Management practices and resilience to shocks: Evidence from COVID-19*

Andrea Lamorgese
Bank of Italy

Andrea Linarello
Bank of Italy

Megha Patnaik
LUISS University & CEPR

Fabiano Schivardi
LUISS University, EIEF & CEPR

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Abstract

We use the spread of COVID-19 in Italy, the first Western country hit by the pandemic, to investigate the role of structured management practices in responding to a large shock. We exploit a survey eliciting expected sales growth for 2020 to set up a Difference-in-Difference analysis with repeated cross-sections, leveraging the fact that the data collection began prior to the pandemic and continued throughout its spread. We find a sizable effect of such practices on firm performance: a one-standard-deviation increase in the management score increases expected sales growth by 2.3%, against an average drop of 8.3%. Results are confirmed with actual sales growth. Firms with more structured practices were more likely to implement a comprehensive set of changes, including a more intense use of remote work.

Keywords: Management, Firm Performance, COVID-19

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1 Introduction

A large body of evidence indicates that structured management practices (SMPs), broadly defined as a set of management practices based on formalized procedures to set targets, monitor outcomes, and incentivize employees, are an important determinant of firm performance. Cross-country studies such as Bloom & Van Reenen (2007*a*) suggest that SMPs explain up to a third of the cross-country differences in firm productivity. Within-country studies based on randomized control trials show that SMPs have a causal effect on performance (Bloom, Eifert, Mahajan, McKenzie & Roberts 2013, Bruhn, Karlan & Schoar 2018). Based on this evidence, the emergent consensus is that building up SMPs can boost firm performance (Bloom, Sadun & Van Reenen 2016, Giorcelli 2019, Schivardi & Schmitz 2020).

Whilst the relationship between SMPs and performance is well-established for "business as usual", little is known about whether such practices can also be useful for adapting to a rapidly changing environment. SMPs are primary "operational capabilities" designed to govern the firm's day-to-day operations (Helfat & Martin 2015). As such, they are not primarily designed to sense opportunities and threats, and to successfully address them (Teece 2007). At the same time, organizational practices centered around monitoring, targets, and incentives might provide firms with timely tools and information useful to do so. Surprisingly, the effects of SMPs on firms' adaptive capacity are still poorly understood, arguably due to the empirical challenges involved in addressing this question.

We exploit an ideal setting to study the effects of SMPs in the face of a large shock: the spread of the COVID-19 pandemic in Italy. Italy was the first Western country to be affected by the pandemic, whose effects on the economic environment could neither be known nor anticipated by Italian firms. This was in contrast to the subsequent spread of the pandemic in other industrialized countries, where the Italian experience served as a precedent.[1] The virus spread from the end of February 2020 with a speed and virulence that was completely unexpected. The Italian government responded via a bundle of measures that included widespread social distancing and school closures from the 8$^{\text{th}}$ of March, and a country-wide lockdown from the 22$^{\text{nd}}$ of March to the beginning of May, consisting of the shutting down of plants producing any goods or services except the ones in the list of essential activities.[2]

[1] For example, German firms updated business expectations twice: first, when there were increased restrictions in Northern Italy, and second, following the announcement of the German national lockdown (Buchheim, Krolage & Link 2022)

[2] In Online Appendix A we give a detailed account of the spread of the pandemic in Italy and the measures adopted by the Italian government to counter its effects.

Firms in Italy thus had to adapt to a completely new and dramatically different environment within a very short period of time.

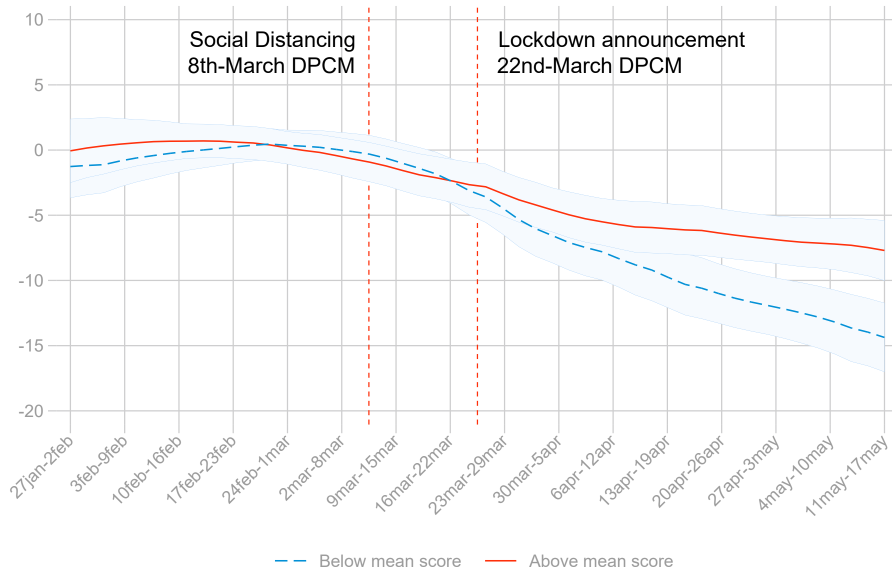
We study the role of management practices in the response of Italian firms to the COVID-19 shock using extremely rich information from surveys conducted by the Bank of Italy through the evolution of the pandemic. Our primary data source is the 2020 INVIND survey, conducted annually since 1984 and representative of firms with at least 20 employees. The 2020 vintage of the INVIND survey includes a module on SMPs based on the Management and Organizational Practice Survey (MOPS) used by Bloom, Brynjolfsson, Foster, Jarmin, Patnaik, Saporta-Eksten & Van Reenen (2019). The INVIND MOPS module explicitly refers to practices in place in 2019, that is, before the spread of the pandemic, and we use this to construct a standardized management score. Our key outcome of interest is the firm's expected sales growth: expectations have the advantage of being highly reactive to changes in the economic environment. The survey was conducted between February and May of 2020, which allows us to track how expectations change week by week across the evolution of the pandemic. We leverage this feature to construct our identification strategy.

Figure 1 illustrates our key result. We plot the evolution of the average expected sales growth in 2020 by the week of response separately for firms with management scores above and below the mean. Before the announcement of the lockdown, which can be seen as the "normal" period, there is no visible difference in expected sales growth between the two groups.[3] As the pandemic spread, firms' expectations about sales growth quickly deteriorated. However, this decline was not uniform: rather, firms with high SMPs reported substantially lower declines in expected sales.

This graphical evidence is fully confirmed in a regression setting, where we estimate the relationship between expected sales growth and the management score separately for firms that answered the survey before the lockdown announcement (for brevity, "pre-lockdown"), and after it ("post-lockdown"). Post-lockdown, SMPs are associated with lower expected sales drops: in our preferred specification, one standard deviation increase in the management score increases expected sales growth by 2.3%, more than one quarter the average drop (8.3%). The effect is twice as large as the one estimated for the pre–lockdown period and the coefficients are statistically different from each other. This indicates that SMPs turned

[3] This is not at odds with the literature cited above that shows that firms with higher SMPs perform better. That evidence, in fact, shows that such firms are more productive, larger, more profitable, etc. *in levels*. This does not imply that they also constantly grow more, a much stronger requirement in terms of performance.

Figure 1: Expected sales growth over the evolution of COVID-19 split by management score



Note: The y-axis of the graph shows smoothed values of mean YoY expected sales growth for 2020 from the INVIND survey across weeks reported on the x-axis for firms in two groups: those with a management score above the mean, and those with one below. The outcome variable is calculated through kernel-weighted local polynomial regressions of YoY expected sales growth on the week of response for firms. The bands shown are 95% confidence intervals and the vertical lines correspond to the announcement dates of widespread social-distancing restrictions in Italy (March 8^{th}) and country-wide lockdown (March 22^{nd}). A detailed description of the management score is in the text and Online Appendix B.

out to be a particularly useful asset in tackling a large shock. We use the richness of our data to corroborate this result by addressing various empirical concerns, such as by using *realized* sales growth from the 2021 vintage of the INVIND survey, and flexibly controlling for firm characteristics to take into account potential correlated effects.

