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Managing to adapt: structured management practices and firm resilience

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Managing to Adapt: Structured Management Practices and Firm Resilience

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Abstract

Why do some firms adapt and even thrive when major unexpected shocks occur? We hypothesise that structured management practices are a General Purpose Technology that helps firms adapt to unforeseen shocks. Using a novel, custom-designed survey, we find that firms with more structured management practices were more resilient to the large and unexpected shock of the Covid-19 pandemic, adopting homeworking and online sales practices more fully, adapting supply chains more effectively, and avoiding larger falls in their sales. Linking at the firm level to a high-frequency business survey, we show that firms with highly structured management practices undertook more product, process and logistics innovation to facilitate enforced changes in working practices and business operations. We conclude that this episode illustrates the many mechanisms by which structured management practices may improve firms' resilience to shocks.

JEL Classification: D22; M10; O30; O33
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1 Introduction

Why do some firms show resilience and even thrive in reaction to a common shock while others struggle? What attributes make firms more resilient and adaptable than others? Defining firm resilience as the ability to adapt contemporaneously to unforeseen shocks, we hypothesise that structured management practices are in essence a General Purpose Technology that helps firms to be more resilient. The Covid-19 pandemic provides a natural experiment to explore this resilience hypothesis since it was an unforeseen shock that had global impact. Five years on, we have a clearer perspective on the effects and demonstrate that firms were differentially equipped to cope with it.

Using a novel, custom-designed survey, we find that firms with more structured management practices are more resilient than their peers. During the pandemic firms with more structured management practices saw a smaller fall in their turnover compared to firms with less structured management practices. Underpinning this better performance was their ability to adopt homeworking and online sales practices more fully and to flex their supply chains in response to enforced changes in business operations. Linking at the firm level to a high-frequency business survey, we show that firms with highly structured management practices undertook more product, process and logistics innovation to facilitate these changes and embedded hybrid working more completely in the long run.

Our paper draws on Bloom and Van Reenen (2007) who show that firms with more structured management practices have higher productivity, profitability, exports and patents (Bloom et al., 2007, 2012). Bloom et al. (2017) argue 'management variation accounts for about a fifth of the spread of productivity across firms, a similar fraction as that accounted for by R&D, and twice as much as explained by IT'. It follows that a key factor behind resilience and adaptability may lie in the management practices a firm has adopted *prior* to a shock.

To protect their populations from adverse health effects of the Covid-19 pandemic, governments imposed non-pharmaceutical interventions (NPIs), which meant that most firms suddenly found their usual working and retail practices non-viable, and their standard way of doing business was threatened.[1] The pandemic forced many businesses to fundamentally change the way they produced and sold their output (Brynjolfsson et al., 2020). Recent studies hypothesise that some firms were better placed to deal with this shock because they had pre-existing arrangements in place (such as

[1] NPIs were meant to slow down the spread of the Covid-19 virus. In the UK, they took the form of stay-at-home orders (lockdowns) during 2020 that restricted on-premise work, travel and hospitality, and some retail stores were closed but online sales continued.

greater use of remote working or IT support) to accommodate its effects (Bai et al., 2021). This suggests firms were ready to respond because they had pre-existing flexibility in key dimensions such as their ability to work from home while government-issued stay-at-home orders were in place.

We argue instead that successful firms had an edge *not* because they were *fortunate* to be well positioned for a specific type of shock, but because they had the right management practices in place to deal with many unforeseen shocks. We conjecture that structured management practices allow firms to respond to sudden and unforeseen events more readily, enabling them to quickly adapt their business operations.[2] We argue that the advantages that derive from structured management practices make it a General Purpose Technology (GPT).[3] Structured management practices as a GPT allow firms to respond to changes and make further adjustments to organisational practices, as demanded by changes in circumstances. Existing research recognises that management ability influences performance (mostly through productivity). Firms with more effective monitoring (Bloom et al., 2012; Halac and Prat, 2016), active personnel management (Bresnahan et al., 2002; Aghion et al., 2021), greater managerial attention and reallocation of tasks to workers that perform better on average (Adhvaryu et al., 2019) all contribute to higher productivity. Firms with more decentralised structures are better able to cope with turbulence (Aghion et al., 2021), while countries with higher management quality show more resilience in production and employment in response to macroeconomic shocks (Cette et al., 2020). As we show here, firms have resilience even in response to sudden shocks by virtue of their management capabilities.[4]

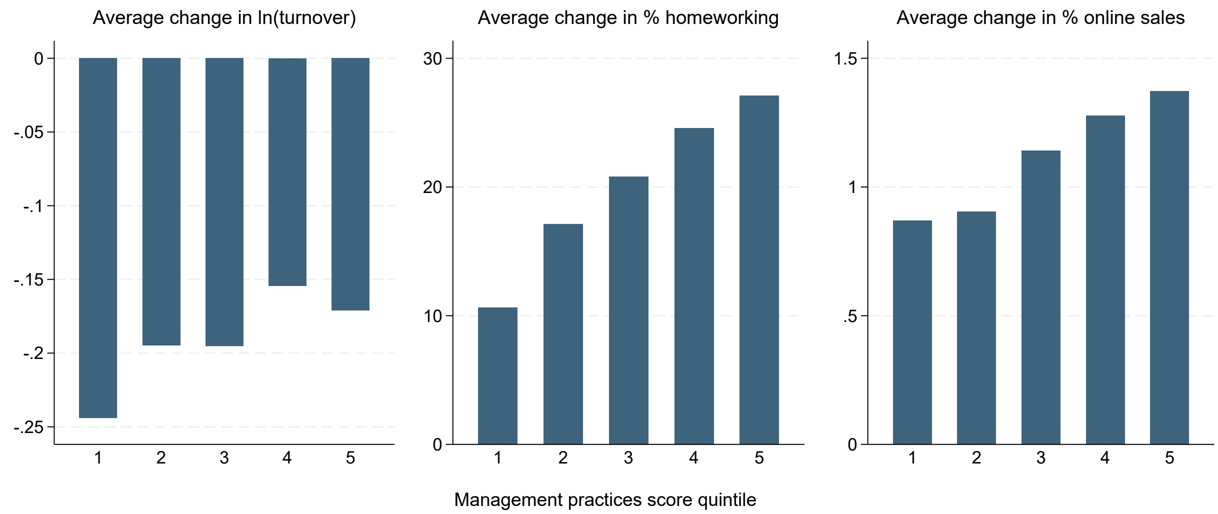
Figure 1 illustrates our central argument about the importance of management for adaptability and resilience by plotting key measures of response against the quintiles of the firm's management practices score distribution (low=1, high=5). The first panel shows that the drop in turnover between 2019 and 2020 is lower for firms with more structured management practices (in the top quintiles of the management practices distribution pre-pandemic). Similarly, firms in these top quintiles adopted remote working more readily (second panel) and pivoted to online sales (third

[2]Not all shocks are sudden. Recent work by Van Reenen and Keiller (2024) shows that better managed firms are also better at adapting to climate risks.

[3]Structured management practices share the three features of a GPT: they are (1) widely used, (2) capable of ongoing improvement, and (3) enable further innovation in applications (Jovanovic and Rousseau, 2005; Bresnahan, 2010). See also similar recent arguments by Sadun et al. (2025).

[4]This contrasts with the traditional management literature which identifies pivoting and adaptation as a gradual response to a performance gap that becomes apparent over time (Cyert et al., 1963; Levitt and March, 1988). As competitive pressures (Agarwal and Helfat, 2009; Röglinger et al., 2022; Williams et al., 2017), new technological innovations (Henderson, 1993; Christensen, 1997; Tripsas, 1997; Gilbert, 2005; Tripsas and Gavetti, 2017), regulations (Barr, 1998) and preferences (Zajac and Kraatz, 1993) lead mature firms with good management to make strategic changes, management responds to the signal from external pressures and brings about change. The focus in this literature is on the ability to respond when needed to external signals over a longer period of time.

Figure 1: Changes in turnover, online sales, and homeworking 2019 to 2020 by 2019 management practices quintiles



Note: Quintiles of management practices score are drawn at the section industry level to better account for structural cross industry variation in management practices scores.

panel).

Taking the analysis a step further, we test whether differences in pre-pandemic management practices explain the differences in pandemic turnover, online sales and homeworking rates using a difference-in-difference (DID) model and data on management practices scores (MPS) derived from the Management and Expectations Survey (MES2020) and performance derived from the MES2020 and the Annual Business Survey (ABS). We then generalize the model to a two-way fixed effects (TWFE) structure that uses continuous MPS and allows for more firm-specific controls.[5] We use an earlier survey wave (MES2017) to conduct placebo tests.

Together with the UK Office for National Statistics (ONS), we developed MES2020 to collect information on management practices, organisational practices and business outcomes both *before* and *after* the pandemic. We link this data at the firm level to other business survey data, including new survey modules we developed for the ONS' high-frequency Business Insights and Conditions Survey (BICS).

We find that firms with more structured management practices see a significantly smaller fall in turnover in the pandemic than their otherwise similar peers in the same industry and region. A

[5]Although baseline management practices are almost certainly endogenous, identification comes from the large and unanticipated Covid-19 shock that affected firms with different preexisting management practices *responding to the same unexpected shocks* differently.

placebo test conducted over the period 2016-2017 shows that, consistent with the literature, structured management practices may support sales growth for some firms in more normal times, but this effect is significantly more evident and pronounced during the pandemic. We then look at the mechanisms and show that firms with more structured management practices exhibit consistently higher homeworking and online sales adoption rates in the pandemic than those with less structured management practices. In our core DID and TWFE regression results, these relationships are robust and statistically significant. However, average results mask significant underlying heterogeneity: we show that it is precisely in industries that experienced the largest challenges to operations that the effect of structured management practices on operational decisions and outcomes is largest. Likewise, when we look at changes in supply chains in 2020, we see that firms with more structured management practices were inclined to react more proactively and view these changes more positively than other firms. This is a further dimension where firms with higher quality management respond to a shock differently than other firms.

Having used MES2020 to explore how structured management practices helped firms pivot during the pandemic, we next take a longer-term view. We examine how structured management practices influence firms' innovation behaviours and working arrangements in the three years following the initial shock. We link MES2020 to the qualitative data in BICS and find that to cope with the shock of the pandemic, firms with more structured management practices innovated more than they expected pre-pandemic across the entire range of product, process and logistics improvements and had more optimistic expectations about their post-pandemic future. Using these data we also observe that firms with higher management scores adopted homeworking and hybrid working earlier and maintained over time an advantage compared with other firms.

The results in this paper are robust to a variety of competing hypotheses: for instance, expanding our main specification to allow for differential responses to the pandemic depending on firms' pre-pandemic labour productivity, and controlling directly for pre-pandemic ICT intensity and forecasting ability, does not affect the sign, size or significance of our coefficient of interest.

Our study is most closely related to Lamorgese et al. (2024), who show using survey evidence that Italian firms with more structured management practices expected to see a smaller drop in their turnover early in the pandemic. Just like their UK counterparts, these Italian firms were more likely to adopt homeworking, alongside other demand and labour management strategies. However, our paper goes beyond Lamorgese et al. (2024) in several ways. First, because we were able to design a purpose-built survey to answer this question, we are able to follow management and organisational practices at the same firm into and out of the pandemic in both the short and medium term. This not only sharpens the identification, allowing us to control for firm fixed effects, but also allows us to track the dynamics and persistence of these changes in working practices, including in the longer term using the BICS. By exploring these dynamics, we can reject the conjecture by Lamorgese et al. (2024) that we should observe convergence over time in homeworking and online sales to pre-pandemic trend growth rates. Second, our data allows us to explore wider innovations, and thus we are able to document how firms that adopted homeworking and online sales had to reshape their entire product, process and logistics apparatus to accommodate these new working practices. Finally, in constrast to Lamorgese et al. (2024) we observe a wider range of sectors across the economy. When we explore how the role of management practices plays in facilitating adaptations to the pandemic, we find effects vary significantly by industry, suggesting that structured management becomes more important the bigger the exposure to the unforeseen shock.

The remainder of the paper is structured as follows. Section 2 presents the Management and Expectations Survey (MES2020) and the Business Insights and Conditions Survey (BICS) in more detail. Section 3 describes our Difference-in-Differences and TWFE strategies. Section 4 discusses our core results, heterogeneous effects by industry, readiness to innovate, attitude to changes in supply chains, the dynamics of remote work adoption and documents a large battery of robustness checks. A brief final Section 5 discusses wider implications and lessons for policy.

