ECONOMIC STATISTICS CENTRE OF EXCELLENCE

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ESCoE Discussion Paper 2024-04

November 2024

ISSN 2515-4664

DISCUSSION PAPER

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ESCoE Discussion Paper No. 2024-03
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Why do some firms adapt and even thrive when major unexpected shocks occur? We argue 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 exogenous shock of the pandemic, adopting homeworking and online sales practices more fully and seeing a smaller fall in their turnover. Linking at the firm level to a high-frequency business survey, we show that firms with structured management practices undertook more product and process and logistics innovation to facilitate this change, switched to homeworking more quickly and adopted hybrid working more completely in the long run. An external validity exercise using a different shock and adjustment margin shows qualitatively similar results, consistent with our argument that structured management practices allow firms to adapt regardless of the nature of the shock.

Keywords: management practices; innovation; adaptation; resilience

JEL classification: D22; M10; O30; O33

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Published by:
Economic Statistics Centre of Excellence
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Managing to Adapt: Structured Management Practices and Firm Resilience

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November 21, 2024

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 unexpected shocks, such as the Covid-19 pandemic, adopting homeworking and online sales practices more fully 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, implemented and adapted positively to supply chain changes, switched to homeworking more quickly and adopted a higher rate of hybrid working more permanently. 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
Keywords: management practices; innovation; adaptation; resilience

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We are grateful to Tera Allas, Yannick Bormans, John Forth, Nadine Hahn, Sara Maioli, John Van Reenen and the audiences at the MaCCI Annual Conference 2023, the 2023 CMA-Nottingham workshop on Management, Innovation and Firm Performance, the annual conferences 2023 of CompNet, ESCoE and the Royal Economic Society, and the UK Government Economic Service seminar series for helpful feedback. This research has been funded by ESRC grant ES/S012729/2 as part of the research programme of the ESCoE. Any views expressed are solely those of the authors and cannot be taken to represent those of the Competition and Markets Authority or the Office for National Statistics. This paper uses Office for National Statistics (ONS) statistical research datasets via the Secure Research Service (SRS). Outputs may not exactly reproduce National Statistics aggregates.
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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? 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 unexpected shocks, such as the Covid-19 pandemic, adopting homeworking and online sales practices more fully and seeing a smaller fall in their turnover. 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 this change, switched to homeworking more quickly and adopted hybrid working more completely in the long run. To test this hypothesis we also look at innovation and supply chains and find firms with structured management practices also adapt these aspects of their operations more swiftly.

Our paper draws on Bloom and Van Reenen (2007) who show that these practices are generally correlated with better performance in most dimensions. 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 large part of the source of resilience and adaptability, as well as innovation and optimism, may lie in the management practices a firm has adopted *prior to the shock*.

Covid forced many businesses to fundamentally change the way they produce and sell their output (Brynjolfsson et al., 2020). The recent literature hypothesises that some firms were better placed to deal with this shock because they had pre-existing arrangements in place (such as 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. This is a very plausible argument supported by the data, but we argue that these firms had an edge not because they were *fortunate* to be well positioned for a specific type of shock, but they had structural management practices in place to deal with many types of shocks.

We conjecture that structured management practices allow firms to respond to sudden and unforeseen shocks more readily, for example by being able to quickly transition to remote working and online sales.[1] We argue that the advantages that derive from structured management practices are a General Purpose Technology (GPT).[2] Structured management practices as a GPT allows firms to respond to changes and make further adjustments to organisational practices, as demanded by changes in circumstances. This view is supported by the literature recognising that management ability influences performance (mostly through productivity) by mitigating the negative effects of many types of shocks. 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 (**?**) all contribute to higher productivity. Firms with more decentralized structures are found to be 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). Firms have resilience even in response to sudden shocks by virtue of their management capabilities.[3]

The recent period of turmoil due to Covid-19 provides an ideal laboratory to explore whether better pre-existing management practices deliver greater resilience, adaptability, innovation and ambition when a sudden shock occurs. This shock impacted business directly as governments around the world implemented a series of non-pharmaceutical interventions (NPIs) to slow down the spread of the Covid-19 virus. To varying degrees, firms adapted by turning to online sales or increasing their homeworking rate to keep their business going and limiting the effects on turnover.[4]

Figure 1 illustrates this adaptability and resilience by plotting key measures of response against the quintiles of management practices scores. 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 in 2019), and simialrly firms in these top quintiles

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

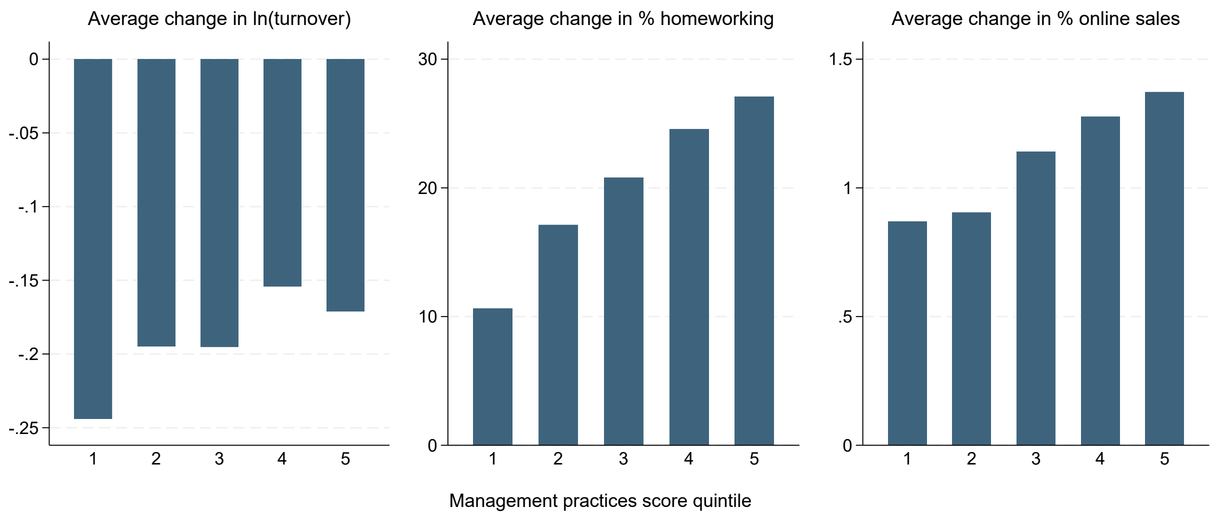
[2]It is apparent that structured management practices share the three features of a GPT: (1) they are widely used, (2) capable of ongoing improvement, and (3) enable innovation in applications (Jovanovic and Rousseau, 2005; Bresnahan, 2010).

[3]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 a greater or lesser extent 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.

[4]In the UK, this 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 (see appendix B). The imposition of these NPIs meant that most firms suddenly found their usual working and retail practices nonviable, and their standard way of doing business fundamentally threatened.

adopted remote working more readily (second panal) and pivoted to online sales (third panel).

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.

Taking the analysis a stage further, we explain the differences in turnover, online sales and homeworking using a difference-in-difference (DID) model to explore the relationship between the management practices score (MPS) derived from MES2020 and performance derived from 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]

The new data required for this analysis was gathered before and after Covid to measure structured management practices and combines it with other survey evidence on turnover, online sales, homeworking and business innovations. We develop and make use of two novel firm-level data sources: (1) the UK Office for National Statistics (ONS) Management and Expectations Survey (MES2020), which collects information on four dimensions of management practices and an array of firm outcomes, and (2) the 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. We then look at mechanisms and show that these firms exhibit consistently higher homeworking and

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

online sales adoption rates in the pandemic than their peers with less structured management. A placebo test shows this difference only arises in the pandemic. In our core DID and TWFE regression results, these relationships are robust and statistically significant. However, average results mask significant underlying heterogeneity: it is precisely in industries that experience a largest change that the effect of structured management practices on operational decisions and outcomes is largest.

Having explored the direct measures of turnover, remote working and online sales using MES2020 we explore the extent to which firms with more structured management practices are more inclined to innovate, view changes to their supply chains in a positive light and adopt homeworking earlier than other firms. We link MES2023 to the qualitative data in ONS Business Insights and Conditions Survey (BICS) and find that during the Covid-19 pandemic, firms with more structured management practices innovate to cope with the shock of the pandemic more than they expected pre-pandemic across the entire range of product, process and logistics improvements and have more optimistic expectations about their post-pandemic future. When we look at changes in supply chains in 2020 we see that firms with more structured management practices were inclined to 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. We observe that firms with higher management scores adopted homeworking and hybrid working earlier and maintained an advantage compared with other firms.