During the lockdowns, firms resorted to remote work to different degrees. We posit that remote work may be easier to implement for firms with SMPs: when managers cannot track the input of workers through direct monitoring, output-based incentives may work better. This is easier when the firm has in place practices to set goals, measure outcomes, and reward employees accordingly. Our analysis confirms this: the management score is positively and significantly associated with increases in the share of employees engaged in remote work in 2020, controlling for the corresponding share in 2019.

Our results on the effects of SMPs during the COVID-19 crisis contribute to different strands of literature. We show that SMPs helped firms to adapt to a large, unforeseen shock, suggesting that they can also contribute to a firm's dynamic capabilities, contrary to the prevailing view in the literature (Teece 2007). Our findings also complement the burgeoning literature on SMEs performance and dynamic capabilities during the COVID-19 pandemic (Clampit, Lorenz, Gamble & Lee 2021, Dyduch, Chudziński, Cyfert & Zastempowski 2021, Rashid & Ratten 2021).

Our paper also contributes to the literature on management and firm performance (Bloom & Van Reenen 2007*b*, Bloom, Sadun & Van Reenen 2012, Bloom et al. 2013, Bruhn et al. 2018, Bender, Bloom, Card, Van Reenen & Wolter 2018, Schivardi & Schmitz 2020). We focus on the role of SMPs in responding to large shocks. The body of recent work on the role of firm organization in responding to large shocks demonstrates that we cannot naively extrapolate our knowledge of normal times.[4] The scant evidence on the role of management practices in responding to large shocks, based on the Great Recession, is inconclusive. Cette, Lopez, Mairesse & Nicoletti (2020) find results that are in line with ours, with cross-country evidence that SMPs were associated with firm resilience and lower declines in productivity in the period following the Global Financial Crisis. Englmaier, Galdon-Sanchez, Gil & Kaiser (2020) find that flexible management styles dominated structured management for firm performance during 2007-2009 in Spain. Direct comparisons are limited by differences in the nature of the shock: while the Great Recession was essentially demand-driven, and might have entailed limited scope for reorganization to tackle it, the COVID-19 crisis started out as supply-driven, as firms were facing strong restrictions on the way they could operate, as well as disruptions in the supply chain. SMPs might have proven particularly useful to address the need for reorganization that emerged during the pandemic.[5]

We also contribute to the literature on personnel economics, which has shown that structured human resource practices positively affect firm productivity (Ichniowski, Shaw & Prennushi 1997, Lazear & Oyer 2012). The abrupt, large-scale shift to remote work that many companies undertook during the pandemic presented new challenges for the organization of

[4]For example, Aghion, Bloom, Lucking, Sadun & Van Reenen (2021) find that, during the Great Recession, decentralization of decision-making became particularly useful to tackle the increased turbulence firms faced. Using stock market data for Italy, Amore, Pelucco & Quarato (2022) show that firms owned and managed by a family, usually associated with poorer performance, had higher abnormal returns during the pandemic period. For the US stock market, Alfaro, Chari, Greenland & Schott (2020) find that, contrary to normal times, investors valued firms with high labor intensity, which could more easily cut costs by shedding labor.

[5]In addition to using a different shock, our work differs along other dimensions that limit the comparability with these two papers. Cette et al. (2020) use sectoral measures of performance and a country-level measure of management practices, while we use firm-level data for both. Englmaier et al. (2020) use productivity as their preferred measure of performance, while we use expected sales. In our setting, expectations are instrumental to detecting the rapid change in performance that occurred with the spread of the pandemic and to setting up a test of differential effects of SMPs in crises with respect to "normal" times.

work. The few studies available, typically based on detailed data from one organization, find contrasting effects on productivity, possibly depending on the need for coordination and communication of the specific firm activity (Emanuel & Harrington 2021, Gibbs, Mengel & Siemroth 2021). Using survey data from employees of a large international corporation, Flassak, Haag, Hofmann, Lechner, Schwaiger & Zacherl (2021) show that remote work involves increased standardization of procedures and greater autonomy to compensate for the reduced possibility of direct supervision. Consistent with these results, we provide evidence from a representative sample of firms that monitoring and incentives practices were particularly useful in shifting to remote work.

The rest of the paper is organized as follows. Section 2 describes the data sources and presents summary statistics of the variables used in our analysis. In Section 3, we describe our empirical strategy and discuss identification challenges. Section 4 documents our results on the role of SMPs for firm performance pre- and post-lockdown, along with robustness results. In Section 5, we examine the higher take-up of remote work following the lockdown by firms with higher SMPs. In Section 6, we conclude.

2 Data

The Bank of Italy administered three firm surveys during 2020 that we use to analyze the response of firms to COVID-19: the INVIND Survey, with expectations about sales growth and a management practices module, the ISECO survey, to measure the impact of COVID-19 restrictions on firms, and the SONDTEL survey, on remote work. In addition, we use the INVIND 2021 survey, from which we construct realized sales growth in 2020 over 2019. This section describes each of our data sources, the construction of our key variables, and the summary statistics of the baseline sample.

2.1 The INVIND Survey

The INVIND survey is the annual business survey conducted by the Bank of Italy since the early 1980s.[6] It collects high-quality data on firms and is regularly used in research (see, among others, Guiso & Parigi 1999, Pozzi & Schivardi 2016, Rodano, Serrano-Velarde & Tarantino 2016). The survey is administered to approximately 5,000 firms and is a rep-

[6] Details about the INVIND survey can be found at https://www.bancaditalia.it/pubblicazioni/indagine-imprese/2019-indagine-imprese/index.html?com.dotmarketing.htmlpage.language=1.

resentative sample of manufacturing and services firms with at least 20 employees.[7] It is conducted directly by the regional branches of the Bank of Italy, and the data collected are used for the official statistics and the econometric models of the Bank of Italy, ensuring high quality of the responses.

Among other things, the INVIND survey collects firm expectations about various outcomes, such as sales, investment, and employment. The survey has been collecting expectations since the early nineties, and such questions have been extensively used in previous research, which finds that they track actual performance well.[8] We use expectations of sales growth in 2020 as our preferred performance measure because –as we argue more rigorously when discussing our empirical strategy in Section 3– expectations are very reactive to changes in the economic environment, a feature crucial to our identification strategy. We also expand our set of results using realized sales from the INVIND 2021 survey. We focus on sales because they depend on the extent to which the firm was subject to the exogenous COVID-19 shock and on the firm's capacity to contain its effects, while other variables, such as employment or investment, are more directly under the control of the firm, and therefore can be viewed as more a measure of the firm's decisions rather than its performance.[9]

The second key ingredient of our analysis is the degree of adoption of SMPs by firms. We obtain this from a module of eight questions included in the INVIND survey of 2020. The design of the module is based on the specialized survey instrument used in Bloom et al. (2019), developed and administered by the US Census Bureau.[10] Crucially for us, the questions explicitly refer to the practices that *already existed* in the organization in 2019, that is, strictly before the pandemic. They, therefore, represent the stock of practices the firm was already endowed with when it was hit by the pandemic.[11] Finding an effect of practices would indicate that it is extant monitoring and incentive practices that matter to tackle the pandemic shock, rather than changes thereof. This would then imply that operational

[7] The sample of interviewed firms is quite stable: the same firms are interviewed every year, adjusting only for attrition and to balance the sector coverage and size profile against that of the population.

[8] See Guiso & Parigi (1999) for early work, and Ma, Ropele, Sraer & Thesmar (2020) and Coibion, Gorodnichenko & Ropele (2020) for more recent work.

[9] In addition, the evolution of employment was heavily influenced by government policies introduced during the pandemic that forbade layoffs and offered an encompassing employment protection scheme.

[10] Details about the Management and Organizational Practices Survey (MOPS) administered by the US Census Bureau can be found at `https://www.census.gov/programs-surveys/mops.html`.