2 Survey Design and Data Linkage

2.1 Survey data sources

To test our central hypothesis we develop and use two novel firm-level data sources. Our primary source for management quality and organisational practices is the Management and Expectations Survey 2020 (MES2020), the second wave of a large, experimental firm-level survey in the UK. The authors worked closely with the ONS to design the survey to collect information on firms' management practices, their current working practices, performance and performance expectations. Our source for innovation data and homeworking dynamics is the Business Insights and Conditions Survey (BICS), a fortnightly business survey introduced during the Covid-19 pandemic that collects information on business performance, workforce, prices, trade, and business resilience. We use multiple waves that contain questions on business innovation since the pandemic, and continued homeworking and online sales usage.

2.1.1 The Management and Expectations Survey 2020 (MES2020)

The UK MES2020 provides a unique longitudinal dataset from one of the largest surveys of management practices worldwide. It is similar to the US MOPS but unlike MOPS it covers both manufacturing and non-manufacturing sectors. When designing the survey, we focused on three features to strengthen the research design. First, the core question modules contained identical questions for 2019 and 2020, to allow us to compare *within-firm* changes in key outcomes and behaviours over the course of the pandemic. Second, the sample is predominantly drawn from the UK's structural business survey, the Annual Business Survey (ABS), linked to the Inter-Departmental Business Register (IDBR) allowing us to match to firm-level performance measures, including productivity and profitability, as well as firms' use of other inputs and investment. This also allows us to follow firms' outcomes beyond the end of the pandemic. Third, we adapted the key management practices questions from previous research by (Bloom and Van Reenen, 2007) to facilitate comparability with the growing literature that employs these metrics. We calculate an overall management practices score for each firm by averaging scores from four categories: (1) continuous improvement, (2) the use of key performance indicators (KPIs), (3) the use of targets and (4) employment practices.

Within each category, scores are simple arithmetic means. The overall management practices score (MPS) is a continuous variable that falls between 0 and 1. At the extremes, a score of 1 corresponds to a firm that has adopted the most structured management practices in all four areas; a score of 0 corresponds to a firm that has failed to adopt even the most basic management practices. We use the MPS as our measure of structured management practices. The survey also contains measures of firm performance and expectations about economic outcomes.[6]

2.1.2 Business Insights and Conditions Survey (BICS)

The BICS is a fortnightly survey that aims to elicit qualitative, rapid-response data on topical issues impacting UK businesses. BICS sends a rotating set of questions to respondents in two-week intervals, with a sampling frame of 50,000 businesses. In our analysis, we design and use questionnaire modules on BICS that contain questions around changes in innovation during the pandemic and post-pandemic working mode information. Additionally, we designed two modules of

[6] An outline of the survey design and a full list of management practices questions can be found at the UK Data Service.

innovation questions to monitor the extent of change in business innovation, the expected impact on year-ahead productivity and expected directional change in year-ahead innovation. These innovation questions come from two BICS waves, 38 and 56.[7] Each wave was sent to around 39,000 businesses and received between 8,100 and 9,200 responses.

We link the MES2020 sample to BICS waves to investigate whether firms with more structured management practices innovate more broadly to cope with the shock of the pandemic. When we merge each BICS wave with MES2020 we obtain a sample of around 1,500 firms (between 1,000 and 1,400 after excluding missing values).[8]

2.2 Descriptive statistics

2.2.1 MES2020 variables

Table 1 shows key descriptive statistics of the variables of interest. First, there was a small statistically significant difference in the pre-pandemic management practice score (0.53) and the pandemic value (0.55).[9] The standard deviations in both years are similar at 0.2. Second, Table 1 demonstrates the magnitude of the shock: it shows that the average turnover fell by 19% in a single year between 2019 and 2020. This average change masks heterogeneity across industries. For instance, the accommodation and food services industry suffered the most with an average 59% drop in turnover, while human health services at the other end of the spectrum only suffered a 5% drop in turnover.[10]

Table 1 also shows that online sales grew from 2019 to 2020, but only by a modest amount: among MES2020 respondents, online sales increased from 5.7% to 6.8% of turnover on average. Once again this average masks underlying heterogeneity across industries as can be seen by very large standard errors. Industry characteristics limit the extent to which firms in some sectors can shift their business online.[11] Adopting homeworking practices is another adaptation that allowed firms to cope with

[7]BICS wave 38 was live from 23 August to 5 September 2021, BICS wave 56 was live from 3 May to 15 May 2022.

[8]The summary statistics in appendix A reveal the two samples have similar moments for variables of interest.

[9]The difference is statistically significant mainly due to the large sample size but the change is quantitatively small. All results reported are unweighted.

[10]Any formal test of the hypothesis needs to take industry, as well as regional, heterogeneity into account to reflect the stay-at-home orders (lockdowns) that restricted on-premise work, travel and hospitality, and in person sales. We use the Standard Industry Classification (SIC) 2007 sections for industry heterogeneity and the eleven regions of Great Britain defined by International Territorial Level 1 (ITL-1) for regional heterogeneity.

[11]Industries like wholesale and retail, accommodation and food services, information and communication, and arts, entertainment and recreation even before the pandemic had online sales shares above 10% and experienced a further substantial increase in 2020, ranging from two to four percentage points. Conversely, industries like construction and human health had the lowest online sales share, at 0.9% in 2019, and saw very little change in 2020.

Table 1: Summary statistics of MES2020

	Mean	SD	Median	Count
Overall management score 2019	0.53	0.20	0.57	12,291
Overall management score 2020	0.55	0.20	0.59	12,291
Overall management score change	0.01	0.09	0.00	12,291
ln(turnover) 2019	8.38	1.70	8.34	12,076
ln(turnover) 2020	8.18	1.81	8.21	12,100
ln(turnover) change	-0.19	0.66	-0.08	12,032
Online sales % of turnover 2019	5.69	18.42	0.00	12,292
Online sales % of turnover 2020	6.80	20.12	0.00	12,292
Online sales change	1.11	6.26	0.00	12,292
Homeworking rate 2019	7.22	19.53	0.00	12,070
Homeworking rate 2020	27.38	36.12	6.00	12,070
Homeworking rate change	20.16	32.53	1.33	12,070
Percentage of international suppliers	8.74	17.25	1.00	12,291
Experienced Supply Changes in 2020	0.36	0.48	0.00	12,292
Negatively Impacted by 2020 Supply Changes	0.10	0.30	0.00	4,371
Not or Minimally Impacted by 2020 Supply Changes	0.43	0.49	0.00	4,371
Positively Impacted by 2020 Supply Changes	0.47	0.50	0.00	4,371

the disruptions brought by the pandemic. Table 1 shows homeworking, measured in MES2020 as the percentage of employees who mainly worked remotely. This jumped 20 percentage points from 7.2% in 2019 to 27.4% in 2020. Once again, industry heterogeneity is a large part of the story.[12] Finally, the disruption of the pandemic necessitated changes in firms' supplier networks. Table 1 shows the percentage of MES2020 respondents that experienced changes to their supplier networks during the pandemic. Of the 36% of businesses experiencing supply changes in 2020, 47% suggested these changes impacted positively their business operations.

2.2.2 BICS variables

We are also interested *how* firms supported major operational changes during this period. Within our linked sample based on BICS 38 data, around 30% of the firms report that they have carried out more innovation since the pandemic. Around 37% of firms expect their innovation to increase in the following year. Further, around 52% of the firms in the linked sample expect these innovations to increase their productivity. Based on BICS 56 data, we construct an indicator variable, which takes a value of 1 if a business has embarked on more innovation since the pandemic and 0 otherwise. We

[12] The biggest increase happened in information and communication services, where on average 70% of employees mainly worked from home in 2020 compared to only 9.5% in the year before. Firms in accommodation and food services had the lowest homeworking rate in both years, at 1.6% and 5.7% respectively.

Table 2: Summary statistics of linked sample of BICS waves 38 and 56 and MES2020

Wave		Mean	SD	Count
38	More innovation in response to pandemic	0.30	0.46	989
	Expect innovation to increase	0.37	0.48	1,077
	Expect productivity to increase	0.52	0.50	884
56	Adoption of home or hybrid working	0.34	0.47	1,389
	Adoption of online sales models	0.08	0.28	1,389
	Improvement of existing products and services	0.22	0.42	1,389
	Improvements in methods of logistics, delivery of distribution	0.10	0.30	1,389
	Improvements in methods of manufacturing products and services	0.09	0.28	1,389
	Introduction of new products and services	0.16	0.37	1,389
	Investment in innovation activities	0.13	0.34	1,389

Note: BICS wave 38 was live from 23 August to 5 September 2021, BICS wave 56 was live from 3 May to 15 May 2022.

report the summary statistics in Table 2. The top three innovation types are "Adoption of home or hybrid working" (34% of firms), "Improvement of existing products and services" (22%), and "Introduction of new products and services" (16%).

Figure A1 in the appendix illustrates how innovation responses vary by industry. We show the share of firms, by industry, who report having innovated more since the start of the pandemic, the share of firms who expect their innovation activity to increase their productivity, and the share of firms who expect their innovation activity to increase compared with their pre-pandemic baseline plans. Real estate, education, and human health see the largest increase of innovation to cope with the pandemic (around 70%). Manufacturing, on the other hand, has a low share of firms aiming to innovate-to-cope (16%), but it is still quite optimistic about future productivity increases. Hard-hit industries, such as accommodation and food services and arts, entertainment and recreation, have reasonably high shares of positive responses to all three questions.

3 Empirical Design and Methodology

Our core empirical analysis consists of two parts. First, we use the full MES2020 panel sample to study the differential response of firms with more structured management to a large, exogenous and unanticipated shock to working practices. We first use a simple difference-in-differences (DID) model to illustrate the effect for firms that are better managed in 2019 (that is, before the pandemic), and subsequently build two-way fixed effects (TWFE) models to fully exploit the richness of our data. Our primary outcomes of interest are firms' sales performance and key behavioural changes underpinning this, such as firms' online sales shares and homeworking rates. For sales turnover we are able to reconstruct our experiment on a panel sample from an earlier time period. This way we demonstrate the different role of structured management practices during the pandemic compared to more normal times.

Second, we use the linked MES2020-BICS samples to add additional qualitative information on the many supporting mechanisms through which firms adapt to make the most of this enforced change in working practices, and their expectations for the performance of their business. Using the MES2020-BICS linked samples we can also assess to what extent this change in working practices is transitory or permanent. The following subsections explain our methodologies in more detail.

3.1 Difference-in-Differences approach

To test our hypothesis, we first employ a DID research design. Specifically, we estimate the following regression equation:

$$y_{it} = \beta_1 Y2020_t + \beta_2 Y2020_t HighMPS_i + \alpha_i + u_{it} \tag{1}$$

where subscript i and t index firm and time (i.e., year), respectively. y_{it} is the response variable, for which we use log turnover, the online sales share, and the homeworking rate respectively. $HighMPS_i$ is an indicator that equals 1 if a firm i's MPS in 2019 is above the median management practices score within its own one-digit industry, and otherwise 0. $Y2020_t$ is a year dummy variable for 2020. Model (1) tests the hypothesis that pre-existing management quality (as measured by MPS) is a determinant of resilience and adaptability and the parameter of interest is β_2, which captures the differential impact of the shock of 2020 on better-managed firms. α_i is a firm-fixed effect that controls for the time-invariant heterogeneity of firms. We estimate the model with robust standard errors clustered at the firm level.

3.2 Two-Way Fixed-Effects approach

Next we employ a TWFE model to fully exploit the variation in the data. We use a continuous MPS measure and allow for an MPS-year interaction. The model is therefore specified as follows:

$$y_{it} = \beta_1 Y2020_t + \beta_2 Y2020_t MPS2019_i + \theta X_{it} + \alpha_i + u_{it} \tag{2}$$

where $MPS2019_i$ is the continuous management practice score, which is also interacted with a year dummy, $Y2020_t$. The coefficient on this interaction, β_2, measures the additional response in the year due to firm i's management level before the pandemic. X_{it} includes two groups of variables comprising (1) variables that change across firms and over time: employment size, total capital expenditure, intermediate consumption expenditure, and management score; and (2) interactions between $Y2020_t$ with time invariant variables: industry, region, size band (allowing for heterogeneous effects of the shock on the outcome of interest by industry, region and firm size), and pre-pandemic performance. The inclusion of the interaction of $Y2020_t$ with firms' pre-pandemic performance addresses the concern that determinants of superior performance other than MPS are driving our results.