Finally, the results in this paper are robust to a variety of competing hypotheses: for instance, including the firm's pre-pandemic labour productivity, its pre-pandemic ICT intensity or its forecasting ability directly do not affect the sign, size or significance

Our results are comparable to Lamorgese et al. (2021), who show using survey evidence that Italian firms with more structured management practices expected to see a smaller fall in their turnover early on in the pandemic. Just as in the UK, these firms in Italy were more likely to adopt homeworking, alongside other demand and labour management strategies. The present paper goes beyond Lamorgese et al. (2021) in several ways by highlighting innovation mechanisms, exploring heterogeneity, examining the dynamics and exploring other shocks. As firms adopted homeworking and online sales management had to reshape their entire product, process and logistics apparatus to accommodate these new working practices. When we explore a range of industries including manufacturing, we observe heterogeneous effects of structured management practices across different sectors. We can also track the dynamics and persistence of these changes in working practices through BIS surveys. Using these dynamics, we can reject the conjecture by Lamorgese et al.

(2021) that we should observe convergence over time in homeworking and online sales to pre-pandemic trend growth rates.

The rest 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 finally proof of robustness. 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 apply two novel firm-level data sources. Our primary source for management quality 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 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 MES2020 provides a unique longitudinal dataset on management practices for the UK. 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 over the course of the pandemic. Second, the sample is predominantly drawn from the regular 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:

- continuous improvement
- the use of key performance indicators (KPIs)
- the use of targets
- 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. The innovation questions are designed to monitor the extent of change in business innovation, the expected impact on year-ahead productivity and expected directional change in year-ahead innovation.[7] These innovation questions come from two BICS waves, 38 and 56.[8] 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). [9]

[6] An outline of the survey design and a full list of management practices questions can be found in appendix A.
[7] Further details of these questions are given in appendix A.
[8] BICS wave 38 was live from 23 August to 5 September 2021, BICS wave 56 was live from 3 May to 15 May 2022.
[9] The summary statistics in appendix C reveal the linked samples and MES2020 have similar moments for variables of interest.

2.2 Descriptive statistics

2.2.1 MES2020 variables

Table 1 shows key descriptive statistics of the variables of interest. First, we see that there was a small statistically significant difference in the pre-Covid management practice score (MPS) and the 2020 value, reported as 0.53 in 2019 and 0.55 in 2020.[10] The standard deviations in both years are similar at 0.2. 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.[11]

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 % 2019	5.69	18.42	0.00	12,292
Online sales % 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

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% 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.[12]

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

[11] Any formal test of the hypothesis will need to take this industry and 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.

[12] 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

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.

Adopting homeworking practices is another adaptation that allowed firms to cope with 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.[13]

2.2.2 BICS variables

We are also interested *how* firms supported operational changes during this period. 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 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%).

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 in our linked sample 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.

Figure C1 in the Appendix illustrates how innovation responses vary by industry. We show the

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.

[13]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.

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 are the top three industries in which firms have innovated more 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 a future productivity increase. 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 turnover, a firm's online sales share and its homeworking rate.

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, and to what extent it represents a more permanent change. The following subsections explain our methodologies in more detail.

3.1 MES2020: 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, online sales share, and 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 the 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 MES2020: Two-Way Fixed-Effects apprach

Next we employ a TWFE model to fully exploit 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 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:

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

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 Linked sample: linear probability model

Using the linked sample of MES2020 and BICS wave 38 surveys, we run cross-sectional regressions for the single outcome year. We test whether structural management practices prior to the pandemic are associated with changes in innovation since the onset of the shock. The dependent variable y_i is an indicator variable for firm i, respectively for "more innovation" during the pandemic, "higher expected productivity" and "higher expected innovation" one year ahead. For simplicity we use a linear probability model of the form:

$$y_i = \gamma_0 + \gamma_1 MPS2019_i + \gamma_2^{'} IND_i + \gamma_3^{'} Sizeband_i + \epsilon_i \tag{4}$$

where $MPS2019_i$ is a firm's management practice score measured in 2019. Again because of the industry heterogeneity in innovations, a set of industry dummies are included. Firm size may play a role in firms' innovation so we include a size band variable indicating whether a firm has more than 250 employees in 2019.[14] In essence, the specification in model (4) corresponds to first differencing a version of model (2) where the X_{it} include interactions between $Y2020_t$ and industry and between $Y2020_t$ and firm size band.

To further explore whether firms with more structured management practices innovate more broadly in the pandemic, we employ the information on innovation type from the BICS wave 56 data together with the firms' 2019 management scores from MES2020. Each innovation type is an indicator variable for "more of that type of innovation" since the pandemic, which we specify as y_i in model (4).

4 Empirical Results

In this section, we first show that firms with more structured management practices prior to the pandemic adopted homeworking and online sales practices more quickly, and saw a smaller fall in turnover during the pandemic. We show that these effects are larger in more affected industries.

[14] Considering the effects of MPS and firm size may depend on industry, we also ran a specification with interaction terms. Results are qualitatively and quantitatively similar and are not reported here.

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. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

We show some of the mechanisms through which more structured management practices improved firms' resilience, including steps to innovate and develop their supply chains. We find that the gap 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.

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 share by 0.5 percentage points and experienced higher homeworking rates of 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: Test of Coefficients across Waves

Model	(2016 - 2017)	(2019 - 2020)	Difference
DID	0.022**	0.050***	0.028*
	(0.009)	(0.011)	
FE	0.095***	0.180***	0.084*
	(0.029)	(0.034)	
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. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table 4 replicates the coefficient of interest from our DID baseline specification for turnover spanning the pandemic 2019-2020 (first row, second column). 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 coefficients reported in column (3) is significant at the 10% level. This suggests 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.

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(capital expenditure)					0.020***	0.020***	0.018***
					(0.002)	(0.002)	(0.002)
ln(intermediate expenditure)					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: CAPEX denotes annual capital expenditure, IC denotes 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The difference between TWFE coefficients in the second row of Table 4 implies that this additional salience alone dampened the fall in turnover by 1.7 percentage points in 2020 (measured on a one standard deviation increase in MPS). In Appendix Table D7 we also compare our baseline regressions for turnover in these same two periods, estimated on the sample of firms that we observe in the MES in both 2016-2017 and 2019-2020 and using realised turnover. The difference between coefficients, from the TWFE model estimated 2019-2020 and 2016-2017 on this sample, 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, an otherwise identical firm with full adoption of structured management practices (MPS=1) sees a roughly 18% smaller fall in turnover than an otherwise identical firm that has not adopted any structured management practices (MPS=0). If the hypothetical change from 0 to 1 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 the pre-pandemic performance are taken into account in column (7) the coefficient is not significantly different from initial estimates in columns (1) - (3). We report further robustness checks, and regression results for all four categories of management practices included separately, in appendix D and discuss them in section 4.6.

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 regression of online sales rates on the same 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 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 one standard deviation (0.2) increase in MPS, ceteris paribus, sees a roughly 6 percentage point larger rise in homeworking rates.

In Appendix D, Table D4, 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 home working. 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 2020. Appendix Table D11 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.

To sum up, we show that in response to the challenges brought by the Covid-19 pandemic and

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(capital expenditure)					-0.048*	-0.048*	-0.050*
					(0.026)	(0.026)	(0.026)
ln(intermediate expenditure)					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: CAPEX denotes annual capital expenditure, IC denotes 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. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

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(capital expenditure)					-0.055	-0.041	-0.060
					(0.099)	(0.097)	(0.097)
ln(intermediate expenditure)					-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: CAPEX denotes annual capital expenditure, IC denotes 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. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

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 more extensively and showed more resilience in their performance.

