Do Well Managed Firms Make Better Forecasts?

Nicholas Bloom[1], Takafumi Kawakubo[2], Charlotte Meng[3], Paul Mizen[4],
Rebecca Riley[4], Tatsuro Senga[5] and John Van Reenen[6]

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Abstract: We link new forecast and management data on over 20,000 firms to data on productivity in manufacturing and services. The panel survey was administered in the UK in July 2017 and November 2020, coinciding with two periods of considerable uncertainty from Brexit and Covid. We find that better-managed firms make more accurate forecasts for firm-level turnover and macro-level GDP. Uniquely, we show better-managed firms are also aware that they make more accurate forecasts and have greater confidence in their predictions. This highlights how superior forecasting ability enables well-managed firms to make improved operational and strategic choices.

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[1] Stanford University
[2] The University of Osaka
[3] Queen Mary University of London
[4] King's College London
[5] Keio University
[6] London School of Economics

1. Introduction

Is one reason that better managed firms are more successful that they make more accurate forecasts? Forecast errors can damage performance, including from mistimed investments, poor hiring decisions and lost sales opportunities. If better managed firms make fewer forecasting errors perhaps this is one factor explaining their higher profitability and growth rates.[1]

In this paper, we test this idea directly by taking data from the new Management and Expectations Survey (hereafter, MES) run on over 20,000 firms. By exploiting cross-sectional differences in the accuracy of forecasting both macro- and micro-level outcomes we robustly isolate the role of management capabilities in driving performance differences across firms. Combined with quantitative management scores building upon well-established survey methodologies[2], and a battery of additional firm-level control variables obtained from ONS micro-data, we show that management capabilities matter for firms' forecasting and business performance.

Our survey distinguishes itself from existing research in a crucial aspect by simultaneously measuring management practices and firm expectations about both macroeconomic indicators (GDP) and microeconomic outcomes (firm-level turnover).[3] This unique feature allows us to investigate the role of management in shaping organizational forecasting capabilities to form

[1] It has been known that judgement errors in estimates of business cases are pervasive among firms but not recognized well by business managers (Kahneman, Rosenfield, Gandhi, and Blaser, 2016).

[2] See Buffington et al. (2017) on the US Management and Organizational Practices Survey (MOPS), Altig et al. (2020) on the Atlanta Fed Survey of Business Uncertainty (SBU), and Bloom et al (2025) on the UK Decision Maker Panel (DMP).

[3] The US MOPS have combined questions on management practices and firm-level sales forecasts; though, our inclusion of GDP forecasts together with turnover forecast is a novel approach in the literature.

accurate expectations about both the broader economic environment and their firm's own performance, an area that has remained largely unexplored in previous studies.[4]

By combining quantitative measures of management practices with direct expectations data from firms about both macro- and micro-outcomes, we present three sets of robust stylized facts. First, we find that management practices vary widely among firms, and like previous studies are robustly correlated with other measures of performance. Better-managed firms consistently outperform their peers in productivity, profitability, and scale (firm size). Second, we show the quality of management practices correlates with forecasting ability, providing better managed firms with a strategic edge. Better-managed firms demonstrate superior precision not only about macro-level GDP but also about their own micro-level turnover. Third, firms with high management scores seem to be aware of their superior forecasting abilities and exploit them. They exhibit lower subjective uncertainty in their predictions, indicating a higher level of confidence in their forecasting accuracy for both micro- and macro-outcomes.

Together these results imply one payoff to better management practices is improved forecasting ability. Moreover, not only are well-managed firms better at forecasting they are also aware of this, allowing them to exploit this skill.

The paper is related to three broad literatures. First, on the formation of expectations, including the seminal works by Coibion and Gorodnichenko (2012, 2015) and Coibion et al. (2018), who study professional forecasters. Other papers including Gennaioli et al. (2016), Bachmann and Elstner (2015), Boneva et al. (2020), Altig et al. (2020), Tanaka et al. (2020), Coibion et al. (2020), Chen et al. (2023) and Bloom et al. (2025) also study firm expectations. One strand of this research focuses on expectations of aggregate variables like inflation, linking forecast accuracy to agent-specific characteristics such as cognitive ability for households (e.g.,

[4] See Candia, Coibion and Gorodnichenko (2023) on firm expectations about macro indicators like inflation and Born et al. (2023) on firm expectations about micro-outcomes like individual prices.