Model (2) allows us to study the differential impact of overall MPS on firms responses. However, during the pandemic, the differential impact of MPS might be industry-specific. To study the effect of MPS on firms' responses by industry, we also report an expanded version of model (2) to include a three-way interaction between MPS, year and industry. This yields the following estimating equation:

$$y_{it} = \sum_j \beta_{1j} Y2020_t IND_{ji} + \sum_j \beta_{2j} Y2020_t MPS2019_i IND_{ji} + \theta X_{it} + \alpha_i + u_{it} \quad (3)$$

Here the subscript j denotes industry. Our coefficients of interest are β_{2j}, which reflect the effect of management in determining the response to the pandemic for firms in industry j. To include the three-way interaction term we also have full two-way interactions in the model. The variables in X_{it} are the same as in model (2).

3.3 Linear probability model of change

In MES2020 and the linked sample of MES2020 and BICS we also observe firms' qualitative responses to questions about *changes* in their behaviour since the onset of the pandemic. For example, firms may indicate whether they have innovated more or less, whether they have increased particular innovation activities, and whether they changed their supplier networks since the pandemic. We run cross-sectional regressions and test whether structural management practices prior to the pandemic are associated with these changes in firms' behaviours since the onset of the shock. The dependent variable Δy_i is an indicator variable for firm i, respectively for "changes to supplier networks" since the pandemic, "more innovation" since the pandemic, "higher expected productivity" and "higher expected innovation" one year ahead. We also explore whether firms with more structured management practices innovate more broadly in the pandemic, using information in BICS on different innovation types. Each innovation type is an indicator variable for "more of that type of innovation" since the pandemic.

For simplicity we use a linear probability model of the form:

$$\Delta y_i = \beta_1 + \beta_2 MPS2019_i + \theta X_i + \epsilon_i \tag{4}$$

where $MPS2019_i$ is a firm's management practice score measured in 2019 and β_2 is the coefficient of interest. X_i includes firm-specific characteristics such as industry, region and firm size. This allows for heterogeneous effects of the shock and differences in behaviour on key dimensions.

4 Empirical Results

In this section, we first show that firms with more structured management practices prior to the pandemic saw a smaller fall in turnover during the pandemic. This was predicated on quick adoption of homeworking, online sales and changes to supplier networks. We show that these effects are larger in more affected industries and that the effects of management practices on turnover are significantly less pronounced in normal times. We show that innovation was a central mechanism through which more structured management practices improved firms' resilience. We find that the gap in working practices between firms with more structured management practices and the rest opened up quickly and persisted beyond the pandemic. We demonstrate that the results are robust to alternative explanations.[13]

4.1 Main results

The starting point of our analysis is a DID estimate reported in Table 3. On average, looking at the first row, firms suffer a 22% drop in revenue in the pandemic, increase their online sales percentage by just under 1 percentage point and their homeworking rate by 15 percentage points. Firms in the *High MPS* group suffered a smaller turnover drop by 5 percentage points, achieved higher online sales shares by 0.5 percentage points and experienced higher homeworking rates of

[13] All our results in this section are presented with the dependent variable in levels, which gives us the maximum number of observations for each regression, and therefore the greatest precision for the coefficient estimates. Were we to follow Lamorgese et al. (2024) and look at growth rates, given our data we would lose a substantial number of observations. This would result in less efficient estimates.

Table 3: A simple DID regression: The impact of MPS on firm outcomes

	(1) ln(turnover)	(2) Online sales	(3) Home-working
Y2020	-0.219***	0.863***	14.959***
	(0.009)	(0.071)	(0.385)
Y2020*HighMPS	0.050***	0.486***	9.837***
	(0.012)	(0.108)	(0.585)
Observations	23,872	23,872	23,872
Clusters	11,965	11,965	11,965
R^2	0.082	0.036	0.292

Note: The header lists the dependent variables which are the natural logarithm of turnover, online sales as a percentage of turnover, and home-working rate in percentages respectively. Robust standard errors in parentheses and are clustered at the firm level. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

around 10 percentage points when compared with otherwise similar firms. We conclude from this that firms with more structured management show more resilience and adaptability when faced with the challenges brought about by the pandemic. Their resilience and adaptability protected their turnover, partly through pivoting to online sales to offset the effects of lockdowns on retail practices, and partly by embracing remote working, which allowed the production of goods and services to continue throughout the lockdown periods. We explore other mechanisms by which structured management practices enabled firms to adapt and to protect their turnover in subsequent sections.

Table 4 replicates the coefficient of interest from our DID baseline specification for turnover spanning the pandemic 2019-2020 (first row, second column), which shows that turnover fell by 5 percentage points less in better managed firms. It also reports the coefficient of interest from our simple TWFE baseline model for the same period (second row, second column). The TWFE coefficient of 0.18 implies that a one standard deviation increase in the MPS results in a smaller turnover drop by 3.6 percentage points in 2020. We also report these same specifications estimated for a pre-pandemic period for which we have comparable MES data, 2016-2017. We focus on turnover because homeworking and online sales outcomes are not available in earlier MES waves. Comparing columns (1) and (2), the table shows that regardless of the econometric approach, management practices are significantly related to changes in turnover in both the pre-pandemic period and the period spanning the pandemic. However, the magnitudes are twice as large in the pandemic period, and the difference between the pandemic period and pre-pandemic period coefficients, reported in

Table 4: The impact of MPS on firm turnover across survey waves

Model	(2016 - 2017)	(2019 - 2020)	Difference
DID	0.022**	0.050***	0.028*
	(0.009)	(0.011)	(0.015)
FE	0.095***	0.180***	0.084*
	(0.029)	(0.034)	(0.045)
Observations (DID)	18,559	23,872	
Observations (FE)	18,554	23,872	

Note: The header lists the period covered. The rows display whether our coefficient of interest is derived from our DID or TWFE baseline specification. The within specification difference in coefficients across the two periods is shown in the final column along with a test for statistical significance. The dependent variable for all models in this output is the natural logarithm of turnover. Robust standard errors in parentheses and are clustered at the firm level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

column (3), is significant at the 10% level. This suggests that management practices are always important for firm success, in line with the broader literature, but underscores our claim that the Covid-19 pandemic (and the unexpected changes to working practices it necessitated) makes their importance all the more salient.

The difference between the TWFE coefficients in the second row of Table 4 implies that this additional salience alone dampened the drop in turnover by 1.7 percentage points in 2020 (measured on a one-standard deviation increase in MPS). In appendix Table B1 we also compare our baseline regressions for turnover in these same two periods, estimated on the sample of firms for which we observe both expected turnover in the MES and realised turnover as recorded in the ABS. The difference between coefficients, from the TWFE model estimated 2019-2020 and 2016-2017 on realised outcomes, is of a similar magnitude to that shown in Table 4 and is estimated more precisely.

In Table 5 we estimate the TWFE model and flexibly control for other observable characteristics of the firm. We use the full continuous MPS measure. The coefficient of interest for turnover is shown with a progressively larger battery of controls. Regardless of specification, the coefficient of interest is positive and statistically significant, and ranges in size between 0.13 and 0.24. In other words, two otherwise identical firms where one has full adoption of structured management practices (MPS=1) and the other has not adopted any structured management practices (MPS=0) reveal a roughly 18% smaller fall in turnover for the full adopter. If the hypothetical change from 0 to 1

Table 5: Fixed-effects: MPS and turnover

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Y2020*MPS2019	0.180***	0.162***	0.165***	0.130***	0.123***	0.150***	0.242***
	(0.034)	(0.034)	(0.034)	(0.033)	(0.032)	(0.036)	(0.036)
ln(employment)				0.405***	0.324***	0.343***	0.323***
				(0.047)	(0.039)	(0.039)	(0.038)
ln(cap. exp.)					0.020***	0.020***	0.018***
					(0.002)	(0.002)	(0.002)
ln(int. exp.)					0.197***	0.196***	0.187***
					(0.022)	(0.022)	(0.021)
MPS							0.977***
							(0.094)
Observations	23,872	23,872	23,872	23,858	23,858	23,842	23,842
Clusters	11,965	11,965	11,965	11,965	11,965	11,949	11,949
R^2	0.083	0.124	0.126	0.151	0.206	0.214	0.226
Sector*Y2020	N	Y	Y	Y	Y	Y	Y
Region*Y2020	N	N	Y	Y	Y	Y	Y
Sizeband*Y2020	N	N	N	N	N	Y	Y
Pre-pandemic TPH*Y2020	N	N	N	N	N	N	Y

Note: ln(cap. exp.) denotes the natural log of annual capital expenditure, ln(int. exp.) denotes the natural log of annual expenditure on intermediate consumption expenditure. Sectors are based on 1-digit Standard Industrial Classification (SIC) code. Regions are defined by International Territorial Level 1 (ITL-1). Sizeband is defined as *small* for *employment* $\leq$ 99, *medium* for 100 - 249, *large* for $\geq$ 250. Pre-pandemic TPH (turnover per head) is measured as ln(turnover/number of employees) in 2019. Robust standard errors in parentheses and are clustered at the firm level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

seems unreasonably large, we could also say that ceteris paribus, if a firm's MPS increases by one standard deviation (0.2), it sees a 3.6 percentage point lower fall in turnover. The coefficient estimate varies when we introduce controls allowing for the amount of capital expenditure, intermediate consumption expenditure or the size band of the firm. When these controls plus pre-pandemic performance are taken into account in column (7) the coefficient is not significantly different from initial estimates in columns (1) - (3).[14] We report further robustness checks in appendix B and discuss them in section 4.5.

Tables 6 and 7 provide evidence on the mechanisms behind the differential performance between firms with more and less structured management practices. Table 6 displays coefficients from a

[14]Controlling for skill (proxied by share of managers and non-managers with degrees)also does not change the findings of our results.

Table 6: Fixed-effects: MPS and online sales

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Y2020*MPS2019	0.993***	1.119***	1.091***	1.067***	1.062***	1.215***	1.305***
	(0.282)	(0.275)	(0.275)	(0.278)	(0.278)	(0.301)	(0.310)
ln(employment)				0.486*	0.494*	0.544*	0.525*
				(0.286)	(0.289)	(0.290)	(0.290)
ln(cap. exp.)					-0.048*	-0.048*	-0.050*
					(0.026)	(0.026)	(0.026)
ln(int. exp.)					0.038	0.034	0.025
					(0.086)	(0.086)	(0.086)
MPS							0.950
							(0.782)
Observations	23,872	23,872	23,872	23,858	23,858	23,842	23,842
Clusters	11,965	11,965	11,965	11,965	11,965	11,949	11,949
R^2	0.035	0.065	0.066	0.066	0.067	0.068	0.068
Sector*Y2020	N	Y	Y	Y	Y	Y	Y
Region*Y2020	N	N	Y	Y	Y	Y	Y
Sizeband*Y2020	N	N	N	N	N	Y	Y
Pre-pandemic TPH*Y2020	N	N	N	N	N	N	Y

Note: ln(cap. exp.) denotes the natural log of annual capital expenditure, ln(int. exp.) denotes the natural log of annual expenditure on intermediate consumption expenditure. Sectors are based on 1-digit Standard Industrial Classification (SIC) code. Regions are defined by International Territorial Level 1 (ITL-1). Sizeband is defined as *small* for *employment* $\leq$ 99, *medium* for 100 - 249, *large* for $\geq$ 250. Pre-pandemic TPH (turnover per head) is measured as ln(turnover/number of employees) in 2019. Robust standard errors in parentheses and are clustered at the firm level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: Fixed-effects: MPS and homeworking

