.0118]
			Panel G		
Patents	-0.101***	-0.00266	-0.100***	0.102***	-0.00213
	[0.0289]	[0.0147]	[0.0287]	[0.0309]	[0.0135]
Province FE	yes	yes		yes	
Industry (6 digits) FE	yes	yes		yes	
N obs.	5070	5070		5070	

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 (dummy measure). The difference between planned R&D expenditure in the COVID-19 survey and the same measure in January 2020 identifies a variable (Δ(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. We control for 6-digits sector fixed effects to further account for the difference between industries restricted by the shutdown and the "essential" ones that stayed in business. Additional controls (not reported) are: past sales growth (realized), dummies for 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 (see the variable definition in the online appendix). Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

A5.3 Controlling for the exact day of the firm's answer

Table A16: Revision in expected future sales: controlling for the exact day of the firm's answer.

Model:	OLS		Ordered Logistic		OLS	
Dependent Variable:	$\mathbb{E}_t$(Sales1Y)	$\Delta\mathbb{E}$(Sales1Y)	$\mathbb{E}_t$(Sales1Y)	$\Delta\mathbb{E}$(Sales1Y)	$\Delta\mathbb{E}^R$(Sales3M)	$\Delta\mathbb{E}^R$(Sales12M)
	(1)	(2)	(3)	(4)	(5)	(6)
Internationalized	-1.180***	-0.168***	-0.555***	-0.494***	-3.033***	-2.032***
	[0.379]	[0.0534]	[0.159]	[0.151]	[0.670]	[0.574]
R&D	1.134**	0.163**	0.440**	0.439**	0.0438	-0.271
	[0.516]	[0.0680]	[0.183]	[0.187]	[0.732]	[0.522]
Innovation	-1.187***	-0.175***	-0.441***	-0.461***	-3.233***	-1.709***
	[0.439]	[0.0545]	[0.156]	[0.160]	[0.894]	[0.556]
Day of Survey FE	yes	yes	yes	yes	yes	yes
Province FE	yes	yes	yes	yes	yes	yes
Industry (2 digits) FE	yes	yes	yes	yes	yes	yes
N obs.	5071	5071	5071	5071	5071	5104
R2 (Pseudo R2)	0.234	0.438	0.138	0.216	0.107	0.127

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 question 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 ($\Delta\mathbb{E}$(Sales1Y) $\in [-4, +4]$). Columns 5 and 6 use expected sales at the 3-month and one-year horizon as alternative dependent variables. In this table, we enrich the specifications in Table 3 with 14 dummies, one for each day of the survey period (March 24–April 7). This perfectly controls for the possible changes in firms' information set between the beginning and the end of the administration. Additional controls (not reported) are: past sales growth (realized), dummies for 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 (see the variable definition in the online appendix). Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table A17: Change in R&D future plans: controlling for the exact day of the firm's answer.

	(1)	(2)	(3)	(4)	(5)
Change in future R&D plan:	Disruption	New Plans	Disruption (-1)	Unaffected (0)	New Plans (+1)
R&D	0.0863***	0.00356	0.0861***	-0.0898***	0.00374
	[0.0154]	[0.00909]	[0.0151]	[0.0160]	[0.00839]
Innovation	0.0730***	0.0166**	0.0722***	-0.0870***	0.0148*
	[0.0151]	[0.00835]	[0.0147]	[0.0159]	[0.00763]
Internationalized	0.0355**	0.0115	0.0352**	-0.0457***	0.0105
	[0.0144]	[0.00908]	[0.0142]	[0.0145]	[0.00841]
Day of Survey FE	yes	yes		yes	
Province FE	yes	yes		yes	
Industry (2 digits) FE	yes	yes		yes	
Estimator	Logit	Logit		Multinomial Logit	
N obs.	5070	5070		5070	
Pseudo R2	0.123	0.100		0.121	

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 (dummy measure). The difference between planned R&D expenditure in the COVID-19 survey and the same measure in January 2020 identifies a variable (Δ(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. In this table, we enrich the specifications in Table 3 with 14 dummies, one for each day of the survey period (March 24–April 7). This perfectly controls for the possible changes in firms' information set between the beginning and the end of the administration. Additional controls (not reported) are: past sales growth (realized), dummies for 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 (see the variable definition in the online appendix). Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

Table A18: Change in R&D future plans: controlling for the exact day of the firm's answer.

	(1)	(2)	(3)	(4)	(5)
Estimator:	Logit	Logit		Multinomial Logit	
Change in future R&D plan:	Disruption	New Plans	Disruption (-1)	Unaffected (0)	New Plans (+1)
Panel A					
R&D Expenditure	-0.00908	0.00741*	-0.00706	0.000267	0.00679*
	[0.00705]	[0.00380]	[0.00728]	[0.00753]	[0.00352]
Panel B					
R&D Outsourcing	0.274***	-0.187**	0.269***	-0.100	-0.169**
	[0.0782]	[0.0911]	[0.0760]	[0.103]	[0.0858]
Panel C					
New R&D	0.0989***	-0.00350	0.0982***	-0.0973***	-0.000840
	[0.0294]	[0.0184]	[0.0296]	[0.0354]	[0.0170]
Panel D					
Product Innovation	0.0359**	0.0150*	0.0361**	-0.0497***	0.0136*
	[0.0158]	[0.00793]	[0.0155]	[0.0171]	[0.00727]
Process Innovation	0.0175	0.00543	0.0177	-0.0228	0.00509
	[0.0152]	[0.00960]	[0.0149]	[0.0167]	[0.00889]
Panel E					
Sales Radical Inn.	0.00107	0.00587**	0.00225	-0.00766	0.00541**
	[0.00598]	[0.00296]	[0.00595]	[0.00603]	[0.00274]
Sales Imitative Inn.	0.00800	-0.00395	0.00810	-0.00461	-0.00348
	[0.00651]	[0.00429]	[0.00642]	[0.00700]	[0.00398]
Panel F					
New Innovation	0.0561***	-0.00351	0.0550***	-0.0523**	-0.00267
	[0.0193]	[0.0122]	[0.0192]	[0.0208]	[0.0111]
Panel G					
Patents	-0.104***	-0.00409	-0.103***	0.107***	-0.00370
	[0.0280]	[0.0154]	[0.0278]	[0.0302]	[0.0141]
Day of Survey FE	yes	yes		yes	
Province FE	yes	yes		yes	
Industry (2 digits) FE	yes	yes		yes	
N obs.	5070	5070		5070	

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 (dummy measure). The difference between planned R&D expenditure in the COVID-19 survey and the same measure in January 2020 identifies a variable (Δ(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. In this table, we enrich the specifications in Table 3 with 14 dummies, one for each day of the survey period (March 24–April 7). This perfectly controls for the possible changes in firms' information set between the beginning and the end of the administration. Additional controls (not reported) are: past sales growth (realized), dummies for 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 (see the variable definition in the online appendix). Clustered standard errors in brackets. *, **, *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

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