D'Acunto et al., 2023). Another strand examines expectations of idiosyncratic outcomes like a firm's own sales (e.g., Bachmann et al., 2021; Enders et al., 2022). Our paper is unique in that we combine direct expectations with large-scale data on management practices, collect information on both firm-level sales forecasts and aggregate GDP forecasts, and span two major macro-economic shocks – the 2016 Brexit vote and the 2020 COVID pandemic.[5]

Second, we also contribute to the literature on subjective uncertainty measures, including papers by Ben-David et al., (2013); Barrero (2022) and Dibiasi et al. (2024). Other related papers focus on higher moments of expectations and uncertainty, including Dew-Becker and Giglio (2023); Hassan et al. (2024); Handley and Li (2020) and Lakdawala and Moreland (2024).

Third, this paper also relates to the literature investigating biases in forecasts. The psychology literature documents that forecasts tend to be too optimistic and overly precise, and such biases persist even though individuals can learn over time (e.g., Weinstein, 1980; Moore and Healy, 2008; Fischhoff, Slovic, and Lichtenstein, 1977; Soll and Klayman, 2004; Sharot, Korn and Dolan, 2011; and Kahneman, 2003, among others). The behavioral economics literature identifies 'motivated belief' as a driver of such biases, whereby business managers deliberately maintain overly optimistic and precise beliefs to help motivate employees and investors (e.g., Benabou and Tirole, 2002, 2016). Our results showing a positive association between forecast accuracy and firm performance suggests this type of motivated reasoning is likely not the main driver of forecasting inaccuracy.

[5] It is a legitimate concern that the results presented in this paper may be specific to these periods of high uncertainty due to the Brexit vote and the COVID-19 pandemic. On the other hand, one strength of the paper is that we combine two rather different periods in which firms across different sizes and industries faced high uncertainty in varying ways, and we show that our findings are robust when extending our sample from the initial Brexit survey period to include the COVID-19 pandemic period (see Bloom et al. 2021 for results from the 2016 survey only, which addresses this external validity concern).

In the following sections, we describe our datasets and variable construction, alongside in-depth description of our analysis on the variation in management practices across firms and the characteristics that appear to "drive" them (Section 2). We then focus on the relationship between management practices and firm forecasts (Section 3). We conclude in Section 4.

2. Datasets

2.1 The Survey Datasets and Variable Construction

Our main data source is the Management and Expectations Survey (MES), which we combine with the Annual Business Survey (ABS) to build our dataset of quantitative management scores and forecasts about GDP and firm-level outcomes such as turnover, together with a battery of firm-level variables. Both surveys are collected by the UK Office of National Statistics (ONS); the MES was conducted in partnership with the Economic Statistics Centre of Excellence. The first wave of the survey was sent in July 2017 to approximately 25,000 firms and covered both the production and services industries. It was a voluntary survey of firms with ten or more employees, with the same sampling frame as the ABS for 2016, allowing us to match to data on value added, employment, output and investment.[6] In November 2020, a second wave of the survey was sent to approximately 50,000 firms drawing from the UK universe of employer firms, the Inter-Departmental Business Register (IDBR) together with a booster sample from the MES first wave.[7] The ABS is a stratified random subsample of the IDBR. Details of the survey questions and sample are given in online Appendix A along with variable definitions,

[6] Employment is defined as the total number of employees registered on the payroll and working proprietors. Further details on the ABS can be found in the ABS Quality and Methodology Information report and the ABS Technical Report.

[7] Three groups of firms are included in the sampling frame: IDBR random selection – 22,330 businesses which is also used for ABS2020, MES 2017 respondents – 8,155 businesses, and ABS 2020 respondents – 20,227 businesses.

but here we briefly explain the construction of the Management Practices Score (MPS) and its interpretation.