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Y2020*MPS2019	34.903***	29.595***	28.965***	28.790***	28.798***	25.299***	26.150***
	(1.362)	(1.252)	(1.248)	(1.255)	(1.256)	(1.343)	(1.376)
ln(employment)				2.340	2.459*	1.291	1.107
				(1.447)	(1.443)	(1.418)	(1.397)
ln(cap. exp.)					-0.055	-0.041	-0.060
					(0.099)	(0.097)	(0.097)
ln(int. exp.)					-0.257	-0.153	-0.235
					(0.418)	(0.410)	(0.404)
MPS							9.066**
							(3.944)
Observations	23,872	23,872	23,872	23,858	23,858	23,842	23,842
Clusters	11,965	11,965	11,965	11,965	11,965	11,949	11,949
R^2	0.306	0.463	0.470	0.471	0.471	0.483	0.484
Sector*Y2020	N	Y	Y	Y	Y	Y	Y
Region*Y2020	N	N	Y	Y	Y	Y	Y
Sizeband*Y2020	N	N	N	N	N	Y	Y
Pre-pandemic TPH*Y2020	N	N	N	N	N	N	Y

Note: ln(cap. exp.) denotes the natural log of annual capital expenditure, ln(int. exp.) denotes the natural log of annual expenditure on intermediate consumption expenditure. Sectors are based on 1-digit Standard Industrial Classification (SIC) code. Regions are defined by International Territorial Level 1 (ITL-1). Sizeband is defined as *small* for *employment* ≤ 99, *medium* for 100 - 249, *large* for ≥ 250. Pre-pandemic TPH (turnover per head) is measured as ln(turnover/number of employees) in 2019. Robust standard errors in parentheses and are clustered at the firm level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

regression of online sales rates on the same sample and specifications used previously for turnover. The coefficient of interest is again positive and significant. Across specifications, a firm with one standard deviation (0.2) increase in MPS, ceteris paribus, sees a roughly 0.2 percentage point larger rise in online sales rates. Likewise, Table 7 shows the coefficients from similar regressions on the same sample with a firm's homeworking rate as the dependent variable. Again, the coefficient of interest is positive and statistically significant. Across specifications, a firm with a one standard deviation (0.2) increase in MPS, ceteris paribus, sees a roughly 6 percentage point larger rise in homeworking rates.

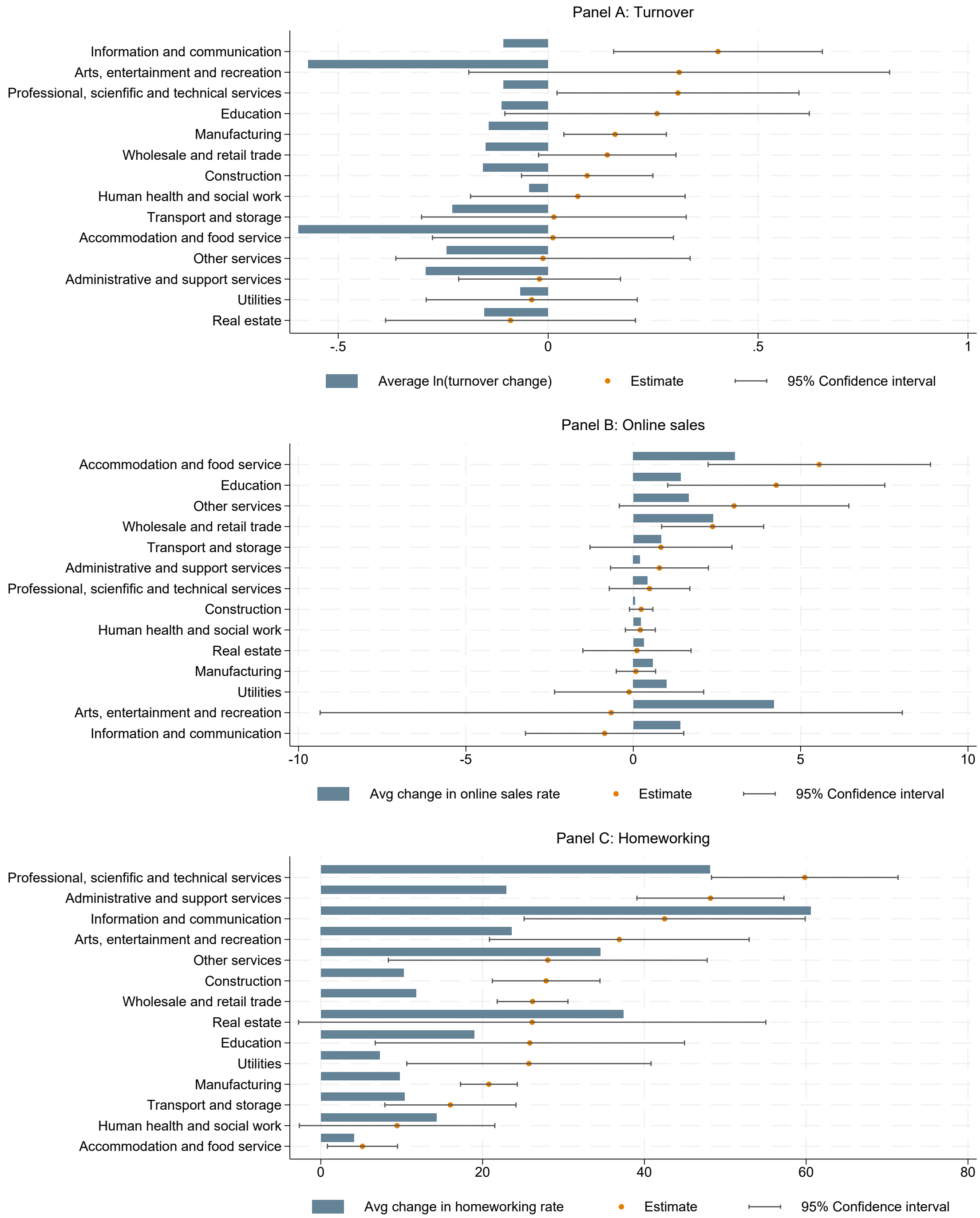
In appendix B, Table B2, we separately examine the impact of four dimensions of management (continuous improvement, key performance indicators, targets and employment practices), using our baseline specification. Continuous improvement positively impacts turnover and home working, but is not statistically significant for online sales. KPIs and targets affect homeworking. Employment practices play an important role for all the three outcome variables. Employment practices measure the process of hiring, promoting and managing of a firm's employees. More structured employment practices before the pandemic are positively associated with better adaptability and resilience during the pandemic. Appendix Table B3 shows the set of individual management practices selected by a LASSO regression for different selection criteria. Consistent with the previous results, selected questions come from all categories, with employment practices and targets being especially relevant in adapting to the disruption to work and business practices during the pandemic.

To sum up, we show that in response to the challenges brought by the Covid-19 pandemic and NPIs introduced in response to it, firms changed how they reach their customers by switching to online sales, and how their employees engage with the work space by adopting homeworking. Importantly, firms with more structured management practices adapted their operations more extensively and showed more resilience in their performance.

4.2 Heterogeneous effects by industry

We provide further evidence of the importance of structured management practices for firms' resilience by exploring the differential impacts of Covid-19 across industries. Selling online is a more feasible option for some industries than others. UK ONS data show that internet sales as a percentage of total retail sales surged from 19.2% in 2019 to 28.1% in 2020. But for manufacturing and construction firms, online sales shares are negligible (below 4% in MES2020) both before and during the pandemic. Similarly, for some industries it is harder to adapt to working from home (for

Figure 2: Differential effects of management on turnover, online sales and homeworking rate, by sector



Note: The dark blue bars represent the change in the metric from 2019 to 2020. The orange markers represent the estimated coefficients on the MPS. The whiskers show upper and lower bounds of the 95% confidence interval of these coefficients.

instance, manufacturing and accommodation and food services). Industry characteristics determine to some extent the amount of work that can be done from home and are largely beyond the scope of management. In general we find that in sectors where online sales were possible, management mattered. And in sectors where significant shifts to homeworking occurred, management was important in facilitating this shift.

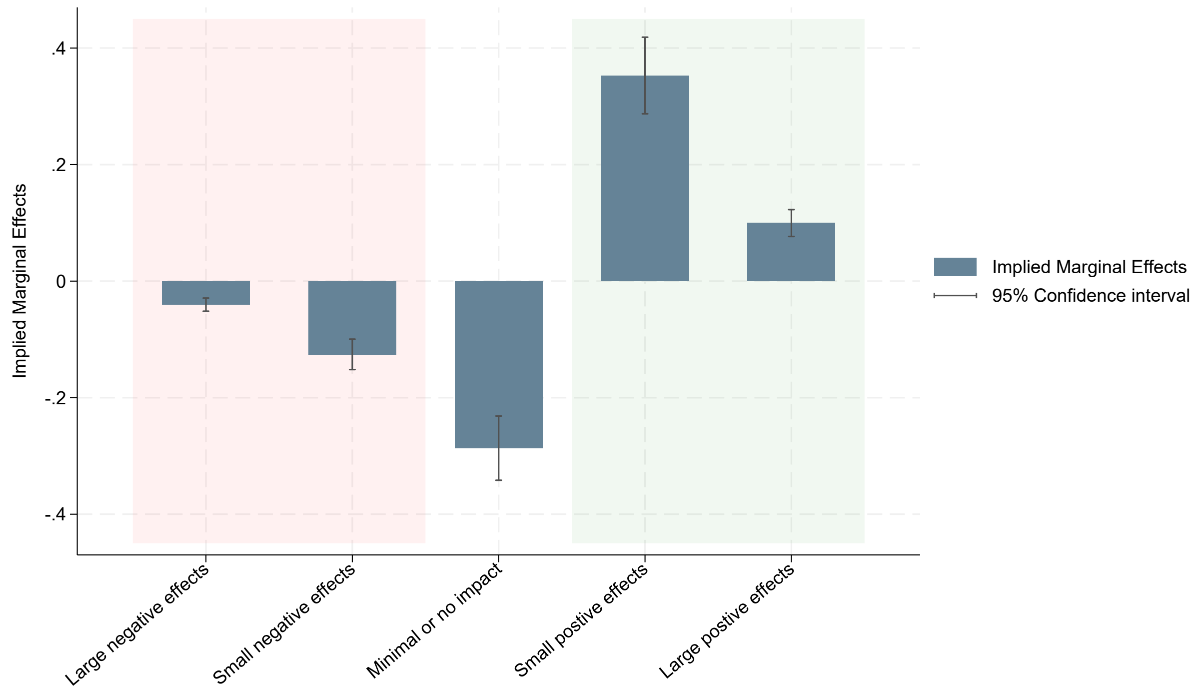
To study the effect of management on firms' responses by industry, we apply model (3) to MES2020 using 14 sectors (SIC section). Panel A of Figure 2 presents the effects of management on pandemic-era turnover changes. The estimated effect of structured management practices on turnover is statistically significant in three sectors: information and communication; professional, scientific and technical activities; and manufacturing. These three sectors experienced a smaller fall in turnover than many other sectors. From Panel A we can also see that the sector where turnover fell the most during the pandemic was accommodation and food services, where the estimated effect of management is close to zero. Structured management could only minimally reduce the impact on turnover of accommodation and food services premises being closed and people being restricted in their movements during Covid lockdowns.

Panel B of Figure 2 presents the differential effects of structured management on online sales (as a share of firm turnover) on average by sector. From Panel B we can see that significant differential effects of management are only found in three sectors: accommodation and food services, education and wholesale and retail trade. The three sectors also see relatively high increases in online sales.[15] When industry characteristics are such that online sales are a possibility, better-managed firms within these industries are better able to shift their sales in response to the pandemic.

Panel C of Figure 2 presents the differential effects of structured management practices on homeworking by sector. In all sectors, structured management has significant positive differential effects on the homeworking rate, with the exceptions of real estate and human health and social work. Better-managed firms adapt more fully to homeworking, and this result holds for all industries. The sectors that see the biggest increases in the homeworking rate tend also to show larger differential management effects.

[15] Looking further into the two-digit industries, we find that within the accommodation and food service sector, it is the food and beverage service industry that sees the largest differential effect of management. Within the wholesale and retail trade sector, it is the retail trade industry.