[11] One potential concern is that firms can also implement changes in SMPs during the pandemic. We believe that this is not a concern for our identification strategy. First, as explained above, firms were explicitly asked to refer to practices in place in 2019, strictly before the pandemic outbreak. Second, even in the presence of reporting bias reflecting changes implemented in 2020, it is unlikely that firms were able to substantially change their practices in the short time span of 16 weeks that we use in our main empirical analysis.

capabilities are beneficial not only in "business as usual" conditions but also, and perhaps particularly, when adapting to an abrupt shift in environmental circumstances (Helfat & Martin 2015).

The survey investigates the use of SMPs along three dimensions: monitoring, targets, and incentives. The monitoring questions ask firms about the collection and use of information, such as Key Performance Indicators (KPI henceforth), to monitor and improve the production process. The targets questions ask about the design and dissemination of production targets, and the incentives questions ask about bonuses, promotions, reassignment and dismissal practices, and how closely these are linked to employee and team performance.

To retain comparability with previous work, we closely follow Bloom et al. (2019) in the construction of a management score from the survey responses. We restrict our sample to firms with complete responses to the management module, which we define as answering at least 5 of the 8 questions. We construct an aggregate management score for a firm as follows. Each question is first scored on a 0-1 scale (low scores indicating lower use of SMPs). The scores for individual questions are then aggregated by taking the average of the question-wise scores. Next, we standardize this aggregate measure across firms, which transforms the measure to have mean zero and unit standard deviation. This is the score we will use in our analysis. Similarly, we create standardized sub-scores on monitoring, targets, and incentives for each respondent using specific questions in the MOPS module. Online Appendix B reproduces the original module included in the INVIND 2020 survey, along with the question-wise scoring scheme. The MOPS survey instrument has been used to assess the use of SMPs in diverse settings and can be considered fairly standardized.[12]

Panel A of Table 1 reports summary statistics for the 1808 firms in the baseline sample used in our analysis, which is defined as all firms responding to INVIND 2020 with complete responses to the management module. Firms are larger than the average Italian firm (in 2019, the INVIND mean number of employees is 483 against 4 for the overall firm population, and average sales is 164 million Euros), since INVIND does not survey firms with less than 20 employees. Three-quarters of the firms reported positive profits in 2019, about two-thirds of

[12]See for example Bloom, Iacovone, Pereira-Lopez & Van Reenen (2022), Kambayashi, Ohyama & Hori (2021) and Choudhary, Lemos & Van Reenen (2018). Prior to using the measure for analysis, we nevertheless validate it for our context. First, we confirm that the relative distribution of management scores in Italy versus the US follows the cross-country findings in the World Management Survey, with a heavier left tail in Italy relative to the US in the management score distribution. Second, we confirm that the management score is correlated with various measures of firm performance, consistent with Bloom et al. (2019). Details on the validation procedure are in Online Appendix B.

Table 1: Summary statistics: INVIND and SONDTEL Surveys

	Mean	Std. deviation	5th percentile	Median	95th percentile
	Panel A: INVIND				
Management score (2019)	0.00	1.00	-1.93	0.09	1.49
Employees (2019)	483.43	3566.25	22.00	79.00	1186.00
$\mathbb{1}_{Exporter}$	0.66	0.47	0.00	1.00	1.00
$\mathbb{1}_{Profits>0}$	0.74	0.44	0.00	1.00	1.00
Sales (2019, million EUR)	163.99	1191.38	2.20	20.21	448.65
YoY sales growth (2018-2019)	2.50	18.36	-21.14	1.23	28.03
Expected YoY sales growth, 2020	-4.48	17.04	-38.43	0.00	16.20
Sales (2020, million EUR)	146.52	919.10	1.80	18.23	399.46
YoY sales growth (2019-2020)	-8.59	20.65	-43.47	-6.64	19.30
	Panel B: SONDTEL				
% Remote work (2019)	1.85	6.40	0.00	0.00	7.50
% Remote work (2020)	11.71	15.61	0.00	2.50	50.00

Notes: Panel (A) describes summary statistics for variables used in the analysis computed over the baseline sample who responded to the INVIND survey with complete responses to the MOPS module. Sales are measured in millions of EUR in 2019. Expected sales growth is trimmed within 5 standard deviations. A detailed description of the management score is in the text and Online Appendix B. Employment is measured by headcount. $\mathbb{1}_{Exporter}$ is equal to 1 for firms reporting positive export sales in 2019, $\mathbb{1}_{Profits>0}$ is equal to one for firms that reported having strong or modest profits in 2019. Panel (B) reports the summary statistics for variables used in the analysis from the SONDTEL survey. % Remote work in 2019 and in 2020 refer to the number of employees working from home as a share of the firm's average workforce in each of the years.

the firms are exporters and about two-thirds are in manufacturing.

To complement our measures of expected performance from the INVIND survey, we use data from the INVIND 2021 survey on realized performance for our baseline sample of firms. This gives us 1598 firms who were part of both the baseline INVIND sample in 2020 and also responded to INVIND 2021. The overall expected YoY sales growth in 2020 for the INVIND sample is -4.5%. However, this varies over the course of the spread of the pandemic: the average expected sales growth for firms answering post-lockdown is -8.3%.[13] This value is very close to the realized YoY sales growth in 2020, which averaged -8.6% (see in Panel A of Table 1), and closely follows the aggregate GDP decline in 2020 (-8.9%).

2.2 The SONDTEL survey

The SONDTEL survey is conducted once a year in September on the same firms that comprise the INVIND sample.[14] The survey measures short-term dynamics of the Italian econ-

[13] Throughout the analysis, we trim the expected sales growth variable within five standard deviations.

[14] Details on the SONDTEL survey can be found at https://www.bancaditalia.it/pubblicazioni/sondaggio-imprese/2020-sondaggio-imprese/index.html?com.dotmarketing.htmlpage.language=1.

omy, and in 2020, the SONDTEL survey included a question on remote work in 2019 as well as in 2020.

Panel B of Table 1 shows the incidence of remote work from the SONDTEL sample. Firms were asked to choose among the following intervals on the incidence of remote work: a) none: 0; b) modest: (0-5%]; c) a little relevant: (5%-10%]; d) fairly relevant: (10%-20%]; e) relevant: (20%-35%]; f) very relevant: (35%-50%]; g) extremely relevant: (>50%). To obtain a quantitative measure, we used the midpoint for the interior intervals and the lower limit (50%) for the highest category. The share of remote work increased almost tenfold from 2019 to 2020. On the extensive margin, in 2019, only 19% of firms in our sample used remote work; in 2020 this increased to 70%. On the intensive margin, the share of remote work went from 1.8 to 11.7 percent. These figures are in line with official employment statistics: according to the Italian Labor Force Survey, the share of private sector workers engaged in remote work increased from 1.4% in the second quarter of 2019 to 14.4% in the same quarter of 2020.

2.3 The ISECO Survey

To provide a timely qualitative assessment of the effects of the pandemic on Italian firms, the Bank of Italy decided to conduct an additional survey, the ISECO survey (*Indagine Straordinaria sugli Effetti del Coronavirus*, or the Extraordinary Survey on the Effects of the Coronavirus). This was administered between March 16th and May 14th 2020, starting from when there were already initial restrictions, and continuing into the period of total lockdown. The ISECO survey directly elicits the channels of impact of COVID-19 on Italian firms as well as the strategies adopted by firms to tackle the impact of the pandemic.[15]

We exploit two unique pieces of information. The first is from the question asking: "In relation to the diffusion of COVID-19, what factors are negatively affecting your operations in Italy?" with the following seven options: 1. Drop in domestic demand; 2. Drop in foreign demand; 3. Problems with logistics and infrastructure; 4. Lack of labor force; 5. Slowdown in the supply of intermediate goods; 6. Problems of liquidity and/or in the financial structure; and finally, 7. None of the above. This question can be interpreted as investigating the channels through which the pandemic affects firm operations. Firms were required to list

[15]The methodology for the ISECO survey can be found at `https://www.bancaditalia.it/pubblicazioni/indagine-imprese/2019-indagine-imprese/metodologia_iseco_2020.pdf` and the questionnaire can be accessed at `https://www.bancaditalia.it/pubblicazioni/indagine-imprese/2019-indagine-imprese/questionnaire_iseco_eng.pdf?language_id=1`.

at most three factors, ranking them in descending order of importance. We group together answers pointing to drop in either domestic or foreign demand as "Demand", and answers pointing to "Problems with logistics and infrastructure" and "Slowdown in the supply of intermediate goods" as "Supply", so that we end up with five possible responses.[16] Next, we assign to each possible response the maximum rank obtained by each option.