Following the established method of the World Management Survey (WMS) and the international Management and Organizational Practices Survey (see Scur et al., 2024), the MPS is a simple average of the firm's score on all individual questions.[8] For each question, scores were awarded to each of the management questions (sections A-D), that ask about practices around monitoring of Key Performance Indicators, targets and incentives on a scale of 0 to 1, where 0 was the least and 1 the most structured management practice. Therefore, the most structured management corresponds to a firm scoring 1 overall based on responses to all 12 questions. In our sample, the average MPS score is 0.554, and a firm with a score of 0.753 is one standard deviation above the mean.[9]

Two other important variables for our study are calculated using data from the ABS survey. Productivity is measured as the logarithm of gross value added per worker, which is a labor productivity measure. Profitability is based on gross operating surplus per worker. This measure can be positive or negative, so we do not take logarithms.

In our sample the average firm age is 19 years old, about 38% of managers have college degrees, 43% of firms are family owned and run, 12% are foreign owned (see Appendix Table A1).

2.2 Interpreting the Management Practice Score and Firm Performance

The variation of the management scores across firms stems from several factors that are consistent with existing studies (e.g. Bloom and Van Reenen, 2007 and Buffington et al., 2017).

[8] See Scur et al (2021) on the world management survey which follows a similar approach.

[9] In the online Appendix, management score distributions across three firm size classes are shown in Figure B1, revealing wide variation within each group. Table B1 confirms this trend across six broad sectors and four size bins, also noting sectoral differences (e.g., low scores in construction, high scores in business services).

For example, firm size (measured by log employment) positively correlates with management scores, remaining significant even after controlling for industry and location. Foreign-owned firms have higher management scores, while family-run firms score lower, except when managed by professional outsiders, perhaps as they adopt more conservative (and less volatile) business strategies (e.g. Bennedsen et al. 2007).[10]

It is well understood that productivity varies substantially across firms and establishments (e.g. Syverson, 2011, 2024). We find management scores are strongly and positively correlated with labor productivity, even after controlling for industry, location, capital-labor ratio, and other factors. Management scores are also positively associated with profitability. Family firms show lower productivity, while multinationals and older firms demonstrate higher productivity.[11]

2.3 Expectations and Uncertainty

The MES collects expectations data at the business level, building on the US MOPS and the Atlanta Fed Survey of Business Uncertainty (SBU) and the UK Decision Maker Panel (DMP).[12] The survey collects data on firm-level forecasts about the distribution of turnover in a similar manner to the US MOPS, while it also uniquely, asks for firm-level forecasts about the growth rate of GDP in the UK (see full survey questions in Appendix Figures A1 and A2).

We use absolute forecast error to measure forecast ability. It is defined as:

[10] Table B2 in online Appendix shows how management scores are correlated with various firm characteristics. The score tends to be higher in larger firms, those owned by foreign multinationals and when managers have higher human capital (as measured by their education). Management scores are lower in family-run firms.

[11] Table B3 in online Appendix reports the relationship between firm performance indicators and management practices. Firms with more structured management practices have higher profits and productivity even after controlling for labor and capital inputs (and a wide variety of other factors). Figure B1 shows that firms with larger management scores have greater scale, as measured by firm size.

[12] See Buffington et al. (2017) on the US MOPS, Altig et al. (2020) on the SBU and Bloom et al. (2025) on the DMP.

$$Absolute\ Forecast\ Error = |Growth_{Forecast} - Growth_{Realised}|,$$

where $Growth_{Forecast}$ is the firm's projected growth over one- or two-year horizons, and $Growth_{Realised}$ is the actual growth realized in the corresponding year. Growth is defined as the change in the relevant variable using the Davis–Haltiwanger–Schuh (DHS) approach. For example, turnover growth in year *t* is calculated as $(Turnover_t - Turnover_{t-1})/(0.5 * (Turnover_t + Turnover_{t-1}))$.

Firms' one-year own sales forecasts were reasonably accurate on average, with a forecast turnover growth of 0.0% compared to an outcome of 0.4%. If we instead look at the absolute forecast error, the median is 5.8%, highlighting the substantial difficulties many firms face in accurately assessing their year-ahead sales growth. This difficulty grows with a longer forecast horizon, with a two-year absolute forecast error of 12.2% (see Appendix Table A1). In contrast GDP forecasts were somewhat pessimistic because the first survey wave was run after the Brexit vote in 2016 and the second wave after the initial COVID lockdown.

Comparing the macro and micro forecast accuracy it appears to be more difficult for firms to forecast their own turnover than GDP. For instance, the median absolute GDP forecast errors are 7.2%, whereas it is 8.9% for firm turnover forecasts (averaged).