Figure 3: Marginal effects of 2020 supply chain changes, based on a unit increase in management score, ordered logit



4.3 Changes to supply chains

Covid-19 also disrupted domestic and international supply chains (Bonadio et al., 2021) and firms necessarily had to implement changes to their supply chains to continue their operations.[16] In Table 8 we explore the extent to which firms with higher management practices scores prior to the pandemic were more likely to report changes to their supply chains during the pandemic. We estimate model (4), where the dependent variable is an indicator variable for firm i of changes to their supplier networks in 2020. These changes may include using new domestic or international suppliers or stopping using existing domestic or international suppliers. As in our main results, the coefficient of interest in Table 8 is shown with a progressively larger battery of controls. In our most stringent specifications we control for the number of domestic and international suppliers in 2019, thus conditioning on supplier networks that predate the pandemic. We see that structured

[16]Covid-19 supply chain issues were compounded by the end of the the transition period for the UK in its exit from the European Union. The end of the transition period created additional trade fictions for UK-based firms trading with other EU countries, and those sourcing inputs from EU countries (Sampson, 2017; Du and Shepotylo, 2022). Affected firms had to rearrange their supply chains, either finding alternative suppliers or complying with higher tariff and compliance costs. Although much of this adjustment would have occurred in the years before the pandemic, the results in this section may partly reflect ongoing adaptation to the Brexit shock.

management practices may have helped firms adapt on these margins too.

This interpretation is further supported by firms' qualitative responses to the question "What impact did changes to your supplier network in 2020 have on business operations?". Figure 3 shows the implied marginal effects of the pre-pandemic management practices score on the impact of changes to firms' supplier networks during 2020. These are obtained from an ordered logit regression of the impact of supply chain changes on pre-pandemic management practices scores. All else equal, firms with more structured management practices are significantly more likely to report positive impacts of changes to their supply chains, and significantly less likely to report negative impacts of changes to their supply chains.[17]

4.4 Longer-term effects

So far, we have considered the relationship between structured management practices and firm resilience to shocks by studying changes to firm behaviours at the height of the pandemic. Using linked MES2020-BICS data we can, in a similar framework albeit on a smaller sample, study the cumulative and longer term effects of structured management practices on firm resilience. In this section we look at the impact of pre-pandemic management practices on firm's innovation activities, expectations and working practices beyond 2020.

As shown in Figure 4, compared to firms with below-median management practices scores, firms with above-median management practices scores were more likely to increase investment in a whole range of innovation activities since the pandemic. Firms' responses to BICS in August/September 2021, after most Covid-19 restrictions were lifted, suggest that better managed firms were more likely: to have increased innovation since the start of the pandemic; to expect innovation to continue at a higher level compared to the pre-pandemic baseline; and to expect innovation to increase their productivity over the year ahead. Firms' responses to BICS in May 2022, after all Covid-19 restrictions were lifted, suggest that better managed firms were more likely to have increased both product and process innovation in the two years since March 2020. These patterns point to the multiple activities involved in pivoting in response to unexpected shocks and that may be better implemented and coordinated in firms with more structured management practices.

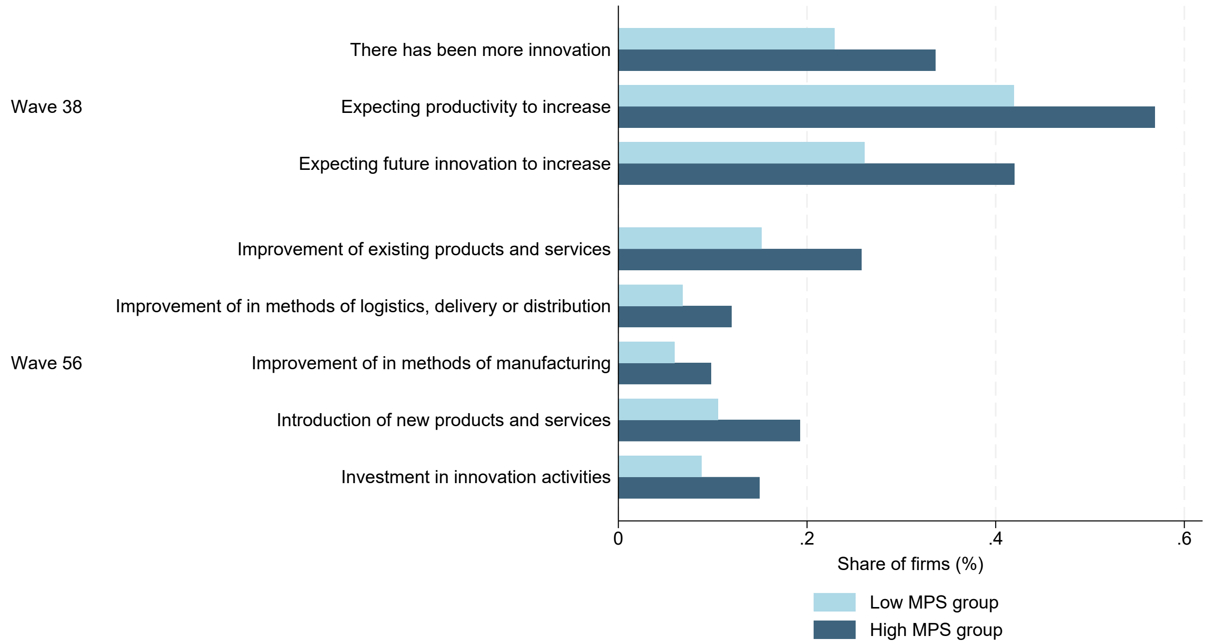
[17]Given the qualitative nature of the data, we estimate an ordered logit model, controlling for the same firm-level variables we employ in our baseline regressions in Table 8. As shown by Table B4 in the appendix, coefficients are very stable across specifications, including where we control for the number of domestic and international suppliers prior to the pandemic.

Table 8: Likelihood of firm reporting changes to supply chains in 2020 based on MPS score: 2020 outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MPS2019	0.305***	0.313***	0.313***	0.284***	0.266***	0.271***	0.264***	0.273***
	(0.020)	(0.020)	(0.021)	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)
Observations	12,291	12,291	12,291	12,134	11,949	11,949	11,949	11,949
Sector	N	Y	Y	Y	Y	Y	Y	Y
Region	N	N	Y	Y	Y	Y	Y	Y
ln(employment)	N	N	N	Y	Y	Y	Y	Y
ln(capital expenditure)	N	N	N	N	Y	Y	Y	Y
ln(intermediate consumption)	N	N	N	N	Y	Y	Y	Y
ln(turnover)	N	N	N	N	Y	Y	Y	Y
Suppliers	N	N	N	N	N	Y	N	Y
International suppliers	N	N	N	N	N	N	Y	Y

Note: Robust errors in parentheses, clustered at the firm level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Figure 4: Percentage of firms adopting innovation since March 2020 among *high* and *low* MPS groups



Note: The top three questions are from BICS wave 38, collected in August/September 2021, the bottom five questions are from BICS wave 56, collected May 2022. The linked samples have sample sizes of around 1,000 compared to the total number of respondents in BICS, which is around 8,000. Firms with above median 2019 MPS in MES2020 are defined as the *High MPS* group, while the rest are assigned to the *Low MPS* group. The median threshold used for *High MPS* is drawn at the SIC section industry level.

More formally, we report in Tables 9a and 9b the coefficient of interest obtained from estimating model (4) using the innovation responses from BICS after most Covid-19 restrictions were lifted (Table 9a) and after all Covid-19 restrictions were lifted (Table 9b). There we see that firms with better management practices scores immediately before the pandemic were more likely to innovate in coping with the shock of the pandemic and its aftermath than firms with lower management practices scores, after controlling for industry and firm size. As shown in Table 9b, firms that had more structured management in 2019 embarked on more innovations to improve their existing products and services (column (1)) as well as introducing new products and services (column (2)), devoted more effort to enhancing their logistics and distribution (column (3)) and manufacturing where relevant (column (4)), and invested more in innovation activities (column (5)). In Table 9a columns (2) and (3), it is also evident that firms with more structured management in 2019 were more optimistic about the effects of their innovations, and expected to increase innovation in the future. Beliefs about the impacts of innovation in the post-pandemic years suggest a lasting effect

Table 9: The impact of management on firms' innovation behaviour and their expectations

(a) Innovation behaviour and expectations

	(1) More innovation	(2) Expect more productivity	(3) Expect more innovation
MPS 2019	0.399***	0.497***	0.591***
	(0.087)	(0.111)	(0.082)
Observations	989	884	1,077
R^2	0.129	0.044	0.056
Sector	Y	Y	Y
Firm size	Y	Y	Y

(b) Management and innovation types

	(1) Existing products	(2) Logistics	(3) Manufacturing	(4) New products	(5) Investment
MPS 2019	0.309***	0.224***	0.090**	0.251***	0.150***
	(0.060)	(0.046)	(0.043)	(0.053)	(0.049)
Observations	1,389	1,389	1,389	1,389	1,389
R^2	0.049	0.033	0.139	0.041	0.067
Sector	Y	Y	Y	Y	Y
Firm size	Y	Y	Y	Y	Y

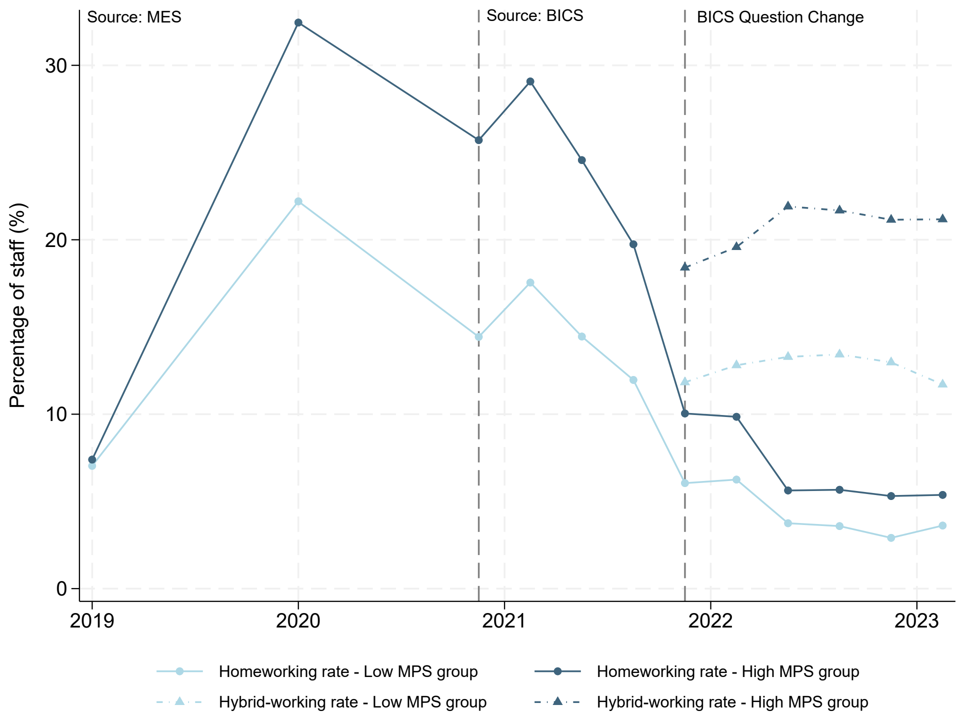
Note: Panel A dependent variables are: having done more innovation since the pandemic; expecting productivity to increase in the following year; and expecting innovation to increase in the following year respectively. Panel B dependent variables are indicators for areas in which firms have done more innovation since the pandemic. Sectors are based on 1-digit Standard Industry Classification (SIC) code. Firm size is defined as *small* for *employment* ≤ 99, *medium* for 100 - 249, *large* for ≥ 250. Robust standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

of these product and process innovations on firms with more structured management practices.

Using the linked MES and BICS samples, we are also able to investigate the firm-level adoption of homeworking and hybrid working over the longer term at a quarterly frequency. We show that compared to other firms, firms with higher management practices scores adopted homeworking and hybrid working rates more quickly and extensively and maintained this higher rate of adoption throughout 2020-2022. Figure 5 plots time series for homeworking rates and hybrid working rates between 2019 and 2022 Q4 for two groups of firms: those with below-median MPS and those with above-median MPS within-each one-digit SIC industry.[18] Both groups start with the same

[18]Within-industry cutoffs account for the fact that management practices and working practices vary systematically

Figure 5: Homeworking and hybrid working rates for above and below median MPS firms.



homeworking rate before the pandemic, but firms with above-median management practices scores quickly increase their homeworking rates differentially, and maintain higher homeworking rates throughout. After the pandemic, they maintain differentially higher hybrid working rates. Before the ONS changed the questions on the BICS to capture hybrid working arrangements, homeworking rates were falling for firms with both more and less structured management practices, but the former had a higher uptake in the pandemic and this difference persists over time. Homeworking was quick to rise in the pandemic but slow to fall. The same is true for hybrid working once it became the dominant margin of adjustment in 2022–2023. Firms that adopted hybrid working earlier were also more likely to maintain hybrid working arrangements permanently instead of reverting to fully in-person or fully remote work.[19]

In Table 10 we report the results from estimating model (4), where the dependent variable is average hybrid working rates in 2022, and include the standard battery of controls from our baseline

across industries.