4.2 Heterogeneous effects by industry

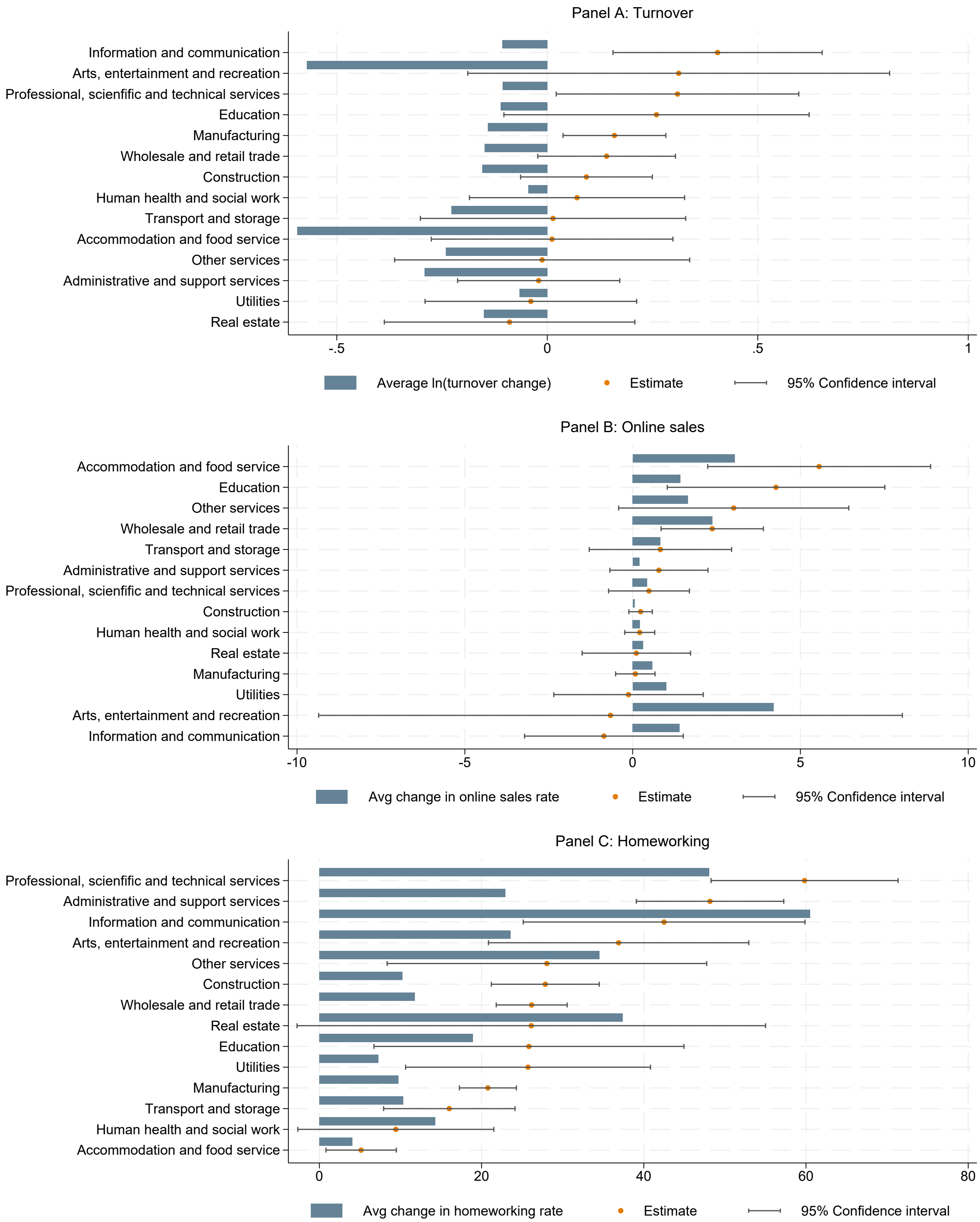
In this subsection, we investigate the effects of structured management practices on firms' responses to Covid-19 in different industries. Online selling is a more feasible option for some industries than others. UK Office for National Statistics data show that internet sales as a percentage of total 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) before and during the pandemic. Similarly, for some industries it is harder to adapt to working from home (for instance, manufacturing and accommodation and food services). Industry characteristics determine the amount of work that can be done from home and are largely beyond the scope of management.

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 effect of structured management practices is strongest in three sectors: manufacturing; information and communication; and professional, scientific and technical activities. These three sectors are those that overall experienced a smaller turnover drop in general. From Panel A we can also see that the sector hit the hardest by the pandemic was accommodation and food services, where the differential effect of management is close to zero. No amount of structured management could reduce the impact of these accommodation and food services premises being closed during Covid lockdowns.

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

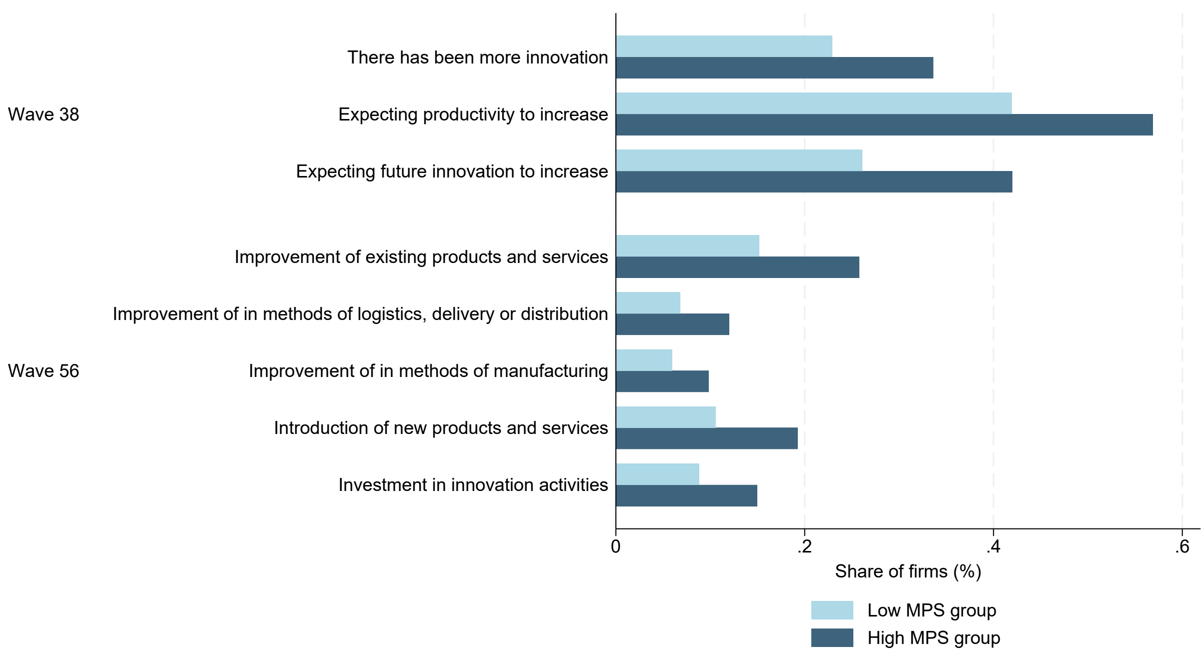
[15] Looking further into the two-digit industries, we find that within the accommodation and food service sector, it is the food and beverage service industry that sees the largest differential effect of management. Within the wholesale and retail trade sector, it is the retail trade industry. The sports and amusement and recreation activities industry also shows a large differential management effect. See appendix D.

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. The whiskers show upper and lower bounds of the 95% confidence interval of these coefficients.

Figure 3: Percentage of firms adopting types of innovation 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.

Panel C of Figure 2 presents the differential effects of structured management on homeworking by sector. In all sectors, structured management has significant positive differential effects on the homeworking rate. Better-managed firms adapt more fully to homeworking, and this result holds for all industries. The sectors that see the biggest increase in homeworking rate also show larger differential management effects.

4.3 Management and innovation

In this subsection, we present the results from the linked MES2020-BICS data set to study the impact of pre-pandemic management practices on firm's innovations and expectations. Figure 3 shows that firms with above-median management practices are more likely to increase investment in all types of innovation during the pandemic, expect this investment to continue at a higher level compared to the pre-pandemic baseline, and expect it to increase their productivity.

In Table 8 we investigate firms' innovation since the pandemic and their expectations about future innovation and productivity. After controlling for industry and firm size, column (1) shows firms with better management scores in 2019 are more likely to innovate to cope with the shock of the pandemic than firms with lower scores. Column (2) and (3) show that they also more optimistic about the effects of innovations on their productivity growth, and expect to increase innovation in the future.