Turnover uncertainty is measured as:

$$Uncertainty_i = \sqrt{\Sigma_j \left(Growth_{ij} - \overline{Growth_i}\right)^2 * Likelihood_{ij}},$$

where $Growth_{ij}$ is the firm *i*'s forecast in bin *j*, $\overline{Growth_i}$ is the sample average of the firm *i*'s forecasts over these bins, and $Likelihood_{ij}$ is the likelihood that firm *i* attached to bin *j*.

Sales growth forecasts are more dispersed than aggregate GDP forecasts, with uncertainty of a firm's own turnover 2.0% vs just 0.6% for GDP growth. This reflects the fact that turnover of the firm is more variable than GDP, making it more difficult to forecast. We also confirm (online Appendix Figure E1) that firms with higher GDP forecasting errors have a higher GDP

forecast uncertainty (Panel A), that there is a strong relationship between turnover forecasting errors and turnover uncertainty (Panel B), and that that firms' GDP and turnover uncertainty are positively correlated (Panel C).

In what follows, we will analyze the factors that might explain the accuracy and confidence with which firms are making their macro- and micro-economic forecasts. A common theme emerges that firms with more structured management practices make more accurate forecasts with greater confidence and as a consequence, make better business decisions.

3. Forecast Accuracy, Uncertainty and Management

In this section, we examine the relationship between management practices and forecast accuracy. Well-managed firms may develop superior forecasting capabilities through various channels. For instance, firms that monitor their operations well may be better positioned to use information in a timely manner and forecast more accurately, and such practices are well captured by the management scores in our survey.[13]

We restrict our sample to satisfy three criteria for "usable responses". Firstly, firms must complete at least two bins with full information. Secondly, the values answered for five scenarios about their own future outcomes must be weakly increasing from the lowest to the highest bin. Finally, the sum of percentage likelihoods in these bins must be within the range

[13] This may affect macro and micro forecasts differently, because the relative importance of macro and micro conditions varies across firms depending on their industry and sector. Thus, better-managed firms monitor and collect information more systematically, but they allocate their resources between macro and micro information gathering depending on the relevance of these factors for their operations.

of 90% to 110%. The share of the firms in our sample which satisfy these criteria is 92% and is comparable to that in the US MOPS (85% in Bloom et al. (2025)).[14]

In the following sections we explore the payoff to higher quality management through two channels: better-managed firms make more accurate forecasts, and they express lower subjective uncertainty around the forecasts, consistent with awareness of their forecasting ability. In a final sub-section, we demonstrate the robustness of the findings as we add productivity into the regressions and show that management scores remain significantly associated with both lower forecast errors and reduced uncertainty.[15]

3.1 Forecast Accuracy is Associated with Superior Business Performance

Before examining whether well-managed firms make better forecasts, we first establish that forecast accuracy is associated with better firm performance. This is important as the theoretical relationship between forecast accuracy and firm performance is ambiguous. On the one hand classic models of dynamic programming suggest that forecast accuracy will improve firm performance, as it helps firms to make optimal decisions when mistakes are costly (e.g. Stokey and Lucas, 1989, or Dixit and Pindyck, 1994). On the other hand, a behavioral economics literature has highlighted issues around "motivated reasoning", in which agents may be better off by holding optimistic beliefs (e.g., Benabou and Tirole, 2002). Managers may be

[14] Firms that can return usable responses have certain characteristics. In the online Appendix Table B4, we regress usable response dummies on various firm characteristics. In general, usable responses are from firms with good management practice and a large fraction of managers with a college degree. These findings are also consistent with those in the US MOPS.

[15] Note that we are not in a position to disentangle cause and effect, and thus our results represent conditional correlations rather than causal relationships. While consistently accurate forecasts over time may suggest superior management capabilities, we cannot rule out that some firms may have achieved better performance through fortunate forecasting combined with sound decision-making based on those forecasts.

deliberately optimistic to motivate employees, investors, customers or themselves to work harder or invest in the firm.