Panel A of Table 2 tabulates responses of the 1587 firms in our baseline sample that answered the above question, with the responses listed by order of importance across the sample. Among these, 1062 firms indicated three factors, 303 firms indicated only two, and 222 just one. As clear from the table, demand was the most important driver affecting firms in Italy during this period, with about 63% of firms ranking the factor highest. Following demand, firms indicated supply as the second-most important factor, with 35% assigning it the second rank. The last column shows the share of firms never mentioning the particular strategy in any of their responses. For example, labor as a driver is very rarely listed, with about 80% of the firms never mentioning it as a factor.

The second key piece of information captured in the ISECO survey is from the question "What strategies have you adopted or are thinking of adopting to counter the negative effect of the spread of the Coronavirus in Italy on the activities of your firm?". Firms were given a series of ten alternative answers. Following the same procedure as before, we group these into five categories: demand policies, production policies, labor policies, investment plans policies, and finance. We report the details of the aggregation procedure in Online Appendix C. In particular, labor policies refer both to changes in the labor input (number of workers/hours/furloughing) and in the use of remote work. Note that firing was forbidden in Italy for all of 2020, meaning that permanent downsizing of the labor force was not an option for firms.

Overall, 1583 firms answered the strategy question described above. Among these, 1026 firms listed three strategies, 280 firms listed two strategies, and 277 listed only one strategy. Panel B of Table 2 shows the share of firms indicating each response by importance. Note that labor-related strategies are the most chosen option: only 26% of firms did not mention labor in one of their possible strategies.[17]

[16] Our final drivers are: Demand, Supply, Labor, Finance and None. See Online Appendix Table C1 for further details.

[17] Crispino (2021) applies to the same data a Bayesian Mallow model, a statistical model to analyze ranking data (including those in the form of top–k rankings like ours), and concludes that labor policies were the most adopted corporate strategy to tackle the effects of the pandemic.

Table 2: ISECO survey: Drivers and Strategies during COVID-19

	Panel A: Drivers			
	1st rank	2nd rank	3rd rank	Never Chosen
Demand	62.9	10.7	2.0	24.4
Supply	19.0	35.2	6.1	39.7
Labor	6.0	9.9	4.4	79.6
Finance	5.2	15.4	6.6	72.8
None	6.8	9.8	4.9	78.4

	Panel B: Strategies			
	1st rank	2nd rank	3rd rank	Never Chosen
Demand	6.9	3.9	3.1	86.1
Supply	13.2	21.4	7.3	58.1
Labor	54.1	16.7	3.7	25.5
Investment	4.2	13.6	9.7	72.5
Finance	14.1	21.0	16.0	48.9
None	7.5	4.6	7.3	80.5

Note: Panel A tabulates responses of the 1582 firms in our baseline sample that responded to the question: "In relation to the diffusion of COVID-19, what factors are negatively affecting your operations in Italy?". Panel B shows responses of 1579 firms to the question "What strategies have you adopted or are thinking of adopting to counter the negative effect of the spread of the Coronavirus in Italy on the activities of your firm?". Each value is the share of firms in the ISECO sample with the response shown in the row for the order of importance for the given column.

3 Empirical strategy and identification

Our goal is to determine if SMPs constitute an asset or a liability when facing a large unexpected shock that requires immediate and radical changes in the functioning of the firm. Ex-ante, the effect of management practices could go either way. On one hand, the practice of constantly setting and reviewing goals and monitoring progress towards achieving them could be useful to redirect firm operations when facing the shock. On the other hand, following these practices requires such targets to be set, shared, and monitored in a structured way. This might be difficult to change abruptly, decreasing the firm's capacity to promptly respond to the shock, whereas a less formalized management style might possibly allow for a faster response in a situation of crisis (Teece 2007, Augier & Teece 2009).

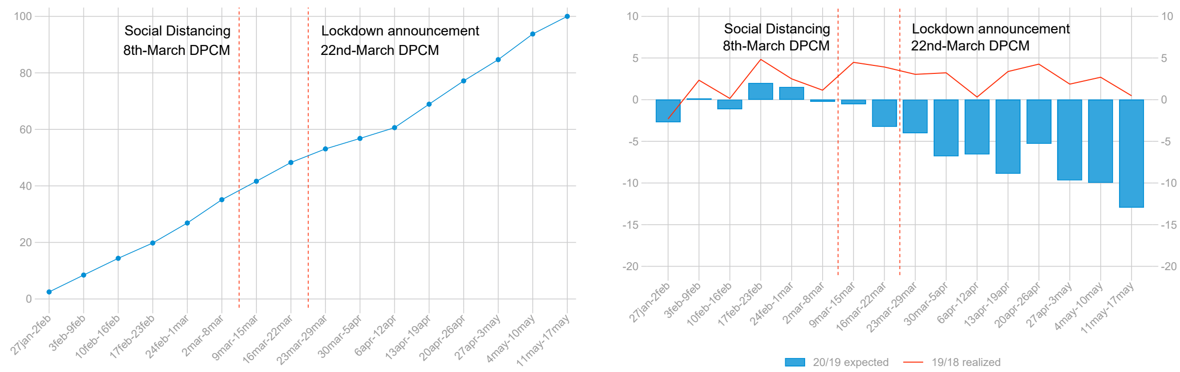
3.1 Empirical strategy

The road to our goal is fraught with empirical challenges. First, one needs a large and unexpected shock that materializes quickly and requires immediate action from firms. Second, it is by now well established that the quality of management practices strongly correlates with firm performance in general (Bloom & Van Reenen 2010, Syverson 2011). A better response by high SMP firms might simply be a reflection of a general superior performance of such firms, rather than something specific to their different reaction to the shock. Third, one also needs to control for correlated effects, such as that firms with higher management scores are also on average larger, more productive, more export-oriented, etc., and these characteristics might contribute to the determination of the response to the shock.

We argue that the outbreak of the COVID-19 pandemic in Italy, and the detailed information on firms' response to it which we have access to, offer an ideal setting to address these challenges. In addition to the strength and the speed with which the pandemic hit Italian firms, two features of the INVIND survey are at the core of our identification strategy. First, the survey is collected every year between the beginning of January and the beginning of May. The left panel of Figure 2 plots the cumulative density function of responses to the 2020 INVIND survey by the week of response, along with two key dates: the announcement of widespread social distancing in Italy on March 8^{th}, and the nationwide lockdown announcement on March 22^{th}. A little less than half of the firms answered the survey before the announcement of the lockdown. Second, the survey collects information on sales growth expectations for the current year (in our case, 2020). Expectations incorporate all information available to the firm at the time of the response. They can therefore capture sharp changes in expected performance as the business environment evolves. This provides a unique opportunity to observe how the evolution of the pandemic drove the expectations of sales growth week by week from the end of January to the beginning of May. The right panel of Figure 2 shows realized sales growth in 2019 (line) and expected sales growth in 2020 (bars) by the week when the INVIND survey was returned by the firm to the Bank of Italy. Before the lockdown, expected sales growth showed no trend. After the lockdown announcement, it quickly deteriorated: while expected sales growth was still close to zero for firms answering up to March 15^{th}, it progressively plummeted during the next three weeks.