Table 8: The impact of management on firms' innovation behaviour and their expectations

	(1) More innovation	(2) Expect productivity to increase	(3) Expect innovation to increase
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

Note: The header lists the dependent variables which 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. Sectors are based on 1-digit Standard Industry Classification (SIC) code. Size-band is defined as *small* for *employment* ≤ 99, *medium* for 100 - 249, *large* for ≥ 250. Robust standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Next we examine the relationship between management and a variety of innovations listed in

Table 9. Structured management practices have a significant positive effect on all five innovation categories, after controlling for industry and size band. Firms that had more structured management in 2019 have embarked on more innovations to improve their existing products and services (column (1)) as well as introducing new products and services (column (2)), they devote more effort to enhancing their logistics and distribution (column (3)) and manufacturing where relevant (column (4)), and they also invest more in innovation activities (column (5)). This indicates that the innovations in new or existing products, logistics delivery are valuable elements in shifting from in-person sales to selling online. The positive relationship between management and investment in innovations is also consistent with more optimistic expectations about the future. Beliefs about the impact in the post-pandemic years suggest a lasting effect of these process innovations on firms with more structured management practices.

Table 9: Management and innovation types

	(1) Existing Products/Services	(2) Logistics	(3) Manufacturing	(4) New products/Services	(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: The header lists the areas in which firms have done more innovation since the . pandemic. These are indicators used as dependent variables. 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

4.4 Changes to supply chains

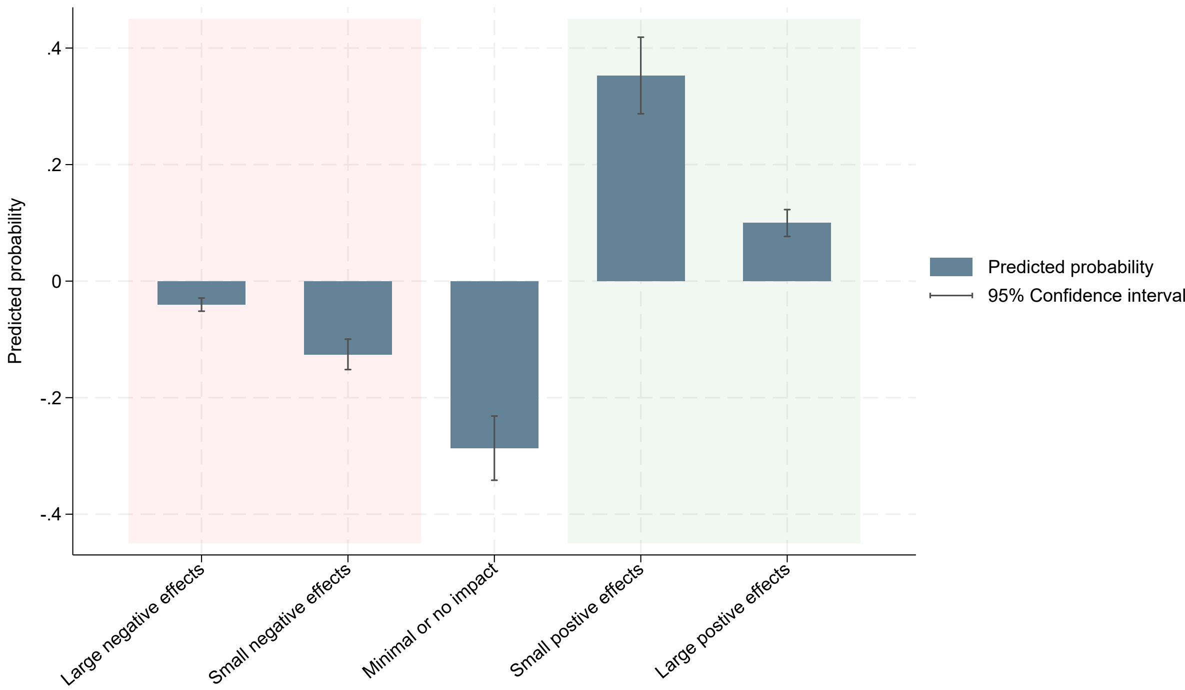
Covid-19 also disrupted domestic and international supply chains (Bonadio et al., 2021) and firms necessarily had to implement changes to their supply chains to continue their operations. In Table 10 we explore the extent to which firms with higher MPS prior to the pandemic were more likely to report changes to their supply chains. We see that structured management practices may have helped firms adapt on these margins too.

Table 10: Likelihood of firm reporting changes to supply chains in 2020 based on MPS score: 2020 outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Management Practices Score (2019)	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	12291	12291	12291	12134	11949	11949	11949	11949
Industry FE	N	Y	Y	Y	Y	Y	Y	Y
Region FE	N	N	Y	Y	Y	Y	Y	Y
ln(Emp) 2020	N	N	N	Y	Y	Y	Y	Y
ln(Cap Exp) 2020	N	N	N	N	Y	Y	Y	Y
ln(IC) 2020	N	N	N	N	Y	Y	Y	Y
ln(Turnover) 2020	N	N	N	N	Y	Y	Y	Y
No. Suppliers	N	N	N	N	N	Y	N	Y
No. International	N	N	N	N	N	N	Y	Y

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

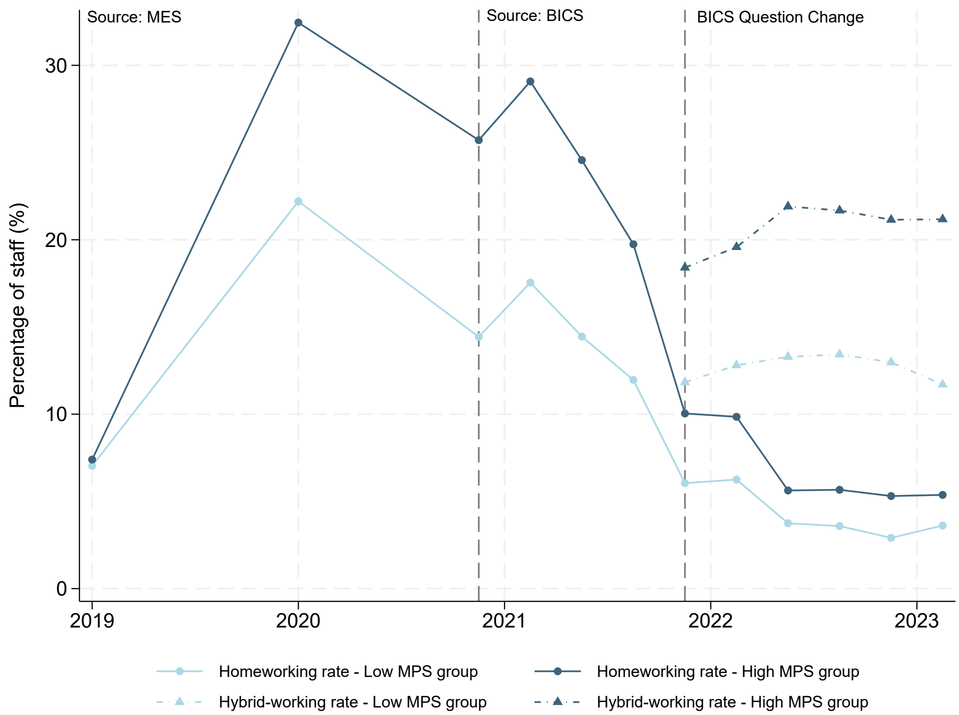
Figure 4: Impact of 2020 supply chain changes, predicted probabilities based on a unit increase in management score



Moreover, as shown in Figure 4, all else equal, firms with structured management practices are significantly more likely to report positive changes to their supply chains, and significantly less likely to report negative changes to their supply chains. We use qualitative questions from MES2020 about the pre-existing complexity of supply chains, including the share of international suppliers, and how supply chains have changed during 2020. 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. As shown by Table D12 in the appendix, coefficients are very stable across specifications, including where we control for the number of international and total suppliers.

2020 was a particularly challenging year for UK firms involved in import or export. 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. The results in this section may also reflect adaptation to this shock.

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



4.5 Adoption rate and permanence of hybrid working

Using the linked MES and BICS sample, we are able to investigate the firm-level adoption of homeworking and hybrid working at quarterly frequency. We show that firms with 'high' scores on management practices adopted homeworking more extensively than firms with 'low' scores 2020-2022, and maintained this higher rate of adoption throughout. This was repeated when hybrid working 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 . Even when controlling for pandemic homeworking rates at the firm level, management practices still had a significant positive effect on long-term hybrid working rates.

Figure 5 shows the 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.[16] Both groups start with the same homeworking rate before the pandemic, but firms with above-median management scores quickly increase their homeworking

[16]Within-industry cutoffs account for the fact that management practices and working practices vary systematically across industries.

rates differentially, and maintain higher homeworking rates throughout. After the pandemic, they maintain differentially higher hybrid working rates. Before ONS introduced a change in the question wording of BICS towards hybrid working arrangements, homeworking rates were falling for both firms with 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 pattern holds across all sectors as seen in Figure D2 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 working-from-home.