Table 1 shows that firms' forecast errors both for macroeconomic conditions (GDP) and their own outcomes (turnover) are significantly associated with subsequent firm performance across multiple dimensions: employment growth, firm survival, and profit growth. Survival is defined as a binary variable that takes the value of 1 if a firm remains active until at least 2022 and 0 otherwise. A firm is considered active if it is included in the sampling frame for the ABS 2022 survey. Employment growth is measured as the percentage change in employment between the survey year and 2022 using the DHS approach, i.e., $(L_{2022} - L_0)/(0.5 * (L_{2022} + L_0))$, where L is employment and subscripts denote years (with "0" as the survey year). Hence, firms that have exited by 2022 are assigned a value of –2, corresponding to the minimum possible DHS growth rate. Profit per worker growth is calculated in the same manner as employment growth but values are not restricted to the –2 to 2 range since negative profits allow for unbounded variation (exiters are dropped from these regressions). Both employment growth and profit growth are winsorised at the top and bottom one percent.

For each outcome, we regress performance on forecast errors while controlling for industry and location fixed effects, as well as firm characteristics including size, age, ownership structure, and managerial education levels.

Firms with larger turnover forecast errors experience significantly worse outcomes across all three performance dimensions. An increase in the absolute turnover forecast error is associated with lower employment growth, a lower probability of survival, and lower profit growth. Similarly, GDP forecast errors are negatively correlated with firm performance. Firms that

poorly forecast macroeconomic conditions show significantly lower employment growth and reduced survival probability, though the impact on profit growth is insignificant.[16]

3.2 Better Managed Firms have More Accurate *Macro-level* GDP Forecasts

We start with macro forecasting ability, using absolute forecast errors as our performance measure. Figure 1 shows the relationship between GDP forecast errors with management (Panel A) and productivity (Panel B). The vertical axis in each panel has absolute GDP forecast error grouped into 40 equal-sized bins. The horizontal axis of Panel A shows the mean values of management scores in each bin. There is a clear negative relationship indicating that better-managed firms make lower GDP forecast errors. Panel B uses productivity instead of management, which also show negative gradients (consistent with Tanaka et al. (2020)), although the relationship is noisier.[17]

We address this issue in Table 2, where we go beyond these bivariate correlations and control for many other factors. Column (1) reports the result of regressing a measure of GDP forecast errors on the management score, confirming the statistical significance of the relationship in Panel A of Figure 1. In column (1), the coefficient of -0.538 implies that an increase in management scores from the 10^{th} to 90^{th} percentile (0.522) is associated with a fall in the

[16] The even columns have larger numbers of observations compared to the odd columns because we can calculate a GDP forecast error whether or not a firm appears in the ABS survey, whereas a turnover forecast error can be calculated only for a firm if it appears in the ABS survey in the relevant year. Similarly, survival can be constructed for all firms, whereas we calculate employment and profit growth for firms present in the ABS survey for the relevant years, which is why there are so many more observations in column (4).

[17] Tables C1–C3 in the online Appendix document a positive association between a firm's management score and its growth expectations for both GDP and firm turnover. This higher optimism translates into greater forecast accuracy, as the average firm in our sample exhibits a pessimistic bias of 1.4%.

absolute value of GDP growth forecast errors of 0.28 percentage points, or 4.7% of the mean of 5.94 the dependent variable (shown in the online Appendix Table A1).[18]

Column (2) adds in industry and location dummies. Firms with more structured management practice still make significantly smaller forecast errors. Column (3) shows the conditional correlations of GDP forecast error with firm size and age, as well as other firm-level controls, which include ownership status (foreign owned, family owned not run, family owned and run) and the share of managers with a college degree. Our central finding—that better management scores are linked to smaller forecast errors—is robust to the inclusion of these controls. In particular, the share of managers with a college degree is important as it allows us to disentangle the effect of systematic management practices from the baseline educational qualifications of the managers and our management score bites beyond the human capital of the managers at the firm level. Although the management coefficient falls to -0.259, it remains significant, showing that better management is associated with a reduced forecast error. We also see that larger firms make significantly better GDP forecasts.[19]

3.3 Better Managed Firms have More Accurate *Micro-level* Sales Forecasts

We now explore the relationship between firms' forecast errors for their own turnover growth at the micro level and their characteristics, especially management. Our measure of forecast errors is the absolute value of the difference between expected and actual turnover growth rate. In the survey, we asked for turnover forecasts for two different horizons: one-year ahead (2017 in MES2017, 2020 in MES2020) and two-year ahead (2018 in MES2017, 2021 in MES2020).