[19]The same pattern holds across all sectors as seen in Figure B1 in the appendix. *High MPS* firms start out looking no different than *low MPS* firms but quickly diverge, and have higher average homeworking and hybrid rates over the entire period. In industries with high working-from-home suitability such as business services, hybrid rates increase over time, in line with with individual-level UK survey evidence on remote working (ONS, 2023).

Table 10: 2022 employee hybrid working rate

	(1)	(2)	(3)	(4)	(5)	(6)
MPS2019	29.536***	25.442***	24.740***	25.751***	19.733***	11.020***
	(2.515)	(2.381)	(2.377)	(2.577)	(2.598)	(2.355)
Industry FE	N	Y	Y	Y	Y	Y
Region FE	N	N	Y	Y	Y	Y
ln(Emp)	N	N	N	Y	Y	Y
ln(Cap Exp)	N	N	N	N	Y	Y
ln(IC)	N	N	N	N	Y	Y
ln(Turnover)	N	N	N	N	Y	Y
Pandemic homeworking rate	N	N	N	N	N	Y
Observations	3,408	3,408	3,408	3,387	3,362	3,345
R^2	0.033	0.251	0.260	0.262	0.279	0.434

Note: Robust errors in parentheses, clustered at the firm level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

model. Across all specifications, structured management practices are positively and significantly associated with higher hybrid working rates in the long term. Moreover, even if we control for firm-level pandemic homeworking rates, which explain a significant share of post-pandemic hybrid and homeworking rates, the effect of structured management practices remains positive and significant.

4.5 Robustness

We conduct a series of robustness checks. First, as shown in Tables 5-7 our main fixed effects estimates are robust to the inclusion of several additional control variables: firms' total capital expenditure, their intermediate expenditure, their contemporaneous MPS (allowing changes over time) and time-varying sector, region and sizeband effects. Tables B5 to B6 in the appendix also include an "essential industries" index used in Lamorgese et al. (2024) and model exposure via an occupations-based remote working suitability index with sector-level fixed effects. We obtain very similar results from these model specifications.

Second, we directly test several competing hypotheses. In our main results Tables 5-7 we control for pre-pandemic labour productivity interacted with Y2020 to allow for differential responses to the pandemic depending on firms' pre-pandemic labour productivity. This is a test of whether our findings come from that firms with more structured management practices just happen to be the most productive firms. In the appendix Tables B5 to B6 we additionally include pre-pandemic ICT intensity to test if firms with structured management practices were simply fortunate to be more prepared. This harks back to the observation we made earlier, citing Bai et al. (2021), that some firms might have been lucky to have characteristics that prepared them for the pandemic, but not particularly by management design. We control for GDP forecasting ability at the firm level, using the expectations questions in the MES to separate out the resilience in the face of unexpected shocks from an ability to better forecast the future, as shown in (Bloom et al., 2025).

Third, since MES2020 was in the field during the course of 2020, turnover figures are preliminary estimates. We therefore link to the Annual Business Survey (ABS) 2020 which reports turnover ex post and rerun our baseline regressions on the linked MES-ABS sample. Table B8 in the appendix shows that our coefficient of interest estimated on this sample is slightly smaller than in our main results estimated on the MES alone, but remains statistically significant and economically meaningful. More importantly, Table B8 shows that our coefficient of interest is little different whether we use predicted or realised turnover values.

Fourth, key to our argument is that structured management practices always help firms adapt, but that the effect is particularly visible during large shocks, such as the Covid-19 pandemic. In Table 4 we tested this hypothesis by comparing the coefficient of interest obtained from MES2020 with that obtained from MES2017, focusing on models of turnover. The effect on structured management practices on turnover during the pandemic in 2020 was significantly larger than in 2017. This is even more evident when we use realised turnover rather than predicted turnover, as shown in Table B1 in the appendix.

Finally, we apply the TWFE model on the linked sample of MES2020 and BICS to check the representativeness of the merged dataset, which is important for our anxillary innovation results. The obtained differential impacts of management on online sales and homeworking are similar to those presented in Table B2. Due to smaller sample size, the turnover effects are not statistically significant. Finally, we apply a binomial logit model on the linked sample of MES2020 and BICS using the same specification as in model (4) to check for model robustness. After calculating the marginal effects of MPS, we obtain very similar results to those presented in Tables 9a and 9b.

5 Conclusion

What characteristics make firms adaptable and resilient in the face of large, unanticipated shocks? Many firms that fared well during the pandemic adapted in key dimensions: they made greater use of remote working or adopted new IT equipment and software. The more intensive use of these novel ways of working could have been due to simple good fortune, or it could be related to structural ways in which these firms are run. The management literature shows that firms with more structured management practices have historically outperformed other firms in terms of productivity, profitability, exports and patents and were able to make better forecasts to plan for the future. We therefore ask: did these management practices make firms more resilient and adaptable and were these changes temporary or permanent?

Using novel data from two surveys conducted on UK firms, we provide evidence to show that firms with more structured pre-pandemic management practices were better able to adopt homeworking and online sales in 2020, making them more adaptable, and saw a smaller drop to their turnover in the pandemic as a result, making them more resilient. In Difference-in-Differences and Two-Way Fixed Effects regressions that exploit the unforeseeable nature of the Covid-19 pandemic, the coefficient of interest is positive, large and significant throughout. It is also larger in industries that were more exposed to the disruptions of the pandemic, and unchanged by controls for many competing hypotheses, from inherent productivity differences to firms' ability to forecast the future to firms' preexisting ICT investments. Moreover, placebo tests from an earlier period confirm our interpretation of the evidence.

We then draw on high-frequency qualitative survey data to examine the evidence beyond the immediate disruption of the pandemic. We consider attitudes towards innovation and the types of innovation undertaken. For a subsample of firms, we can link this to the pre-pandemic management score to assess how firms with more structured management practices were able to pivot so quickly to new ways of working. We report that firms with higher management scores innovated along many dimensions, product, process and logistics alike, alongside the adoption of homeworking and online sales. They had more positive attitudes about innovation, expected higher productivity and expected to do more innovation in the future, relative to their pre-pandemic expectations. We also investigate the dynamics of homeworking and find that firms with more structured management practices, while no more likely to adopt homeworking and online sales before the pandemic, quickly pulled ahead of peers with less structured management, and maintained their advantage throughout the pandemic. Post-pandemic, they shifted to hybrid working at higher rates than their peers. We show that while different types of management practices matter slightly more for different adjustment margins, in general, structured management practices matter jointly.

When firms were faced with one of the largest unforeseeable shocks to their ways of working in living memory, structured management practices helped them survive, adapt and even thrive. We conjecture that structured management in this sense is a General Purpose Technology: rather than improving firm outcomes in a specific dimension, it provides firms with a platform to adapt more quickly to unforeseen changes in their environment, as circumstances require. Moreover, it appears that this adaptability when faced with unexpected shocks has persistent effects on innovation and business operations. Our findings likely have implications for other large and small disruptions firm face in their business environment, from the roll-out of artificial intelligence to disruptive innovations by competitors.

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A Descriptive statistics

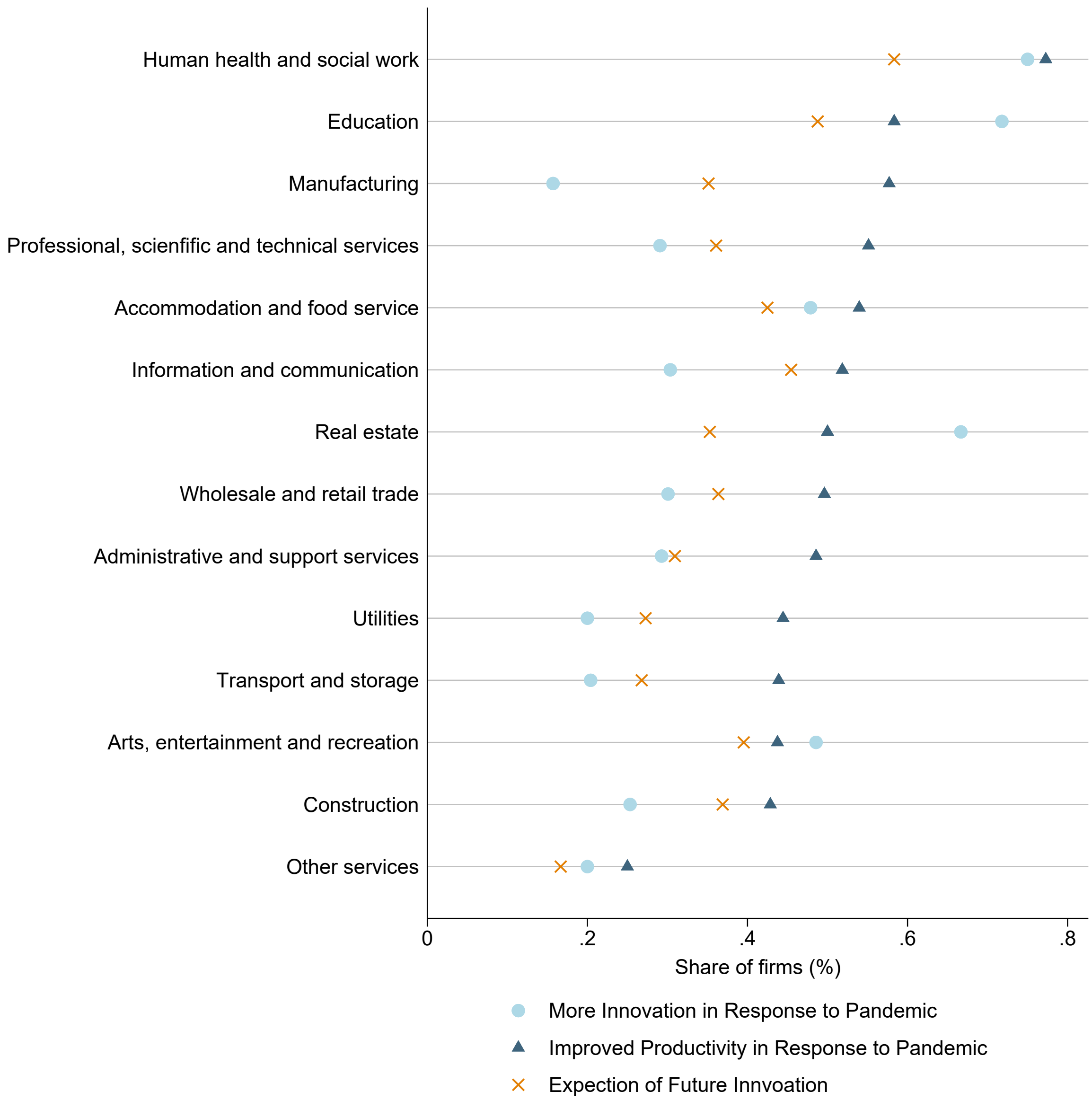
Table A1: Summary statistics of merged MES2020 and BICS38

	Mean	SD	Median	Count
Overall management score in 2019	0.59	0.18	0.63	1,640
Overall management score in 2020	0.60	0.18	0.64	1,640
Overall management practices score change	0.01	0.08	0.00	1,640
ln(turnover) 2019	9.39	1.60	9.33	1,626
ln(turnover) 2020	9.21	1.70	9.15	1,629
ln(turnover) change	-0.19	0.61	-0.09	1,622
Online sales % of turnover 2019	5.93	18.44	0.00	1,640
Online sales % of turnover 2020	7.24	20.09	0.00	1,640
Online sales change	1.31	7.01	0.00	1,640
Homeworking rate 2019	6.47	18.86	0.00	1,619
Homeworking rate 2020	26.55	35.52	5.25	1,619
Homeworking rate change	20.08	32.60	1.89	1,619
Percentage of international suppliers	8.74	16.13	2.00	1,640
Experienced Supply Changes in 2020	0.37	0.48	0.00	1,640
Negatively Impacted by 2020 Supply Changes	0.09	0.29	0.00	608
Not or Minimally Impacted by 2020 Supply Changes	0.45	0.50	0.00	608
Positively Impacted by 2020 Supply Changes	0.46	0.50	0.00	608