In Table 11 we report the results of average 2022 hybrid working rates with the standard battery of controls from our baseline 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 rate, the effect of structured management practices remains positive and significant.

Table 11: 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) 2020	N	N	N	Y	Y	Y
ln(Cap Exp) 2020	N	N	N	N	Y	Y
ln(IC) 2020	N	N	N	N	Y	Y
ln(Turnover) 2020	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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

4.6 Robustness checks

We conduct a series of robustness checks. First, we test the assumption, implicit in our baseline regressions, that the effect of structured management practices is approximately linear. We compare the results of the DID model and TWFE model. The variable *HighMPS* in the DID model is an indicator for above-median MPS and the mean MPS of the high group is 0.2 higher than that of the comparison group. If we multiply the coefficients of Y2020*MPS2019 in column (4), (5), and(6) from Table 3 by 0.2 respectively, we obtain close values to the coefficients of Y2020*MPS high in column (1), (2), and (3) from the same table. Separate regressions at different quantiles of the management score distribution, not reported here, further validate our choice of baseline estimating equation.

Second, as shown in Table 5 our 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 region fixed-effects. Tables D1 to D2 in the Appendix also include an "essential industries" index used in Lamorgese et al. (2021) and model exposure via an occupations-based working-from-home suitability index with sector-level fixed effects. We obtain very similar results from these model specifications.

Third, we directly test several competing hypotheses. In our main results Tables 5-7 we control for labour productivity to test whether firms with more structured management practices just happen to be the most productive firms. In the Appendix Tables D1 to D2 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. We also rerun our regressions with labour productivity as the dependent variable to ensure the turnover effect is not driven by the adjustment of the input mix. Results for these tests can be found in Appendix D, but none of the alternative specifications affect the sign, size or significance of our coefficient of interest.

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. Table D6 in the appendix shows that our coefficient of interest is of the same sign and significance, and if anything slightly larger than in our baseline regressions.

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 D7 in the Appendix, we test this hypothesis by linking MES2020 to the previous wave, MES2016. We expect estimates for our baseline regressions in the pre-pandemic period, to be of similar size, but perhaps smaller and less precisely estimated. For a subsample of approximately 5,000 firms that appear in both waves, and for turnover as the outcome variable, we are able to conduct this placebo test. As expected, the coefficient of interest is of the same size, but smaller, and less statistically significant. We estimate these regressions with both estimated and realised turnover, with the latter giving more precision.

Fifth, 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 D4. Due to smaller sample size, the turnover effects are not 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 Table 8 and 9.

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?

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 and the heterogeneous impact it had on firms, 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.

We then draw on high-frequency qualitative survey data on attitudes towards innovation and on the types of innovation undertaken and link this to the management score for a subsample of firms 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 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, generally 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 management in this sense is a General Purpose Technology: rather than improving firm outcomes in a specific dimension, it gives firms the power to forecast the future more accurately and adapt more quickly to these forecasts as circumstances require. Although our paper has focused on recent events to study the process of adaptation facilitated by structured management in extraordinary conditions, future work will tell if this adaptation carries over to other, more gradual evolutionary pressures as well.

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A Survey background

A.1 MES 2020 questionnaire

The MES sampled approximately 50,000 businesses trading in Great Britain with 10 or more employees in 2020. The MES2020 survey was dispatched on 9 November 2020 and returns were accepted until 31 March 2021. We collected data on firms' management practices, online sales percentages and homeworking practices for reference years 2019 and 2020, as well as information on business expectations and characteristics (such as ownership structure, input use and turnover). After excluding missing values, MES2020 provides responses from approximately 12,000 businesses (yielding response rate of roughly 24%). The following questions in the Management and Expectations Survey were used to construct the Management Practices Score (MPS).

In 2019, in general what was the most common response to problems faced within [your business]?

- We resolved the problems but did not take further action
- We resolved the problems and took action to try to ensure they do not happen again
- We resolved the problems and had a continuous improvement process to anticipate similar problems in advance
- No action was taken

In 2019, how many key performance indicators (KPIs) did [your business] monitor?

- 1-2 key performance indicators
- 3-9 key performance indicators
- 10 or more key performance indicators
- No key performance indicators

In 2019, how frequently was progress against the key performance indicators (KPIs) reviewed by managers? (Only asked if KPIs were monitored in 2019)

- Annually
- Quarterly

- Monthly
- Weekly
- Daily
- Hourly or more frequently
- Never

In 2019, how frequently was progress against the key performance indicators (KPIs) reviewed by non-managers? (Only asked if KPIs were monitored in 2019)

- Annually
- Quarterly
- Monthly
- Weekly
- Daily
- Hourly or more frequently
- Never

In 2019, which of the following best describes the main timeframes for achieving targets within [your business]?

- Main timeframe was less than one year
- Main timeframe was one year or more
- Combination of timeframes of less than and more than a year
- There were no targets

In 2019, how easy or difficult was it to achieve these targets? (Only relevant if targets used)

- Very easy (Possible to achieve without much effort)
- Quite easy (Possible to achieve with some effort)

- Neither easy nor difficult (Possible to achieve with normal effort)
- Quite difficult (Possible to achieve with more than normal effort)
- Very difficult (Possible to achieve with extraordinary effort)

In 2019, approximately what proportion of managers were aware of these targets? (Only relevant if targets used)

- All
- Most
- Some
- None

In 2019, approximately what proportion of non-managers were aware of these targets? (Only relevant if targets used)

- All
- Most
- Some
- None

In 2019, what were performance bonuses for managers usually based on within [your business]?

- Their own performance as measured by targets
- Their team's or shift's performance as measured by targets
- Their site's performance as measured by targets (A site is an individual business premise, for example an office, factory or workshop)
- The business's performance as measured by targets
- Performance bonuses were not related to targets
- No performance bonuses

In 2019, what were performance bonuses for non-managers usually based on?

- Their own performance as measured by targets
- Their team's or shift's performance as measured by targets
- Their site's performance as measured by targets (A site is an individual business premise, for example an office, factory or workshop)
- The business's performance as measured by targets
- Performance bonuses were not related to targets
- No performance bonuses

In 2019, how were managers usually promoted within [your business]?

- Based solely on performance or ability
- Based partly on performance or ability, and partly on other factors (For example, partly based on length of service or business restructuring)
- Based mainly on factors other than performance or ability (For example, length of service or business restructuring)
- No managers were promoted

In 2019, how were non-managers usually promoted?

- Based solely on performance or ability
- Based partly on performance or ability, and partly on other factors (For example, partly based on length of service or business restructuring)
- Based mainly on factors other than performance or ability (For example, length of service or business restructuring)
- No non-managers were promoted

In 2019, on average how many days training and development did managers undertake within [your business]?

- Less than a day

- 1 day
- 2 to 4 days
- 5 to 10 days
- More than 10 days

In 2019, on average how many days training and development did non-managers undertake?

- Less than a day
- 1 day
- 2 to 4 days
- 5 to 10 days
- More than 10 days

In 2019, which of the following best describes the timeframe that action was taken to address under-performance among managers within [your business]?

- Within 6 months of identifying under-performance
- After 6 months of identifying under- performance
- No action was taken to address under-performance
- There was no under-performance

In 2019, which of the following best describes the timeframe that action was taken to address under-performance among non-managers?

- Within 6 months of identifying under-performance
- After 6 months of identifying under- performance
- No action was taken to address under-performance
- There was no under-performance

A.2 BICS38 questions on innovation

We use three innovation questions from BICS38.

1. "How has your business's innovation changed since the start of the coronavirus (COVID-19) pandemic?" with five options: "There has been more innovation"; "Innovation has not changed"; "There has been less innovation"; "Not sure"; and "Not applicable".[17]

2. "How do you expect these innovations to affect your business's productivity over the next 12 months?" with four options "will increase"; "will not change"; "will decrease"; and "not sure". Again "not sure" is treated as missing values. Options "will not change" and "will decrease" are grouped together[18].

3. "What are your expectations for your business's innovation over the next 12 months, compared with before the coronavirus pandemic?" with the same four options as in the second question[19].

A.3 BICS56 questions on innovation

We use a question about innovation types from this wave.
"In which of the following areas, if any, did your business increase innovation since March 2020?" The options are "Adoption of home or hybrid working"; "Adoption of online sales models"; "Improvement of existing products and services"; "Improvements in methods of logistics, delivery or distribution"; "Improvements in methods of manufacturing products and services"; "Introduction of new products and services"; "Investment in innovation activities"; "Not sure"; and "Business did not increase innovation". Again "Not sure" are treated as missing and excluded from our analysis.