[18] Using Table 1, column (2) (−16.579; errors scaled × 0.001), this translates into an expected increase in employment growth of roughly 0.46 percentage points ($0.28 \times 16.579 \times 0.001 \approx 0.00464$).

[19] Our measure of forecast quality is the absolute size of forecast errors, but the results presented in the paper are robust when we use mean-squared errors instead (see Tables D1 and D2 in online Appendix D).

Taking the average of two forecast errors, we use it as a measure of forecast accuracy and study its relationship with management capabilities. The need to observe the same firm over two years to obtain realizations and calculate the actual growth rate of turnover reduces the number of observations analyzed in this section compared to previous sections.

Panel C in Figure 1 shows a negative relationship between management score and productivity (respectively) against absolute turnover forecast error implying that better-managed firms (as well as those with higher productivity) make significantly more accurate forecasts about their own sales. There appear to be more outliers, however, with some very large errors of 100% or more (even after winsorizing at the top and bottom percentiles). To investigate whether the relationship is driven by outliers we drop all observations with large forecast errors, finding the negative relationship between management and forecast errors remains (see Appendix Figure D1).

The columns (4) – (6) in Table 2 use forecast accuracy about firm-level turnover as the dependent variable. Turnover forecast errors are significantly smaller for better-managed firms as shown in column (4). The coefficient of -6.635 implies that shifting management scores from the 10^{th} to 90^{th} percentile (0.522) is associated with a fall in the absolute value of the forecast error of 3.46 percentage points. This is 20% of the mean of the dependent variable (17.40) – a substantial effect and larger than for GDP.[20] The magnitude of the management coefficient becomes larger at -6.831 in column (5) after including industry and location fixed

[20] Using Table 1, column (1) ($\beta = -0.975$; errors scaled $\times 0.001$), this translates into an expected increase in employment growth of roughly 0.34 percentage points ($3.46 \times 0.975 \times 0.001 \approx 0.00337$). This is a substantial effect when compared to the median of employment growth, which was a fall of 1.2 percentage points (see online Appendix Table A1).

effects. Column (6) shows the fully saturated model with all controls.[21] Firm's turnover volatility[22] in the past five years is associated with greater forecasting errors as one might expect. The management coefficient remains negative, significant and large at -8.29.[23]

3.4 Well Managed Firms are Aware of their Superior Forecasting Ability

Superior forecasting ability will be advantageous to the firm, particularly if the firm is aware of its forecasting ability. In this sub-section we explore the awareness of the forecasting ability by observing the subjective uncertainty that a firm has around its own forecast. As noted in Section 2, we construct a measure of uncertainty over the firm's macro and micro forecast. Columns (1) - (3) of Table 3 use subjective uncertainty on GDP forecasts. We find that management scores are negatively and significantly correlated with GDP uncertainty, except in the saturated model of column (3), where the magnitude of the management coefficient becomes small compared to those in columns (1) and (2) and insignificant.

Column (4) of Table 3 reports how subjective uncertainty over turnover forecasts is significantly and negatively correlated with management. An increase in the score from the 10th to 90th percentile is associated with a 0.30 log point decrease in uncertainty, which is 15% of the mean of the dependent variable (1.93 as noted in Appendix Table A1). This relationship remains significant when the usual control variables are added in columns (5) and (6), although

[21] While management practices emerge as a statistically significant predictor of forecast accuracy, the relatively low R-squared values in our turnover forecasting regressions indicate that a substantial portion of forecast error variation remains unexplained by our model. This suggests that firm-level forecasting performance is influenced by numerous idiosyncratic factors beyond management quality, including firm-specific shocks, market conditions, and other unobservable characteristics that are difficult to capture systematically. The higher explanatory power observed for GDP forecasts likely reflects the more systematic nature of macroeconomic forecasting compared to the inherently more variable firm-specific forecasting environment.

[22] Volatility is measured as the five-year standard deviation of the firm's annual change in log(turnover).