We exploit these two features to set up a Difference-in-Difference analysis with repeated cross-sections, in which the pre-period is before the lockdown and the post-period is after

Figure 2: Cumulative share and sales growth by week of response to the 2020 INVIND survey



Note: The line in the left panel represents the cumulative density function of responses to the INVIND 2020 survey by the week of response shown on the x-axis. The sample consists of 1808 firms that responded to the survey. In the right panel, the y-axis represents the average YoY sales growth from INVIND of the firms that responded during the week reported on the x-axis. The bars are the average 2020 YoY expected sales growth, while the line is the average 2019 YoY realized sales growth. The vertical lines in both panels correspond to the announcement dates of widespread social-distancing restrictions in Italy (March 8^{th}) and country-wide lockdown (March 22^{nd}).

it.[18] In this setting, the treatment is the level of SMPs and our goal is to assess if there are differences in its impact on performance between before (the "normal" period) and after (the "shock" period) the lockdown. In a standard diff-in-diff setting with longitudinal data, we would use sales growth expectations measured for the same firm both in the pre- and the post-period. Missing this, we estimate the relationship between expected sales growth and management score separately for firms that answered the survey before and after the lockdown. Our analysis, therefore, rests on the assumption that firms that replied to the survey before the COVID-19 shock can be used to build a counterfactual scenario for those that replied after the shock. We discuss this assumption in detail in the next subsection.

Formally, we run the following regression:

$$\text{SalesGr}_i = \alpha_0 + \alpha_1 \text{Manag}_i + \alpha_2 \text{Manag}_i * \mathbb{1}_{LD} + \alpha_3' \mathbf{X}_i + W_i + (S_i + P_i) * (1 + \mathbb{1}_{LD}) + \epsilon_i \quad (1)$$

[18] As shown in the right panel of Figure 2, the two weeks around the beginning of the lockdown recorded sales growth that are halfway between the pre-lockdown and the lockdown period. In the week of March 16^{th}-22^{nd}, when the situation was rapidly deteriorating, firms started to revise the expectations in the light of the escalating restrictions, for example by incorporating the possible introduction of a nation-wide lockdown. Moreover, firms that returned the questionnaire the following week (March 23^{rd}-29^{th}) might have filled it in before the announcement of the lockdown and filed it afterwards, and therefore with a different outlook on the future sales dynamics than once the lockdown was already in place. Data for these two weeks are not clearly classifiable as referring to before or after the moment in which the severity of the shock was fully understood, and might attenuate the results. We therefore exclude firms that answered in those weeks (207 out of 1808 firms). All our results hold and are slightly weaker when we include all firms and we define the post-period starting from the lockdown announcement (see Online Appendix Table D3)

where SalesGr_i is the firm's i expected sales growth, Manag_i is the management score, $\mathbb{1}_{LD}$ is a dummy equal to one post-lockdown and $\mathbf{X}_i$ is a vector of firm controls, discussed below. In all regressions we include the following fixed effects. First, as shown by Figure 2, expected sales are heavily dependent on the week of response. To account for this, we include fixed effects for the week of response W_i, so that we only use the within-week, cross sectional variability to estimate the parameters. Second, given that the pandemic had very differentiated effects at sectoral and geographical level, we control for 3-digit NACE sector fixed effects (S_i), as well as a set of NUTS3 province fixed effects (P_i). To fully account for the differential change in performance both at the sectoral and geographical level occurring with the lockdown, sector and province dummies are also interacted with the lockdown dummy $(1 + \mathbb{1}_{LD})$. Finally, we also include a dummy for whether the survey was conducted over the phone or via email. Given the strong sectoral component of the pandemic shock, standard errors are clustered at the 3-digit industry level.

3.2 Identification concerns

For the firms that answered in the pre-period to provide a valid counterfactual for those that answered in the post-period, firms in the two periods must share the same observable characteristics. This is the typical common support assumption of the Difference-in-Differences literature (see for example Roth, Sant'Anna, Bilinski & Poe 2023). Intuitively, if all high SMP (or large, or highly profitable) firms answered the survey in the pre-period, we would be comparing very different firms. In Online Appendix Figures D1 and D2 we plot the distribution and the mean of the average management score, firm size and productivity by week of response. We find that not only the range of variation, but also the mean is very similar across weeks of response. To further corroborate this point, we construct an indicator variable equal to one for firms that submitted the survey in a given week and zero otherwise. We then run sixteen regressions of each of these "week dummies" on the firm characteristics that we included in our baseline regression: management score, firm size, an indicator that equals one for exporters, firm productivity measured as the log of revenue per worker, and an indicator that takes value one for firms with positive profits, where we take 2019 values of each variable. The results from this exercise are shown in Online Appendix Table D1. Out of the eighty coefficients (five for each regression), only nine are significant at 10%.[19] We conclude that firm characteristics cannot predict the week of response to the survey,

[19]Note that, with eighty coefficients, the expected number of significant estimated coefficients at 10% significance level when the true coefficients are actually equal to zero is eight, in line with the nine we find.

indicating that selection in the week of response in terms of observable characteristics is effectively as good as random.[20]

Another concern is that expectations might systematically differ according to the presence of SMPs, and that this difference might change during the pandemic. Consider for example a situation in which, compared to firms with low SMPs, firms with high SMPs become relatively more optimistic in the pandemic period and tend to over predict their sales in 2020. In this case, a positive correlation between expected sales and the management score in the post-period might capture this expectation bias rather than true differences in performance. Our data allow us to directly address this concern. First, we will show that our results with expectations are confirmed with realized sales.[21] Second, we will compute the expectation error, i.e., the difference between expected and realized sales growth, and show that there is no correlation with the management score both pre- and post-lockdown.[22]

Despite being an aggregate shock, the COVID-19 pandemic hit different firms with different intensities, most notably in terms of belonging to an essential sector, but also along other dimensions. The key assumption for the consistency of our estimates is that these differential effects are not systematically related to SMPs. Ex-ante, there is no obvious reason why this correlation could arise. The effects were clearly heterogeneous at the sectoral level, and in our regressions we will always control for sectoral differences through fixed effects. Still, theoretically there might be within-sector effects that are not captured by our controls. We use a unique piece of information contained in the ISECO survey to test this assumption directly: the ISECO asks firms about the factors related to COVID-19 that negatively

[20] Following D'Haultfœuille, Hoderlein & Sasaki (2023), we also check a more stringent condition: that the similarity in characteristics also holds conditional on the management score. We do this by running our pre-post specification, where we use an observable firm characteristic as an outcome (employment, productivity, etc.), and we include in our regression both the management score level and its interaction with the post-lockdown dummy. Online Appendix Table D2 shows the results.We find that the interactions between the management score and the post-lockdown dummy are always close to zero and statistically insignificant, which indicates that in our sample, firms with similar management scores also have similar characteristics in the two periods. This further ensures the comparability of the two samples.

[21] We use realized sales as a robustness check rather than our preferred performance measure because we cannot implement our diff-in-diff identification strategy, as realized sales are independent from the week in which the firm filed the survey, and therefore the estimates cannot be interpreted in terms of the difference between the crisis period and the normal period.

[22] Note that systematic biases (such as the tendency to under or over predict sale) correlated with SMPs would invalidate expectations as a measure of performance. Differences in accuracy would instead translate into heteroskedasticity of the error term, which does not lead to biased estimates. Consequently, we use the difference between expected and realized sales growth, rather than its absolute value or its square, which is the typical measure of accuracy used in the literature (see for example Altig, Barrero, Bloom, Davis, Meyer & Parker (2020)). Our measure and our findings using expectation error align with Bloom, Davis, Foster, Lucking, Ohlmacher & Saporta-Eksten (2020).

affected the firm's operations in Italy, that we grouped into factors in terms of demand (domestic and foreign), supply (logistics, supply chain), labor, finance and none (as described in Section 2). Firms were asked to choose up to three factors, ranking them according to their relevance. The setting of the question is suitable to be analyzed with the conditional logit model of McFadden (1974), where each factor corresponds to a choice and "none" represents the outside option; there are no characteristics specific to the factors, while we do observe firm characteristics. In Online Appendix C we report the details of how we construct the model and how we adapt it to the fact that, compared to the standard model, firms could choose up to three options. We also discuss the conditions under which the model produces consistent estimates, arguing they are likely to be met in our setting. Table 3 reports the odds ratios from the estimation, where a coefficient larger than one indicates that the corresponding variable is positively correlated with the probability of choosing that alternative. No correlation between the management score and the likelihood of indicating any particular factor emerges. This is consistent with the assumption that the shock was exogenous with respect to SMPs in place in a firm.