Table A2: Summary statistics of merged MES2020 and BICS56

	Mean	SD	Median	Count
Overall management score in 2019	0.61	0.17	0.64	1,569
Overall management score in 2020	0.62	0.17	0.65	1,569
Overall management practices score change	0.01	0.08	0.00	1,569
ln(turnover) 2019	9.48	1.57	9.43	1,552
ln(turnover) 2020	9.30	1.66	9.31	1,558
ln(turnover) change	-0.17	0.58	-0.08	1,550
Online sales % of turnover 2019	6.20	18.30	0.00	1,569
Online sales % of turnover 2020	7.53	20.04	0.00	1,569
Online sales change	1.33	7.14	0.00	1,569
Homeworking rate 2019	7.06	19.66	0.00	1,548
Homeworking rate 2020	29.25	36.72	7.70	1,548
Homeworking rate change	22.19	33.70	2.55	1,548
Percentage of international suppliers	8.82	16.52	2.00	1,569
Experienced Supply Changes in 2020	0.38	0.49	0.00	1,569
Negativly Impacted by 2020 Supply Changes	0.09	0.29	0.00	596
Not or Minimally Impacted by 2020 Supply Changes	0.48	0.50	0.00	596
Positively Impacted by 2020 Supply Changes	0.43	0.50	0.00	596

Figure A1: Share of firms giving positive answers to innovation questions by industry



Source: Linked sample of BICS wave 38 and MES2020.

B Additional results and robustness checks

Table B1: Coefficient of interest (ln turnover) across survey waves and using predicted or actual turnover and inputs

	2016 - 2017	2019 - 2020	Difference	Equality test p-value
Predicted inputs and outputs	0.012	0.120**	0.108*	0.078
	(0.029)	(0.054)	(0.061)	
Actual inputs and outputs	-0.013	0.111**	0.124**	0.043
	(0.031)	(0.053)	(0.061)	
Difference	0.025	0.009		
	(0.042)	(0.076)		
Equality test p-value	0.550	0.909		

Note: The header lists the period covered by our specification. The rows display whether our coefficient of interest is derived from a model estimated using predicted inputs and outputs reported in the MES survey or actual inputs and outputs reported in the ABS. The difference in coefficients and test for significance is reported in the final two rows. We estimate the model for the pre-pandemic survey wave 2016-2017 and the pandemic survey wave 2019-2020. The difference in coefficients across the two waves and test for significance is shown in the final two columns. The dependent variable for all models in this output is the natural logarithm of turnover. All models are estimated on the linked MES-ABS samples. Robust standard errors in parentheses and are clustered at the firm level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table B2: TWFE model results by management practices category

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(turnover)		online sales (%)		homeworking(%)	
Y2020*MPS2019	0.160***		1.221***		25.293***	
	(0.037)		(0.301)		(1.341)	
Y2020*mpsImprove2019		0.058*		-0.326		5.732***
		(0.033)		(0.254)		(1.151)
Y2020*mpsKPI2019		0.028		0.201		4.268***
		(0.033)		(0.308)		(1.380)
Y2020*mpsTarget2019		0.044		0.332		13.646***
		(0.031)		(0.266)		(1.248)
Y2020*mpsEmploy2019		0.055*		0.771***		4.056***
		(0.028)		(0.249)		(1.159)
Observations	23,842	23,840	23,842	23,840	23,842	23,840
Clusters	11,949	11,948	11,949	11,948	11,949	11,948
R^2	0.159	0.160	0.067	0.067	0.483	0.485
Sector*Y2020	Y	Y	Y	Y	Y	Y
Region*Y2020	Y	Y	Y	Y	Y	Y
Sizeband*Y2020	Y	Y	Y	Y	Y	Y
Pre-pandemic TPH*Y2020	Y	Y	Y	Y	Y	Y

Note: The header lists the dependent variables which are the natural logarithm of turnover, online sales as a percentage of turnover, and home-working rate in percentages respectively. Each dependent variable has two columns of estimates. One uses the overall MPS, another uses four aspects of MPS. The other explanatory variables of the three regressions are the same. Sectors are based on 1-digit SIC code. Regions are defined by International Territorial Level 1 (ILT-1). Sizeband is defined as Small for $employment \leq 99$, Medium for 100 - 249, Large for ≥ 250. Pre-pandemic TPH (turnover per head) is ln(turnover/number of employees) in 2019. Robust errors in parentheses and are clustered at the firm level. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table B3: Selected individual questions from a LASSO regression

In 2019, ...	CV	Adaptive
7a. In general what was the most common response to problems faced within [Ru Name]?		
8a. How many key performance indicators (KPIs) did [Ru Name] monitor?	X	X
8b. How frequently was progress against the key performance indicators (KPIs) reviewed by managers?		
8c. How frequently was progress against the key performance indicators (KPIs) reviewed by non-managers?		
10a. Which of the following best describes the main timeframes for achieving targets within [Ru Name]?		
10b. How easy or difficult was it to achieve these targets?	X	X
10c. Approximately what proportion of managers were aware of these targets?	X	
10d. Approximately what proportion of non-managers were aware of these targets?		
12a. What were performance bonuses for managers usually based on within [Ru Name]?		
12c. What were performance bonuses for non-managers usually based on within [Ru Name]?		
13a. How were managers usually promoted within [Ru Name]? a. Based solely on performance or ability		
13c. How were non-managers usually promoted?	X	X
14a. On average how many days training and development did managers undertake within [Ru Name]?	X	
14c. On average how many days training and development did nonmanagers undertake?		
15a. [How quickly] action was taken to address under-performance among managers within [Ru Name]? (%)		
15c. [How quickly] action was taken to address under-performance among non-managers within [Ru Name]? (%)	X	X
Sector FE	Y	Y
Region FE	Y	Y
Sizeband FE	Y	Y
Controls	Y	Y

Note: Regression in first differences. Controls include labour, investment and materials. Outcome is turnover. "CV" and "adaptive" denote different selection criteria. Results not dependent on initial seed.

Table B4: Supply chain regressions: 2020 outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Large negative impacts	-0.0344***	-0.0341***	-0.0342***	-0.0401***	-0.0404***	-0.0403***	-0.0404***	-0.0403***
	(0.00503)	(0.00499)	(0.00499)	(0.00565)	(0.00575)	(0.00575)	(0.00575)	(0.00575)
Small negative impacts	-0.111***	-0.110***	-0.110***	-0.126***	-0.126***	-0.126***	-0.126***	-0.126***
	(0.0118)	(0.0118)	(0.0118)	(0.0130)	(0.0133)	(0.0133)	(0.0133)	(0.0133)
Minimal or no impacts	-0.255***	-0.251***	-0.251***	-0.288***	-0.287***	-0.287***	-0.287***	-0.287***
	(0.0248)	(0.0249)	(0.0249)	(0.0274)	(0.0281)	(0.0281)	(0.0281)	(0.0281)
Small positive impacts	0.310***	0.306***	0.306***	0.354***	0.353***	0.353***	0.353***	0.353***
	(0.0297)	(0.0297)	(0.0297)	(0.0326)	(0.0335)	(0.0335)	(0.0335)	(0.0336)
Large positive impacts	0.0895***	0.0890***	0.0892***	0.100***	0.0998***	0.0997***	0.0998***	0.0997***
	(0.0104)	(0.0104)	(0.0104)	(0.0115)	(0.0117)	(0.0117)	(0.0117)	(0.0118)
Observations	4,370	4,370	4,370	4,297	4,261	4,261	4,261	4,261
Log likelihood	-5089.49	-5074.33	-5065.13	-4964.67	-4921.18	-4921.18	-4921.18	-4921.17
Sector	N	Y	Y	Y	Y	Y	Y	Y
Region	N	N	Y	Y	Y	Y	Y	Y
ln(employment)	N	N	N	Y	Y	Y	Y	Y
ln(capital expenditure)	N	N	N	N	Y	Y	Y	Y
ln(intermediate expenditure)	N	N	N	N	Y	Y	Y	Y
ln(turnover)	N	N	N	N	Y	Y	Y	Y
Suppliers	N	N	N	N	N	Y	N	Y
International suppliers	N	N	N	N	N	N	Y	Y

Note: Robust errors in parentheses, clustered at the firm level. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Figure B1: Homeworking and hybrid working rates for above and below median MPS firms by broad sectors.