[23] The management score remains significant even after controlling for productivity and profitability from Figures 1. The results are also robust to trimming on outliers as in Figure D1.

the coefficient drops from -0.470 to -0.121.[24] It is tempting to conclude that well-managed firms are better at forecasting their own outcomes, which are presumably more relevant for their performance than GDP. However, the magnitudes are of a similar scale and not that different. Using our usual experiment of increasing management by its 90-10 spread of 0.522 implies that turnover uncertainty is reduced by 3.3% of the mean (1.93) in column (6) compared to 1.7% of the mean in the equivalent GDP uncertainty of column (3).

3.5 More Productive Firms Make Better Forecasts and are less Uncertain

The superior performance of better-managed firms is evident in the previous sub-sections, but it is possible that a measure of management ability is simply a proxy for firm level productivity. We acknowledge that better-managed firms are more productive. But in this sub-section we will explore whether we can 'knock out' the management effect by including productivity measured using log GVA per worker in our regression estimates.

The first four columns of Table 4 examine forecast errors. For GDP forecast errors (columns 1-2), log GVA per worker is negatively and significantly correlated with the dependent variable, consistent with Figure 1(a). This relationship remains significant as further controls are added, and the management score variable introduced in column (2) shows a negative and significant relationship with GDP forecast errors. Columns (3)-(4) examine turnover forecast errors. Here, log GVA per worker again shows a strong negative correlation with turnover forecast errors across specifications. In addition, the management score in the fully saturated model (column 4) significantly reduces own turnover forecast errors over and above the reduction due to log GVA per worker.

[24] We exclude firms reporting zero turnover in both MES and ABS from the analysis.

The latter half of the table examines the relationship between uncertainty over forecasts and productivity. In columns (5)-(6), where we have GDP forecast uncertainty as a dependent variable, Log GVA per worker shows a consistently negative and statistically significant relationship. The management score, introduced in column (6), shows a negative but statistically insignificant relationship with GDP forecast uncertainty, which is consistent with our result in Table 3. Finally, in columns (7)-(8), we have turnover forecast uncertainty as the dependent variable. Log GVA per worker again shows a negative and significant relationship with turnover forecast uncertainty. The management score, introduced in column (8), shows a strong negative and significant relationship with turnover forecast uncertainty (-0.153), suggesting that better-managed firms have lower uncertainty about their own turnover forecasts.

In summary, Table 4 suggests that higher productivity is associated with lower forecast errors and uncertainty for both GDP and firm turnover. Additionally, the effect of the management score is distinct from productivity; better management practices seem to be particularly important in reducing forecast errors and are strongly associated with reducing uncertainty about a firm's own turnover forecasts.

4. Conclusions

This paper uses a new dataset created from the Management and Expectations Survey, one of the UK Office of National Statistics management surveys, to show that firms with more structured management practices make more accurate forecasts with greater confidence and as a consequence make better business decisions. Our results reveal that management practices vary widely among firms and (like previous studies) are correlated with other measures of superior performance. Providing novel insight, our results also show that management practices correlate with forecasting ability, giving better managed firms a strategic edge. Better-managed firms demonstrate a distinctly superior capability for generating precise

predictions, not only about macro-level GDP but also about their own micro-level turnover. Firms use this superior forecasting ability and a higher level of confidence in their forecasting accuracy to deliver superior performance in business decision making on operational and strategic actions.

If better management enables superior predictions of growth, then firms are more likely to be making better decisions over the appropriate composition of factor inputs as well as other more strategic decisions such as when to undertake investment. To put it simply, better managed firms make better forecasts and as a consequence better business decisions. The higher productivity and profitability of well-managed firms may rest, at least in part, over this better allocation of factors, a micro-level equivalent of the macro-level findings in Hsieh and Klenow (2009). A task for future work, with the collection of additional data, is to compare the longer-term outcomes of firms with their forecasting ability and subjective uncertainty to ascertain whether they have sustained higher levels of productivity, which would further underline the payoff to better management.