Table 3: Drivers of negative effect of COVID-19

	Demand	Supply	Labor	Finance
Management	1.053	1.069	1.110	0.955
	(0.082)	(0.073)	(0.096)	(0.075)
Log(Employment)	0.893*	0.967	1.089	0.818***
	(0.052)	(0.051)	(0.063)	(0.050)
Log(Revenue/Employment)	0.754***	0.856**	0.733***	0.656***
	(0.056)	(0.053)	(0.059)	(0.049)
$\mathbb{1}_{Exporter}$	2.822***	1.904***	2.190***	1.770***
	(0.443)	(0.263)	(0.367)	(0.277)
$\mathbb{1}_{Profits>0}$	0.866	0.867	0.751	0.541***
	(0.153)	(0.135)	(0.137)	(0.091)

Note: The table shows the results of the conditional logit regression. Drivers are displayed at the top of each column. The coefficients shown are odds ratios, where the omitted category is *"None of the above drivers"*. A detailed description of the management score is in the text and Online Appendix B. Employment is based on headcount; revenues refer to total sales, for both we take the 2019 value. $\mathbb{1}_{Exporter}$ is equal to 1 for firms reporting positive export sales in 2019, $\mathbb{1}_{Profits>0}$ is equal to one for firms that reported having strong or modest profits in 2019. Standard errors are shown in parentheses and clustered at the 3-digit sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4 Results

Figure 1 showed evidence on the relationship between performance and the management score during the pandemic. The trends of expected sales growth by week of response for firms above and below the mean value of the management score did not differ before the lockdown, but diverged as the shock spread and restrictions were introduced, becoming statistically different by mid-April. However, this evidence is just suggestive, because SMPs can be correlated with other determinants of performance. We employ the richness of our data and examine this further by estimating Equation 1.

Baseline specification. We start with a parsimonious specification in which we only include the full set of fixed effects: sector and province dummies and their interaction with the post-lockdown dummy, week of response dummies and interview type dummies. The results are reported in Column (1) of Table 4. The coefficient of the management score is positive and equal 0.77 in the pre-lockdown period, but statistically insignificant. Its value increases to 2.3 (0.77+1.58) in the post-lockdown, with the difference between the two estimates statistically significant at the 5% level. As the average decline in expected sales growth in the post-lockdown period is -8.3%, the effect of one standard deviation increase in the management score is more than a 25 percent reduction in the expected sales drop in the post-lockdown period.

In Column (2) we add a set of firm controls that may be correlated with both the management score and expected performance, all measured in 2019. We include size (log of the number of employees) and labor productivity (log of revenue per employee), as larger and more productive firms may be better equipped to face the pandemic relative to smaller and less productive ones.[23] We also include indicator variables that capture if the firm has positive exports and if it recorded positive profits. These variables are readily available in INVIND, allowing us to maximize the size of our baseline sample (below we add additional controls from other data sources, in which case we lose some observations). The results are virtually the same as in Column 1, indicating that SMPs are not proxying for these firm characteristics.[24]

In the specification of Column (2) we impose a unique coefficient in the two periods for firm characteristics. One possible concern is that the effect of these characteristics on performance changed, too, during the pandemic with respect to normal times. To level the playing field, in Columns (3) and (4) we report the results of two regressions in which we separately estimate the model for the pre-lockdown and the post-lockdown period, therefore allowing

[23] In the context of the US, Bartik, Bertrand, Cullen, Glaeser, Luca & Stanton (2020) show that small firms experienced a significantly negative impact of COVID-19.

[24] To address potential collinearity concerns, in columns 1-4 of Table D4 of the Online Appendix we show the results when controls are added sequentially one by one, finding that they remain very stable.

Table 4: Management and sales growth

Dependent variable:	Expected sales growth					Realized sales growth	
			Sample split				
			Before	After			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Management	0.768	0.882	1.005	2.333***	1.066	1.675***	2.074***
	(0.650)	(0.656)	(0.660)	(0.646)	(0.666)	(0.536)	(0.575)
Management* $\mathbb{1}_{LD}$	1.581**	1.631**			2.114**		
	(0.756)	(0.774)			(0.816)		
Log(Employment)		-0.198	-0.723	0.300	-0.615	-0.157	-0.135
		(0.402)	(0.561)	(0.521)	(0.441)	(0.512)	(0.540)
Log(Revenue/Employment)		0.695	-0.796	2.282**	-0.264	1.216	1.835*
		(0.587)	(0.885)	(0.891)	(0.711)	(0.975)	(1.066)
$\mathbb{1}_{Exporter}$		-1.563	-1.778	-1.648	-1.713	-1.393	-0.815
		(1.381)	(1.653)	(1.689)	(1.432)	(1.577)	(1.623)
$\mathbb{1}_{Profits>0}$		-2.059**	-0.435	-4.133**	-1.297	2.677*	2.471
		(1.028)	(1.122)	(1.704)	(1.149)	(1.527)	(1.585)
Closed sector					-1.391		-8.695***
					(2.335)		(2.931)
Closed Sector* $\mathbb{1}_{LD}$					-9.597**		
					(3.942)		
Log(average wage)					2.467		-0.686
					(1.722)		(2.471)
Skill (% white-collar)					0.031		-0.041
					(0.030)		(0.038)
Average human capital					-6.258		-14.121*
					(6.771)		(8.280)
Manager human capital					3.679		5.340
					(5.434)		(6.634)
Advanced technologies					1.041		-0.448
					(1.215)		(1.159)
Fixed effects							
Sector	Y	Y	Y	Y	Y	Y	Y
Province	Y	Y	Y	Y	Y	Y	Y
Week of response	Y	Y	Y	Y	Y	Y	Y
Interview type	Y	Y	Y	Y	Y	Y	Y
Sector* $\mathbb{1}_{LD}$	Y	Y			Y		
Province* $\mathbb{1}_{LD}$	Y	Y			Y		
Observations	1535	1535	719	816	1287	1385	1172

Note: The dependent variable in columns 1-5 is the expected YoY sales growth in 2020 sourced from INVIND. The dependent variable in columns 6-7 is realized YoY sales growth in 2020 from INVIND. A detailed description of the management score is in the text and Online Appendix B. $\mathbb{1}_{LD}$ is an indicator variable that takes value 1 if the firm answers the 2020 INVIND survey after 22$^{\text{nd}}$ March. Employment is based on headcount; revenues refer to total sales, for both we take the 2019 value. $\mathbb{1}_{Exporter}$ is equal to 1 for firms reporting positive export sales in 2019, $\mathbb{1}_{Profits>0}$ is equal to one for firms that reported having strong or modest profits in 2019. Closed sector is a dummy for 5-digit sectors whose activities were not permitted during the lockdown. Average wage is measured in 2019. The share of white-collar workers, average human capital and manager human capital are sourced from social security data and measured in 2018 (the most recent available year). Average human capital and manager human capital are obtained from individual workers' fixed effects estimated over the period 2005–2018. Average human capital is the mean of these fixed effects in the within-firm distribution and manager human capital is the mean in the top quartile of the within-firm distribution (see Bender et al. (2018) for further details). Advanced technologies is an indicator variable that takes value one if the firm uses at least one of the following: cloud computing, big data, or artificial intelligence. Sectors are defined according to the 3-digit Nace rev. 2 classification. Provinces refer to NUTS3 Eurostat classification. Interview type is a dummy for interviews conducted over the phone (as opposed to email). Standard errors are clustered at the 3-digit industry level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

all the coefficients to vary between the two periods. The results are fully in line with those of Column (2): the coefficient of the management score is positive but not significant in the pre-lockdown period, and more than twice as large and significant at the 1% level post-lockdown. Moreover, we reject the hypothesis that the two coefficients are statistically equal (p-value 0.023). Post-lockdown, the coefficient of productivity becomes positive and significant, indicating that more productive firms were able to limit the effects of the shock. However, accounting for this does not decrease the coefficient of the management score.