[17]We treat "Not sure" and "Not applicable" as missing values and group together "Innovation has not changed" and "There has been less innovation" as the less innovation group is very small, accounting for around 2% of responses.

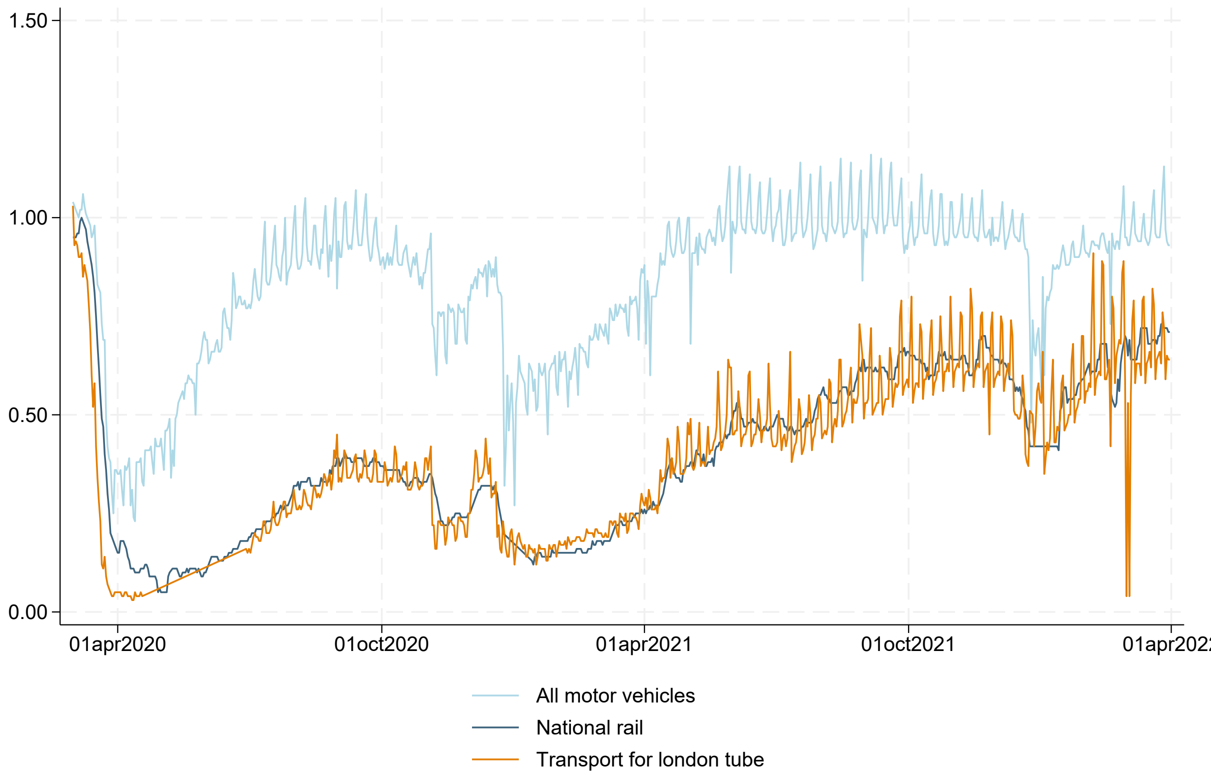
[18]The decrease group of this question accounts for only around 2.6% of the sample.

[19]The decrease group of this question accounts for around 1.3% of the sample.

B Covid-19 and NPIs in the UK, 2020-2022

March 2020	The UK government asks people reduce "non-essential" travel, avoid contact with others, and turn to home-working, and announces a first lockdown on 23 March.
May 2020	Prime Minister Boris Johnson announces a conditional plan for lifting lockdown in England. The lockdown is unchanged in Scotland, Northern Ireland, and Wales.
June 2020	Schools and non-essential shops reopen in England. The national lockdown is relaxed on 23 June.
July 2020	The UK's first local lockdown is introduced but more restrictions are eased in England.
August 2020	Lockdown restrictions are eased further.
September 2020	New restrictions are announced for England, including a return to homeworking.
October 2020	A new three-tier system of local Covid-19 restrictions starts in England.
November 2020	The second national lockdown begins in England. A five-tier system comes into force in Scotland.
December 2020	The second lockdown ends on 2 December. Later a new Tier 4 "Stay at Home" level is introduced in England.
January 2021	The UK enters a third national lockdown.
March 2021	The government begins a phased reopening of the economy.
April 2021	Non-essential retail, personal care services, outdoor hospitality venues, and gyms reopen.
May 2021	Indoor hospitality, entertainment venues, and indoor exercise classes reopen. Larger outdoor gatherings are permitted.
July 2021	Most legal limits on social contact are removed, and the final closed sectors, including nightclubs, reopen.
December 2021	PM announces precautionary measures for the Omicron variant, including compulsory face masks.
January 2022	Omicron measures are lifted.
February 2022	All legal Covid restrictions are lifted in England.
April 2022	All legal Covid restrictions are lifted in Wales and Scotland.

Figure B1: Daily Transport for London commuter traffic, March 2020-March 2022 (gov.uk, 2023)



C Descriptive statistics

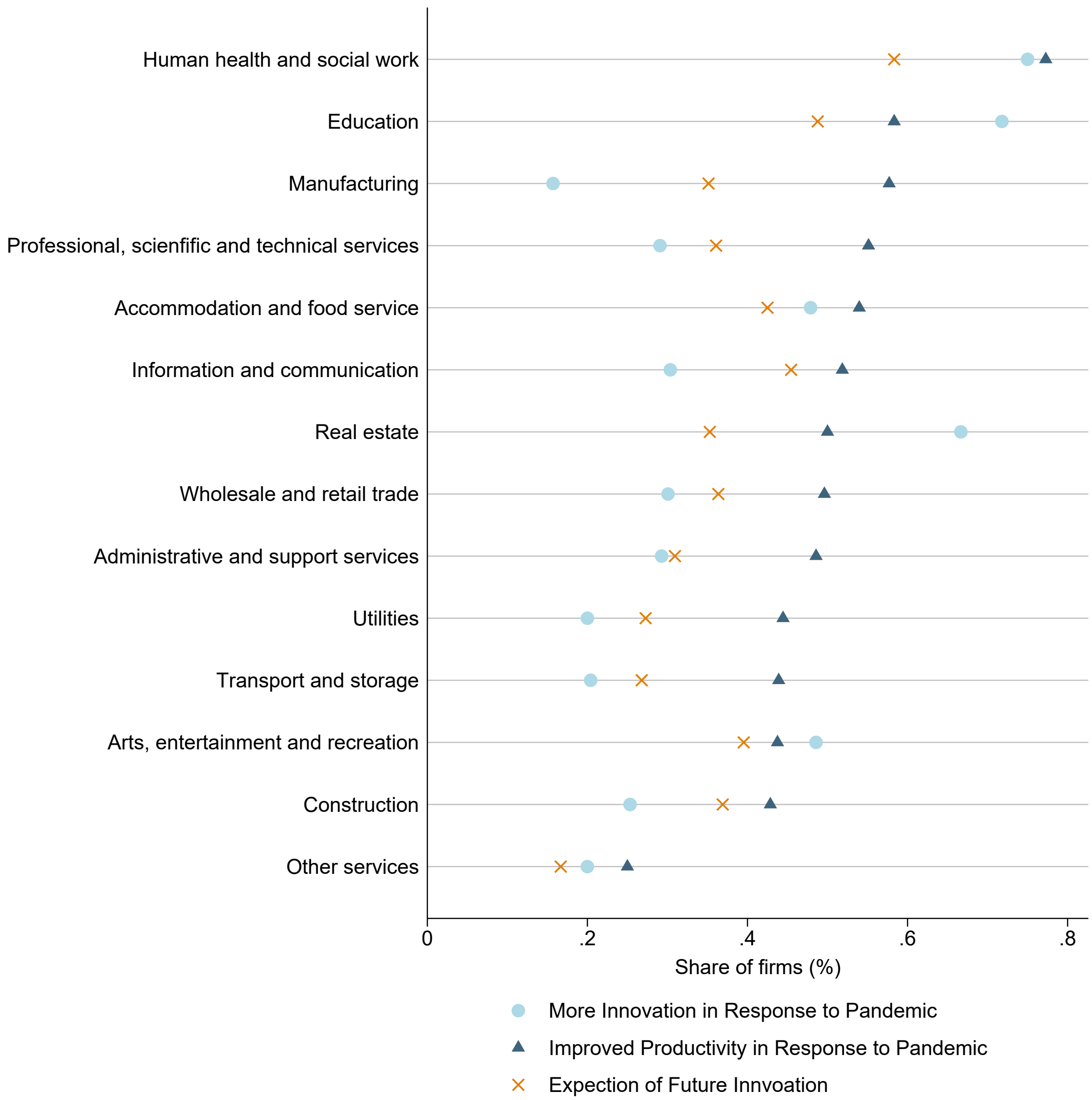
Table C1: Summary statistics of merged MES2020 and BICS38