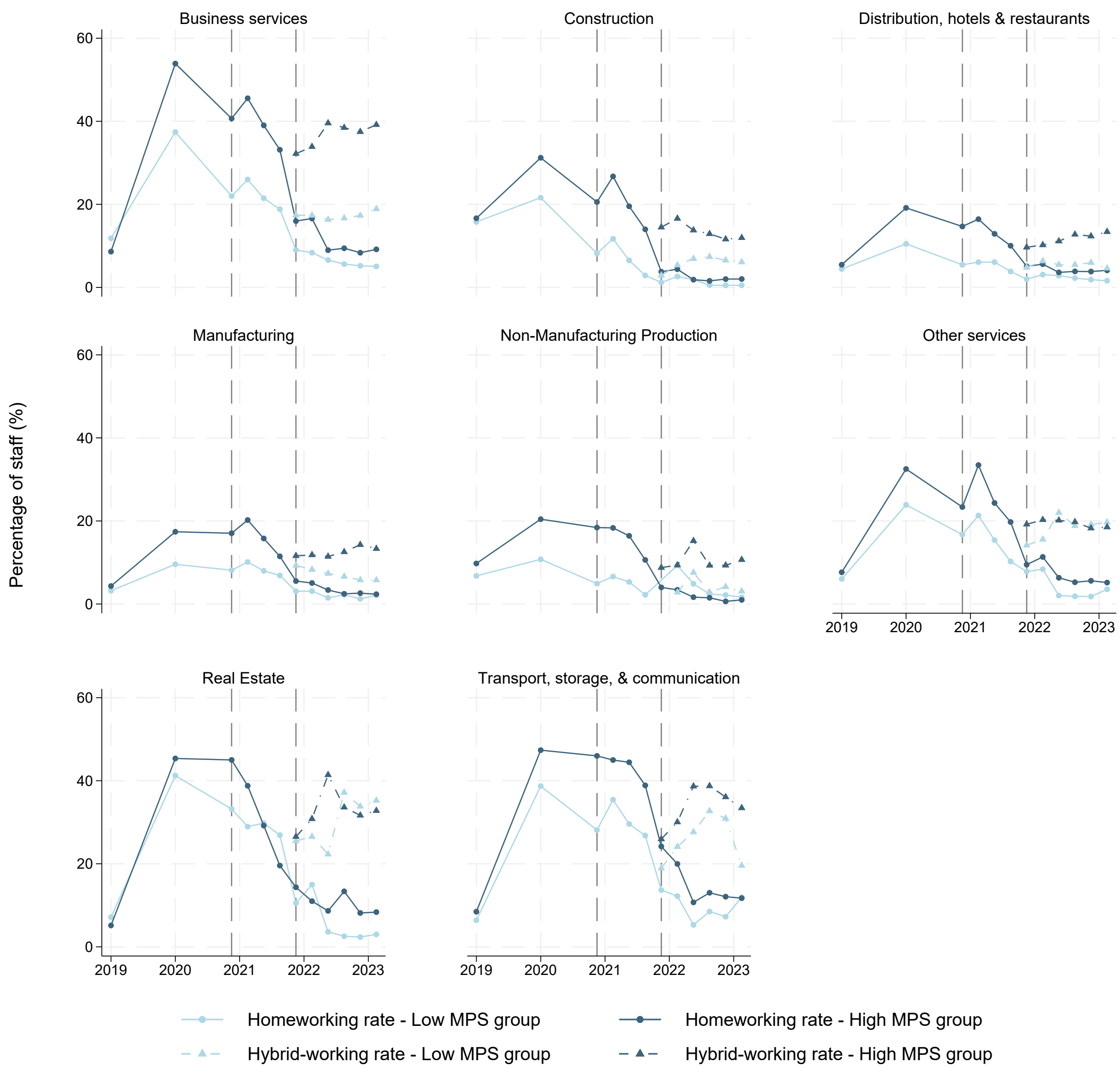


Table B5: Coefficient of interest (ln turnover) under alternative specifications

Robustness check	Coefficient	s.e.	p-value	Adj. R^2	Clusters	Observations	Model
Base	0.180	0.034	0.000	0.083	11,965	23,872	1
Base	0.162	0.034	0.000	0.124	11,965	23,872	2
Base	0.165	0.034	0.000	0.125	11,965	23,872	3
Base	0.130	0.033	0.000	0.150	11,965	23,858	4
Base	0.123	0.032	0.000	0.205	11,965	23,858	5
Base	0.150	0.036	0.000	0.213	11,949	23,842	6
Base	0.242	0.036	0.000	0.225	11,949	23,842	7
WFH suitability index	0.180	0.035	0.000	0.083	11,965	23,872	1
WFH suitability index	0.168	0.034	0.000	0.125	11,965	23,872	2
WFH suitability index	0.170	0.034	0.000	0.126	11,965	23,872	3
WFH suitability index	0.135	0.034	0.000	0.150	11,965	23,858	4
WFH suitability index	0.127	0.033	0.000	0.205	11,965	23,858	5
WFH suitability index	0.153	0.036	0.000	0.213	11,949	23,842	6
WFH suitability index	0.244	0.037	0.000	0.225	11,949	23,842	7
Essential industry index	0.151	0.036	0.000	0.102	10,603	21,151	1
Essential industry index	0.148	0.036	0.000	0.133	10,603	21,151	2
Essential industry index	0.151	0.036	0.000	0.134	10,603	21,151	3
Essential industry index	0.118	0.036	0.001	0.158	10,603	21,141	4
Essential industry index	0.114	0.035	0.001	0.215	10,603	21,141	5
Essential industry index	0.145	0.038	0.000	0.224	10,588	21,126	6
Essential industry index	0.239	0.039	0.000	0.236	10,588	21,126	7
ICT intensity index	0.147	0.042	0.000	0.077	7,692	15,350	1
ICT intensity index	0.150	0.042	0.000	0.109	7,692	15,350	2
ICT intensity index	0.152	0.042	0.000	0.111	7,692	15,350	3
ICT intensity index	0.114	0.040	0.004	0.138	7,692	15,340	4
ICT intensity index	0.119	0.039	0.002	0.182	7,692	15,340	5
ICT intensity index	0.135	0.043	0.001	0.190	7,685	15,333	6
ICT intensity index	0.218	0.044	0.000	0.200	7,685	15,333	7
Labour productivity	0.192	0.035	0.000	0.100	11,075	22,118	1
Labour productivity	0.189	0.035	0.000	0.145	11,075	22,118	2
Labour productivity	0.190	0.035	0.000	0.146	11,075	22,118	3
Labour productivity	0.158	0.034	0.000	0.169	11,075	22,107	4
Labour productivity	0.147	0.033	0.000	0.230	11,075	22,107	5
Labour productivity	0.126	0.036	0.001	0.231	11,075	22,107	6
Labour productivity	0.214	0.037	0.000	0.242	11,075	22,107	7
Forecasting error	0.173	0.034	0.000	0.084	11,965	23,872	1
Forecasting error	0.157	0.034	0.000	0.124	11,965	23,872	2
Forecasting error	0.160	0.034	0.000	0.125	11,965	23,872	3
Forecasting error	0.126	0.033	0.000	0.150	11,965	23,858	4
Forecasting error	0.119	0.032	0.000	0.205	11,965	23,858	5
Forecasting error	0.147	0.036	0.000	0.213	11,949	23,842	6
Forecasting error	0.239	0.036	0.000	0.225	11,949	23,842	7

Table B6: Coefficient of interest (online sales rate) under alternative specifications

Robustness check	Coefficient	s.e.	p-value	Adj. R^2	Clusters	Observations	Model
Base	0.993	0.282	0.000	0.035	11,965	23,872	1
Base	1.119	0.275	0.000	0.064	11,965	23,872	2
Base	1.091	0.275	0.000	0.065	11,965	23,872	3
Base	1.067	0.278	0.000	0.065	11,965	23,858	4
Base	1.062	0.278	0.000	0.066	11,965	23,858	5
Base	1.215	0.301	0.000	0.066	11,949	23,842	6
Base	1.305	0.310	0.000	0.067	11,949	23,842	7
WFH suitability index	0.955	0.287	0.001	0.035	11,965	23,872	1
WFH suitability index	1.106	0.277	0.000	0.064	11,965	23,872	2
WFH suitability index	1.080	0.277	0.000	0.065	11,965	23,872	3
WFH suitability index	1.054	0.280	0.000	0.065	11,965	23,858	4
WFH suitability index	1.049	0.280	0.000	0.066	11,965	23,858	5
WFH suitability index	1.196	0.304	0.000	0.066	11,949	23,842	6
WFH suitability index	1.286	0.312	0.000	0.067	11,949	23,842	7
Essential industry index	1.202	0.308	0.000	0.041	10,603	21,151	1
Essential industry index	1.256	0.304	0.000	0.066	10,603	21,151	2
Essential industry index	1.228	0.304	0.000	0.066	10,603	21,151	3
Essential industry index	1.198	0.306	0.000	0.067	10,603	21,141	4
Essential industry index	1.193	0.306	0.000	0.067	10,603	21,141	5
Essential industry index	1.295	0.332	0.000	0.068	10,588	21,126	6
Essential industry index	1.371	0.343	0.000	0.068	10,588	21,126	7
ICT intensity index	0.545	0.366	0.137	0.041	7,692	15,350	1
ICT intensity index	0.472	0.349	0.176	0.077	7,692	15,350	2
ICT intensity index	0.418	0.348	0.229	0.078	7,692	15,350	3
ICT intensity index	0.385	0.350	0.271	0.079	7,692	15,340	4
ICT intensity index	0.380	0.350	0.278	0.081	7,692	15,340	5
ICT intensity index	0.523	0.377	0.165	0.082	7,685	15,333	6
ICT intensity index	0.575	0.381	0.131	0.082	7,685	15,333	7
Labour productivity	0.971	0.287	0.001	0.035	11,075	22,118	1
Labour productivity	1.073	0.280	0.000	0.067	11,075	22,118	2
Labour productivity	1.043	0.280	0.000	0.068	11,075	22,118	3
Labour productivity	1.019	0.282	0.000	0.068	11,075	22,107	4
Labour productivity	1.015	0.282	0.000	0.069	11,075	22,107	5
Labour productivity	1.178	0.307	0.000	0.070	11,075	22,107	6
Labour productivity	1.287	0.314	0.000	0.070	11,075	22,107	7
Forecasting error	1.027	0.284	0.000	0.035	11,965	23,872	1
Forecasting error	1.142	0.279	0.000	0.064	11,965	23,872	2
Forecasting error	1.115	0.278	0.000	0.065	11,965	23,872	3
Forecasting error	1.091	0.281	0.000	0.065	11,965	23,858	4
Forecasting error	1.086	0.281	0.000	0.066	11,965	23,858	5
Forecasting error	1.231	0.303	0.000	0.066	11,949	23,842	6
Forecasting error	1.323	0.312	0.000	0.067	11,949	23,842	7

Table B7: Coefficient of interest (homeworking rate) under alternative specifications

Robustness check	Coefficient	s.e.	p-value	Adj. R^2	Clusters	Observations	Model
Base	34.903	1.362	0.000	0.306	11,965	23,872	1
Base	29.595	1.252	0.000	0.463	11,965	23,872	2
Base	28.965	1.248	0.000	0.470	11,965	23,872	3
Base	28.790	1.255	0.000	0.471	11,965	23,858	4
Base	28.798	1.256	0.000	0.471	11,965	23,858	5
Base	25.299	1.343	0.000	0.483	11,949	23,842	6
Base	26.150	1.376	0.000	0.483	11,949	23,842	7
WFH suitability index	26.807	1.258	0.000	0.443	11,965	23,872	1
WFH suitability index	27.799	1.226	0.000	0.489	11,965	23,872	2
WFH suitability index	27.217	1.221	0.000	0.496	11,965	23,872	3
WFH suitability index	26.979	1.227	0.000	0.497	11,965	23,858	4
WFH suitability index	26.987	1.228	0.000	0.497	11,965	23,858	5
WFH suitability index	23.238	1.315	0.000	0.507	11,949	23,842	6
WFH suitability index	24.174	1.349	0.000	0.507	11,949	23,842	7
Essential industry index	35.493	1.467	0.000	0.321	10,603	21,151	1
Essential industry index	30.622	1.349	0.000	0.474	10,603	21,151	2
Essential industry index	29.912	1.347	0.000	0.480	10,603	21,151	3
Essential industry index	29.659	1.352	0.000	0.481	10,603	21,141	4
Essential industry index	29.663	1.353	0.000	0.481	10,603	21,141	5
Essential industry index	26.273	1.450	0.000	0.492	10,588	21,126	6
Essential industry index	27.104	1.489	0.000	0.493	10,588	21,126	7
ICT intensity index	29.340	1.623	0.000	0.348	7,692	15,350	1
ICT intensity index	26.889	1.519	0.000	0.472	7,692	15,350	2
ICT intensity index	26.310	1.511	0.000	0.480	7,692	15,350	3
ICT intensity index	26.146	1.521	0.000	0.480	7,692	15,340	4
ICT intensity index	26.136	1.521	0.000	0.480	7,692	15,340	5
ICT intensity index	21.928	1.649	0.000	0.495	7,685	15,333	6
ICT intensity index	22.123	1.679	0.000	0.495	7,685	15,333	7
Labour productivity	33.282	1.364	0.000	0.315	11,075	22,118	1
Labour productivity	28.156	1.263	0.000	0.466	11,075	22,118	2
Labour productivity	27.657	1.259	0.000	0.472	11,075	22,118	3
Labour productivity	27.521	1.266	0.000	0.472	11,075	22,107	4
Labour productivity	27.553	1.269	0.000	0.472	11,075	22,107	5
Labour productivity	24.248	1.364	0.000	0.483	11,075	22,107	6
Labour productivity	24.736	1.399	0.000	0.483	11,075	22,107	7
Forecasting error	34.815	1.362	0.000	0.306	11,965	23,872	1
Forecasting error	29.486	1.254	0.000	0.463	11,965	23,872	2
Forecasting error	28.863	1.249	0.000	0.470	11,965	23,872	3
Forecasting error	28.682	1.256	0.000	0.471	11,965	23,858	4
Forecasting error	28.689	1.258	0.000	0.471	11,965	23,858	5
Forecasting error	25.256	1.343	0.000	0.483	11,949	23,842	6
Forecasting error	26.107	1.377	0.000	0.483	11,949	23,842	7

Table B8: Coefficient of interest (ln turnover) using predicted or actual turnover and inputs (2019-2020), linked sample

Specification	Source: MES	Source: ABS	Difference
1	0.143**	0.135**	0.008
	(0.059)	(0.055)	(0.081)
2	0.145**	0.131**	0.014
	(0.058)	(0.055)	(0.080)
3	0.151***	0.126**	0.025
	(0.057)	(0.055)	(0.079)
4	0.119**	0.110**	0.008
	(0.055)	(0.054)	(0.077)
5	0.120**	0.111**	0.009
	(0.054)	(0.053)	(0.076)
6	0.129**	0.174***	-0.045
	(0.057)	(0.056)	(0.080)

Note: In MES2020, timing differences mean that respondents are asked to give an expected turnover for 2020 rather than an actual outcome. To test the robustness of our coefficient of interest to potential prediction error we create a linked sample of MES2020 - ABS2019 - ABS2020 and rerun each of our main specifications sourcing all turnover information from the actual turnover given in ABS. The header lists whether turnover information is derived from the MES or the ABS. The within specification difference in coefficients across the two sources of turnover and input information is shown in the final column along with a test for statistical significance. The dependent variable for all models in this output is the natural logarithm of turnover. Robust standard errors in parentheses and are clustered at the firm level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.