Additional controls. While we include the controls readily available in INVIND, we cannot exclude that there are other characteristics correlated with both performance and SMPs. We see two main sources of correlated effects. The first is human capital. Using matched employer-employee data for Germany, Bender et al. (2018) show that SMPs and human capital are positively associated, and that the association between SMPs and productivity decreases by 30-50% when including measures of human capital. Cornwell, Schmutte & Scur (2021) find similar results for Brazil. Human capital might also be a factor in the response to the COVID-19 shock, for example because more educated workers can more efficiently work remotely. INVIND has no direct measure of the workers' human capital. We first use as a proxy the average wage of the employees, based on the assumption that –conditional on controls– firms that pay higher wages also employ more skilled workers. However, the average wage is an imperfect measure of human capital.[25] To obtain alternate measures, we use the matched employer-employee version of INVIND based on administrative social security data, for which we have information on workers for the years 2005-2018.

The administrative data do not report the education but only the occupational status. We compute the share of white-collar workers. Accounting for occupational status is important, both because typically white-collar workers have higher human capital and because they are more likely to be able to work remotely, an important factor during the lockdown. We also estimate worker fixed effects from a standard two-way fixed effects regression following Bender et al. (2018). The worker fixed effect captures the average worker's wage over her career, and therefore is a summary measure of ability, under the (reasonable) assumption that workers with higher skills earn on average higher wages (Card, Heining & Kline 2013). Following Bender et al. (2018), we construct two measures: the average worker effects and the average effects of the top 25% of the skill distribution. In fact, Bender et al. (2018) show

[25]For example, a large employer-employee literature shows that there is a wage component at the firm level that is not explained by workers' skills (Abowd, Kramarz & Margolis 1999). Moreover, labor market regulation on wage determination can weaken the link between human capital and wage.

that the latter is more strongly correlated with the quality of SMPs.

The second potential source of correlated effects is technology. It is well known that structured management is complementary to IT (Bloom et al. 2012, Schivardi & Schmitz 2020). It might then be that the firms with higher management scores also have invested more in IT, and the level of IT in a firm was a factor in determining the firm's response to the shock, confounding the role of SMPs. The 2020 INVIND elicited the use of advanced technologies, asking if firms were using cloud computing, big data or artificial intelligence. We construct a dummy which is equal to 1 if the firm uses at least one of these technologies.[26]

Another issue is that performance could vary systematically for firms operating in essential sectors relative to others, as these sectors were allowed to operate even during the lockdown. To control for this, we construct a dummy for "closed" sectors (C_i) defined at 5-digit NACE level. This is the same detail of classification that was used to define essential goods and services.[27] Given that this dummy should matter only in the lockdown period, we also interact it with the post-lockdown dummy.

Table 4, Column (5), shows the results when including these additional controls. If anything, the effect of SMPs in the post-lockdown period increases. Of the additional controls, only the interaction for the closed sectors dummy and the post-lockdown dummy is significant.[28] Results are extremely similar also when we allow the coefficient of all variables to differ between pre- and post-lockdown periods by estimating the model separately for the two subperiods (tabulations unreported for brevity): in this case, in the pre-period the coefficient on management score is equal to 1.18 (p-value 0.074) and it increases to 2.82 (p-value 0.002) in the post-lockdown period. The difference between the two (1.64) is statistically significant

[26] Of course, advanced technologies only measure one aspect of IT, and others might have mattered during the pandemic. Unfortunately, this is the only measure of IT available in the survey. Despite not fully capturing the degree of digitization of the firm, we show below that it is positively correlated with the extent to which firms adopted remote work, suggesting that it is a useful variable to include in the regression to control for the possibility that firms with more SMPs might also adopt better IT technologies.

[27] Our three-digit sector dummies account for most of the essential sector status. However, within 17 out of the 159 three-digit sectors covered by our firms, some sub-sectors are classified as essential and others are not. A list of essentials sectors as defined by the Italian government can be found in the annex 1 of the DPCM of March 22$^{\text{nd}}$, available at `https://www.gazzettaufficiale.it/eli/gu/2020/03/22/76/sg/pdf`.

[28] One might be surprised by the fact that none of the human capital and technology controls are significant. As explained above, however, it is important to distinguish between the effects of these variables on sales level and on growth rates. In unreported regressions, we have used the logarithm of sales level in 2019 as the dependent variable, finding that most of the controls are significant and with the expected sign, while the management score loses significance. This lends further support to the hypothesis that, compared to other firm characteristics, SMPs are particularly important to counter a large shock. Moreover, to investigate the possibility that the lack of significance is due to multicollinearity, in Columns 5-10 of Online Appendix Table D4 we repeat the estimation including one variable at a time, finding that the estimates are very stable.

(p-value 0.084). Overall, we conclude that the correlation between expected sales growth and the management score during the lockdown is extremely robust and survives the (flexible) inclusion of the most likely confounding effects.[29]

Using realized sales. One potential concern discussed above is that expectations might be an incorrect measure of performance if the expectation error is systematically related to SMPs. The INVIND 2021 survey reports data on realized sales in 2020, which allows us to do two things to address it. First, we use realized sales as the dependent variable. Note that in this case, we cannot perform any pre-post analysis, so we simply regress realized sales on the management score. Column (6) of Table 4 reports the results using the specification of Column (2), that is, with the basic firm controls. Firms with higher management scores show sizable larger sales growth in realization as well, in line with the results based on expected sales. The magnitude is similar to that of Column (4) for the post sample, despite being slightly lower (1.7 vs. 2.3).[30] In Column (7) we repeat the estimation including all the controls for human capital and technology, obtaining similar results.[31]

In addition to directly using realized sales, we can also check if expectation errors systematically correlate with SMPs. To check for this possibility, we run the same regressions as in our baseline result (Table 4) but using the expectation error for 2020, defined as expected sales growth minus realized sales growth, as the dependent variable. The results, reported in Online Appendix Table D6, show that both the coefficient of the management score and that of its interaction with the post dummy are never significantly different from zero. This confirms that our results are not driven by systematic differences in expectation errors according to the management score, neither in the pre- nor in the post-period.

[29] We have performed additional robustness checks. First, we have computed the expected growth rate of sales in 2020 with respect to average 2017-2019 sales, to make sure that the results are not driven by some specificity of 2019. Second, we have shown above that for three weeks SMPs could weakly predict the week of response (10-16feb, 20-26apr, and 4-10may; see Online Appendix Table D1). To check that selection is not driving our results, we have repeated the estimation excluding these weeks from our sample. In both cases, we find that results become stronger (available upon request).

[30] Part of the difference is due to the fact that some firms that answered the INVIND survey in 2020 did not in 2021. It turns out that these are firms with low MOPS and low expected sales, which possibly exited the market. If we run the regression of Column (4) excluding these firms, the coefficient drops to 2.0, reducing the gap. Moreover, we have chosen a very conservative treatment of outliers, excluding firms with expected sales growth above or below the mean plus or minus five times the standard deviation (see section 2.1 for more details). If we trim at the first and last percentiles, another common strategy used to deal with outliers, we get exactly the same estimates using expected and actual sales.

[31] In Online Appendix Table D5 we repeat the regressions with realized sales including the controls sequentially and show that the point estimates are highly stable.