	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
Log of turnover 2019	9.39	1.60	9.33	1,626
Log of turnover 2020	9.21	1.70	9.15	1,629
ln(turnover) change	-0.19	0.61	-0.09	1,622
Online Sales % 2019	5.93	18.44	0.00	1,640
Online Sales % 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

Table C2: 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
Log of turnover 2019	9.48	1.57	9.43	1,552
Log of turnover 2020	9.30	1.66	9.31	1,558
ln(turnover) change	-0.17	0.58	-0.08	1,550
Online sales % 2019	6.20	18.30	0.00	1,569
Online sales % 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

Figure C1: Share of firms giving positive answers to innovation questions by industry



Source: Linked sample of BICS wave 38 and MES2020.

D Robustness checks

Figure D1: Correlation between pre-pandemic online sales rate, pre-pademic homeworking rates and MPS at the 2-digit SIC industry level.

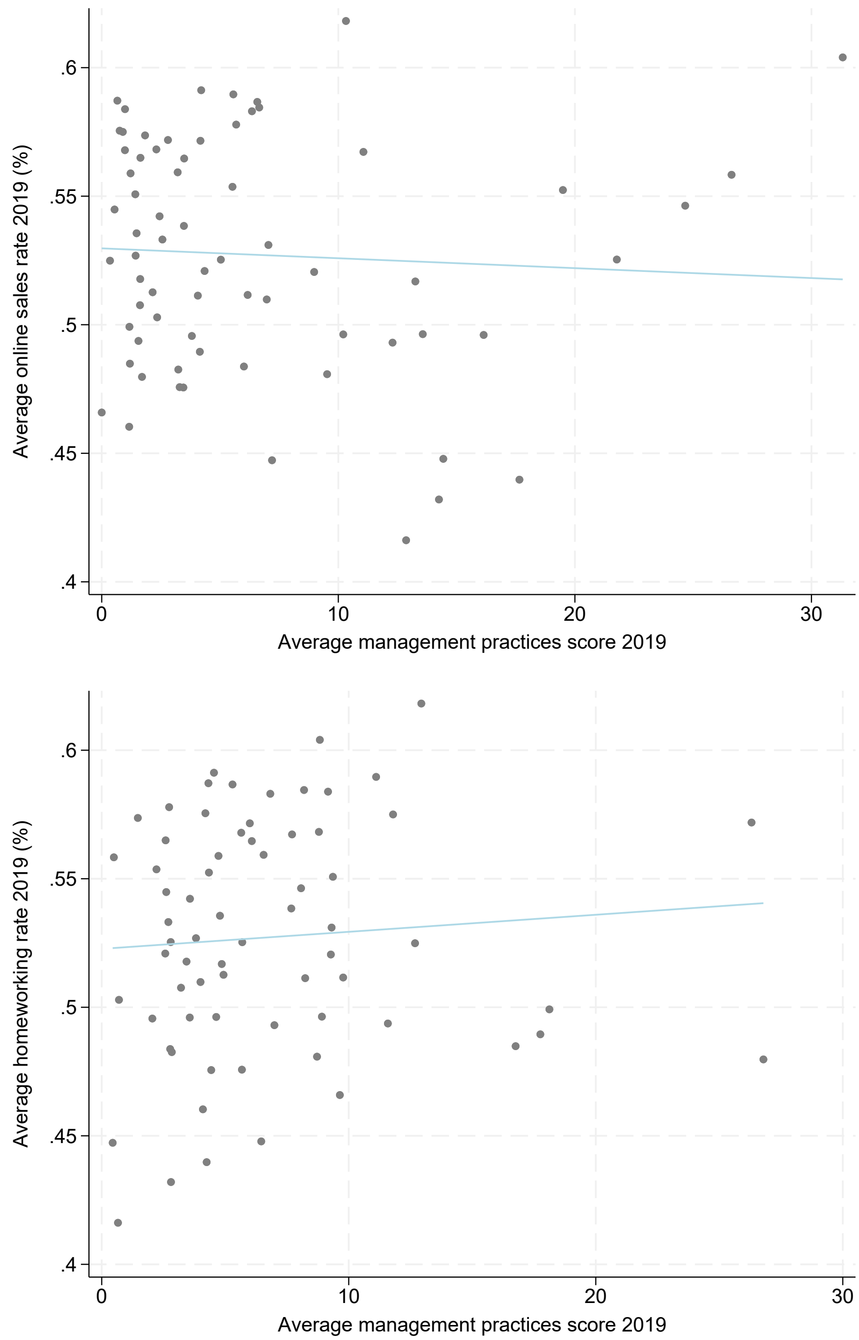


Table D1: Coefficient of interest (ln turnover) under alternative specifications

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
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
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

Table D2: 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
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
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

Table D3: 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
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
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

Table D4: 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	23842	23840	23842	23840	23842	23840
Number of clusters	11949	11948	11949	11948	11949	11948
R-squared	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	
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 D5: TWFE model results for labour productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Y2020*MPS	0.072	0.068	0.071	0.109**	0.107**	0.134***	0.232***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.049)	(0.049)
ln(employment)				-0.637***	-0.651***	-0.637***	-0.657***
				(0.062)	(0.061)	(0.061)	(0.059)
ln(capital expenditure)					0.020***	0.020***	0.018***
					(0.004)	(0.004)	(0.004)
ln(intermediate expenditure)					0.021	0.019	0.009
					(0.021)	(0.021)	(0.021)
MPS							1.074***
							(0.122)
Observations	21649	21649	21649	21649	21649	21642	21642
Number of clusters	11378	11378	11378	11378	11378	11371	11371
R-squared	0.029	0.050	0.052	0.087	0.091	0.093	0.102
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 Turnover per Head*Y2020	N	N	N	N	N	Y	Y

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

Table D6: Comparison of predicted vs 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)	
2	0.145**	0.131**	0.014
	(0.058)	(0.055)	
3	0.151***	0.126**	0.025
	(0.057)	(0.055)	
4	0.119**	0.110**	0.008
	(0.055)	(0.054)	
5	0.120**	0.111**	0.009
	(0.054)	(0.053)	
6	0.129**	0.174***	-0.045
	(0.057)	(0.056)	

Note: In MES2020, timing differences mean that respondents are asked to give an expected turnover for 2020. To test the robustness of these predictions we create a linked sample of MES2020 - ABS2019 - ABS2020 and rerun each of our main 6 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. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table D7: Comparison of (2016-2017) and (2019-2020) plus test of actual vs realised turnover and inputs

	2016 - 2017	2019 - 2020	Difference	Equality test p-value
Predicted inputs	0.012	0.120 **	0.108 *	0.078
	(0.029)	(0.054)		
Actual inputs	-0.013	0.111 **	0.124 **	0.043
	(0.031)	(0.053)		
Difference	0.025	0.009		
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 predicted inputs and outputs within the MES survey or actual inputs and outputs reported in the ABS. The within specification difference in coefficients across the two periods along with a test for statistical significances is shown in the final two columns. 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. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table D8: MPS and turnover: with 2-digit SIC FEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Y2020*MPS2019	0.180***	0.160***	0.162***	0.128***	0.122***	0.146***	0.227***
	(0.034)	(0.034)	(0.034)	(0.033)	(0.032)	(0.036)	(0.036)
ln(employment)				0.395***	0.321***	0.337***	0.321***
				(0.047)	(0.039)	(0.039)	(0.038)
ln(capital expenditure)					0.018***	0.018***	0.017***
					(0.002)	(0.002)	(0.002)
ln(intermediate expenditure)					0.184***	0.184***	0.177***
					(0.021)	(0.021)	(0.020)
MPS							0.851***
							(0.094)
Observations	23872	23872	23872	23858	23858	23842	23842
Number of clusters	11965	11965	11965	11965	11965	11949	11949
R-squared	0.083	0.166	0.167	0.190	0.238	0.243	0.252
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 Turnover per Head*Y2020	N	N	N	N	N	Y	Y