5 Why did firms with SMPs perform better?

During the most acute phase of the pandemic, as well as after it, many companies moved extensively to remote work (Barrero, Bloom & Davis 2021). SMPs might be a fundamental asset to successfully move a substantial amount of workers to remote work very quickly, and with no possibility to plan the move in advance. In fact, one of the fundamentals of SMPs is to assign workers clearly defined responsibilities, systematically keeping track of outcomes and taking decisions based on the information collected. This "organization philosophy" enables delegation and worker autonomy ex-ante and assessment of outcomes ex-post.[32] This approach to human resource management reduces the need to monitor progress and effort by direct interaction and allows for a more productive use of remote work. Our hypothesis is therefore that better-managed firms were more ready to shift abruptly and substantially to remote work.

We test this hypothesis in Table 5 using the information on remote work from the SONDTEL survey, which reports the percentage of employees working remotely in 2020. In Column (1) we find that the management score does correlate with remote work usage: we estimate a coefficient of 1.5, significant at the 5% level. Given that the average remote work in 2020 is 11.7%, one standard deviation increase in the management score implies an increase in the share of remote work of 13 percentage points with respect to the mean. Next, we also control for the use of remote work in 2019. It might be that firms using remote work already in 2019 were more prepared to increase its utilization in 2020. In Column (2) we add remote work in 2019 to the regression and find that the coefficient of the management score decreases only marginally (from 1.5 to 1.4) and remains significant at the 5% level.

To delve into this deeper, we examine if the effect is related to any specific component of SMPs. To do this, we keep the same specification as in Column (2) and now use the management sub-scores on monitoring, targets, and incentives as regressors. We report the results in Columns (3), (4), and (5) of Table 5. We find that the overall result is driven by the monitoring and incentives components of the management scores. This is expected: the monitoring section captures how many KPIs the firm tracks, including worker absenteeism. Monitoring performance through measurable outcomes may help substitute for direct monitoring of workers at the workplace. The same holds for incentives: using

[32] In fact, early studies on changes in firm organization related to the diffusion of IT stressed the importance of the decentralization of authority, the "delayering" of managerial functions, team-based work organization (Caroli & Van Reenen 2001, Bresnahan, Brynjolfsson & Hitt 2002).

Table 5: Remote work and management in 2020

	Overall		Monitoring	Targets	Incentives
	(1)	(2)	(3)	(4)	(5)
Management	1.485***	1.375***	1.209***	0.596	0.869**
	(0.432)	(0.414)	(0.340)	(0.389)	(0.366)
Log(Employment)	2.919***	2.622***	2.691***	2.853***	2.754***
	(0.394)	(0.370)	(0.373)	(0.360)	(0.376)
Log(Revenue/Employment)	2.809***	2.533***	2.563***	2.598***	2.521***
	(0.568)	(0.523)	(0.524)	(0.537)	(0.523)
$\mathbb{1}_{Exporter}$	0.147	0.329	0.236	0.421	0.522
	(0.739)	(0.722)	(0.730)	(0.742)	(0.743)
$\mathbb{1}_{Profits>0}$	-0.472	-0.257	-0.134	-0.0145	-0.261
	(0.701)	(0.675)	(0.683)	(0.679)	(0.685)
Advanced technologies	1.842**	1.714**	1.925***	2.080***	1.949**
	(0.740)	(0.741)	(0.725)	(0.730)	(0.770)
Skill (% white-collar)	0.163***	0.152***	0.153***	0.153***	0.152***
	(0.024)	(0.023)	(0.023)	(0.023)	(0.023)
% Remote work (2019)		0.395***	0.391***	0.396***	0.401***
		(0.056)	(0.056)	(0.055)	(0.057)
Observations	1500	1495	1493	1491	1491

Note: The dependent variable is the percentage of employees at the firm working remotely in 2020. A detailed description of the management score is in the text and Online Appendix B. Employment is based on headcount; revenues refer to total sales, for both we take the 2019 value. $\mathbb{1}_{Exporter}$ is equal to 1 for firms reporting positive export sales in 2019, $\mathbb{1}_{Profits>0}$ is equal to one for firms that reported having strong or modest profits in 2019. Advanced technologies is an indicator variable which takes value 1 if the firm uses at least one of the following technologies: cloud computing, big data or artificial intelligence. The share of white-collar workers is measured 2018 from social security data (last year available). % Remote work (2019) refers to the number of employees working from home as a share of the firm's average workforce in 2019. Regressions include 3-digit sector and province fixed effects. Standard errors are shown in parentheses and are clustered at the 3-digit sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

structured incentives-based schemes requires some measurable notion of output, this can be used to assess worker performance when working remotely. In contrast, targets are not significant, arguably because this component captures setting medium to longer-term targets, which may not be particularly relevant in the acute phase of the pandemic and lockdown.

The overall score bears a larger coefficient than any of the components, suggesting that the different dimensions of SMPs are complementary in allowing a more efficient organization of remote work. This is in line with the experimental results of Bruhn et al. (2018) on Mexican SMEs, who show that there is no silver bullet, that is, no single managerial practice that in itself improves firm performance. Our results are consistent with the framework of Brynjolfsson & Milgrom (2013), who emphasize the role of complementarities in practices within organizations, i.e., the added value of clusters of practices working in concordance relative to their independent effects.

One may argue that structured management mattered mostly because it was instrumental in switching activity to remote work in the context of the pandemic, limiting the generality of our findings. We leverage the ISECO survey to investigate more in general the strategies the firms adopted or considered adopting to counter the negative effects of the pandemic. We estimate the same conditional logit model introduced in Section 3 and report the results in Online Appendix Table D7. We find that firms with higher management scores were more active in addressing the shock along all the inquired dimensions (demand, supply, investment plans) except finance. This indicates that SMPs were instrumental to reorganizing the "real" part of the firm activity along a broad set of dimensions, suggesting that our results are likely to generalize beyond the specific context of the COVID-19 pandemic.

6 Discussion and Conclusions

We study the role of modern SMPs in responding to a large, unanticipated shock, the COVID-19 pandemic in Italy. We find that firms with better SMPs were more likely to take action to address the challenges posed by the pandemic and were able to limit its negative effects. One special feature of our empirical setting is that we can compare the relationship between SMPs and expected sales growth in a narrow window around the outbreak of the pandemic. Therefore, we can conclude that SMPs were particularly useful to tackle a large, totally unanticipated shock, above and beyond their contribution to firm management in "normal times".

One important question is external validity, due to the specificity of the COVID-19 shock. The pandemic induced a large, unexpected, and extremely rapid disruption in the firm operations. As such, our results are likely to extend to other unexpected events that severely constrain firm operations, such as natural disasters, wars, disruptions in the supply chain, etc. They apply to a lesser extent to demand-driven recessions, where firms are not constrained in their operations but by the lack of demand. This can explain the contrasting results found by the (small) literature focused on the Great Recession (Cette et al. 2020, Englmaier et al. 2020).

The features of our exercise have important implications about what we can (and cannot) learn about SMPs. Our empirical design measures changes in the relationship between SMPs and performance occurring over a very short period of time, so we capture the ability to cope with the immediate effects of the pandemic. Our analysis indicates that, to tackle the immediate effects of an unexpected shock, it is extant monitoring and incentive practices that mattered, rather than changes thereof, as it is unlikely that firms radically changed SMPs in the short time frame we consider around the outbreak of the pandemic. We therefore conclude that, despite being primarily designed for operations management, SMPs are also a good "fit" for adaptation, and that there is no trade-off between the two dimensions. On the contrary, our results cannot be extrapolated to firms re-positioning to long-term changes induced by the pandemic (the so-called "new-normal"). This is indeed an important and exciting area of future research for strategic management and organization design (Englmaier, Foss, Knudsen & Kretschmer 2018). Finally, due to the sample size, we could not investigate the heterogeneity of firm responses. Along with going deeper into the mechanisms, this is another important topic for future research.

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