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

Table D9: MPS and homeworking rate: with 2-digit SIC FEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Y2020*MPS2019	34.903***	26.344***	25.729***	25.466***	25.459***	22.009***	22.956***
	(1.362)	(1.214)	(1.209)	(1.215)	(1.216)	(1.293)	(1.329)
ln(employment)				3.129**	3.077**	2.153	1.963
				(1.357)	(1.351)	(1.347)	(1.328)
ln(capital expenditure)					-0.013	-0.011	-0.030
					(0.095)	(0.094)	(0.093)
ln(intermediate expenditure)					0.160	0.198	0.114
					(0.403)	(0.398)	(0.392)
MPS							9.938***
							(3.734)
Observations	23872	23872	23872	23858	23858	23842	23842
Number of clusters	11965	11965	11965	11965	11965	11949	11949
R-squared	0.306	0.517	0.523	0.524	0.524	0.532	0.532
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 Turnover per Head*Y2020	N	N	N	N	N	Y	Y

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

Table D10: MPS and online sales: with 2-digit SIC FEs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Y2020*MPS2019	0.993***	1.229***	1.200***	1.176***	1.170***	1.216***	1.333***
	(0.282)	(0.278)	(0.278)	(0.281)	(0.281)	(0.303)	(0.311)
ln(employment)				0.407	0.414	0.461	0.438
				(0.292)	(0.295)	(0.296)	(0.296)
ln(capital expenditure)					-0.051**	-0.051**	-0.053**
					(0.026)	(0.025)	(0.025)
ln(intermediate expenditure)					0.042	0.041	0.031
					(0.085)	(0.085)	(0.085)
MPS							1.226
							(0.777)
Observations	23872	23872	23872	23858	23858	23842	23842
Number of clusters	11965	11965	11965	11965	11965	11949	11949
R-squared	0.035	0.084	0.085	0.085	0.086	0.087	0.087
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 Turnover per Head*Y2020	N	N	N	N	N	Y	Y

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

Table D11: 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.

Figure D2: Homeworking and hybrid working rates for above and below median MPS firms by broad sectors.

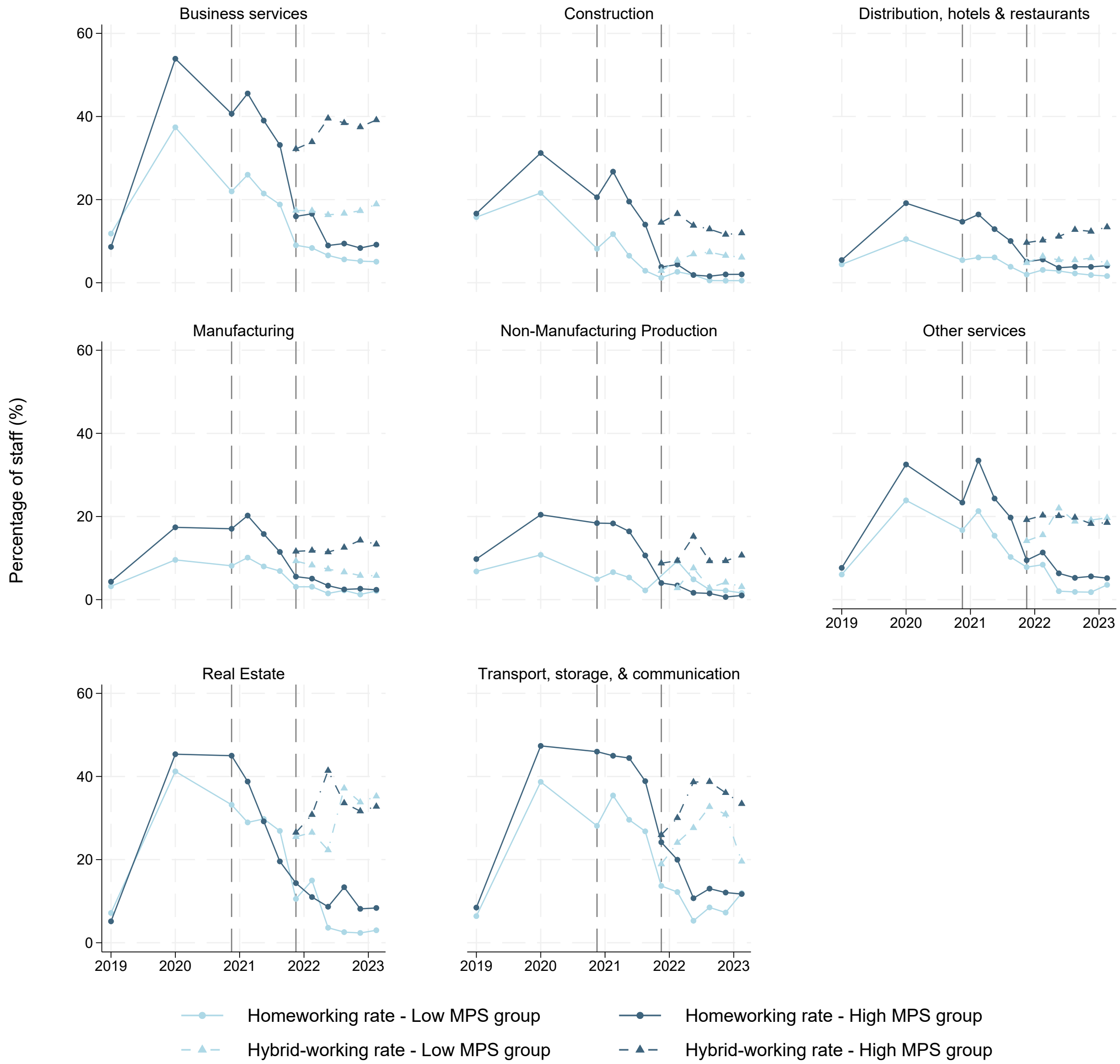


Table D12: Supply chain regressions: 2020 outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Large negative impacts	-0.0344***	-0.0341***	-0.0342***	-0.0401***	-0.0396***	-0.0404***	-0.0403***	-0.0404***	-0.0403***
	(0.00503)	(0.00499)	(0.00499)	(0.00565)	(0.00564)	(0.00575)	(0.00575)	(0.00575)	(0.00575)
Small negative impacts	-0.111***	-0.110***	-0.110***	-0.126***	-0.125***	-0.126***	-0.126***	-0.126***	-0.126***
	(0.0118)	(0.0118)	(0.0118)	(0.0130)	(0.0132)	(0.0133)	(0.0133)	(0.0133)	(0.0133)
Minimal or no impacts	-0.255***	-0.251***	-0.251***	-0.288***	-0.284***	-0.287***	-0.287***	-0.287***	-0.287***
	(0.0248)	(0.0249)	(0.0249)	(0.0274)	(0.0278)	(0.0281)	(0.0281)	(0.0281)	(0.0281)
Small positive impacts	0.310***	0.306***	0.306***	0.354***	0.349***	0.353***	0.353***	0.353***	0.353***
	(0.0297)	(0.0297)	(0.0297)	(0.0326)	(0.0331)	(0.0335)	(0.0335)	(0.0335)	(0.0336)
Large positive impacts	0.0895***	0.0890***	0.0892***	0.100***	0.0990***	0.0998***	0.0997***	0.0998***	0.0997***
	(0.0104)	(0.0104)	(0.0104)	(0.0115)	(0.0116)	(0.0117)	(0.0117)	(0.0117)	(0.0118)
Observations	4,370	4,370	4,370	4,297	4,297	4,261	4,261	4,261	4,261
Log likelihood	-5089.49	-5074.33	-5065.13	-4964.67	-4963.71	-4921.18	-4921.18	-4921.18	-4921.17
Section	N	Y	Y	Y	Y	Y	Y	Y	Y
Region	N	N	Y	Y	Y	Y	Y	Y	Y
Log employment	N	N	N	N	Y	Y	Y	Y	Y
Log capital expenditure	N	N	N	N	Y	Y	Y	Y	Y
Log intermediate expenditure	N	N	N	N	Y	Y	Y	Y	Y
Pre-pandemic performance	N	N	N	N	N	Y	Y	Y	Y
International suppliers	N	N	N	N	N	N	N	Y	Y
Suppliers	N	N	N	N	N	N	Y	N	Y

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