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Table 1: Firm Forecast Errors and Performance

Dependent Variable	(1) Employment Growth	(2) Employment Growth	(3) Firm Survival	(4) Firm Survival	(5) Profitability Growth	(6) Profitability Growth
Turnover forecast error	-0.975**		-0.3340***		-4.650***	
	(0.4171)		(0.1117)		(1.6325)	
GDP forecast errors		-16.579***		-2.6272***		16.961
		(4.5729)		(0.9905)		(29.7432)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Year & Missing FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5898	8993	8851	19185	5233	6156
R^2	0.073	0.145	0.065	0.066	0.020	0.017

Notes: Estimation by OLS with standard errors (clustered by firm) in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable in columns (1)-(2) is employment growth, in columns (3)-(4) is firm survival, and in columns (5)-(6) is profitability (profits per worker) growth. Growth calculated in DHS terms (see text) GDP forecast errors are the absolute value of the difference between expected and actual real GDP growth rates, multiplied by 0.001. For 2016 forecast errors, we do this for 2016-2017 and also 2016-2018 (and re-weight the regression if the firm error is available in both years so that each firm is only counted once). For 2019 forecast errors, we do this for 2019-2020 and also 2019-2021 (and re-weight the regression if the firm error is available in both years so that each firm is only counted once). Turnover forecast errors are the absolute value of the difference between expected (in MES) and actual turnover growth rates, multiplied by 0.001. We exclude firms from reporting zero turnover in both MES and ABS from the analysis. Firm employment and age are from the ABS. Other controls include log employment and log age, ownership status (foreign owned, family owned not run, family owned and run) and the share of managers with a college degree. Industry fixed effects are two-digit SIC codes. Location fixed effects are the 9 NUTS1 regions. Survey year fixed effects and an indicator for multi-site are also included.

Table 2: Forecast Errors in Firm's Estimate of Future Turnover and GDP

Dependent Variable	(1) GDP Forecast Errors	(2) GDP Forecast Errors	(3) GDP Forecast Errors	(4) Turnover Forecast Errors	(5) Turnover Forecast Errors	(6) Turnover Forecast Errors
Management score	-0.538***	-0.487***	-0.259***	-6.635***	-6.831***	-8.290***
	(0.0659)	(0.0678)	(0.0742)	(1.7705)	(1.8030)	(1.9715)
Log employment			-0.052***			0.569
			(0.0144)			(0.3515)
Log age			0.038*			-2.698***
			(0.0197)			(0.5634)
Five-year turnover volatility			0.073			20.202***
			(0.1011)			(3.0457)
Industry FE	No	Yes	Yes	No	Yes	Yes
Location FE	No	Yes	Yes	No	Yes	Yes
Other Controls	No	No	Yes	No	No	Yes
Year & Missing FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19546	19546	19546	9069	9069	9069
R^2	0.797	0.799	0.800	0.012	0.051	0.075

Notes: Estimation by OLS with standard errors (clustered by firm) in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. The dependent variable in columns (1) to (3) is the average of the absolute value of the difference between actual and expected growth rates. For 2016 forecast errors, we do this for 2016-2017 and also 2016-2018 (and re-weight the regression if the firm error is available in both years so that each firm is only counted once). For 2019 forecast errors, we do this for 2019 – 2020 and also 2019-2021 (and re-weight the regression if the firm error is available in both years so that each firm is only counted once). We exclude firms from reporting zero turnover in both MES and ABS from the analysis. The dependent variable in columns (4) to (6), is the absolute value of the difference between expected (in MES 2016) and actual real GDP growth rate 2017-18. Firm employment and age are from the ABS. Other controls include ownership status (foreign owned, family owned not run, family owned and run) and the share of managers with a college degree. Industry fixed effects are two-digit SIC codes. Location fixed effects are the 9 NUTS1 regions. Survey year fixed effects and an indicator for multi-site are also included.

Table 3: Uncertainty Over Forecasts and Management Scores

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	GDP Uncertainty	GDP Uncertainty	GDP Uncertainty	Turnover Uncertainty	Turnover Uncertainty	Turnover Uncertainty
Management score	-0.066***	-0.054***	-0.019	-0.569***	-0.470***	-0.121***
	(0.0150)	(0.0154)	(0.0168)	(0.0408)	(0.0412)	(0.0443)
Log employment			-0.008***			-0.134***
			(0.0029)			(0.0074)
Log age			-0.017***			-0.108***
			(0.0045)			(0.0121)
Industry FE	No	Yes	Yes	No	Yes	Yes
Location FE	No	Yes	Yes	No	Yes	Yes
Other Controls	No	No	Yes	No	No	Yes
Year & Missing FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18267	18267	18267	18422	18422	18422
R^2	0.072	0.078	0.082	0.045	0.106	0.139

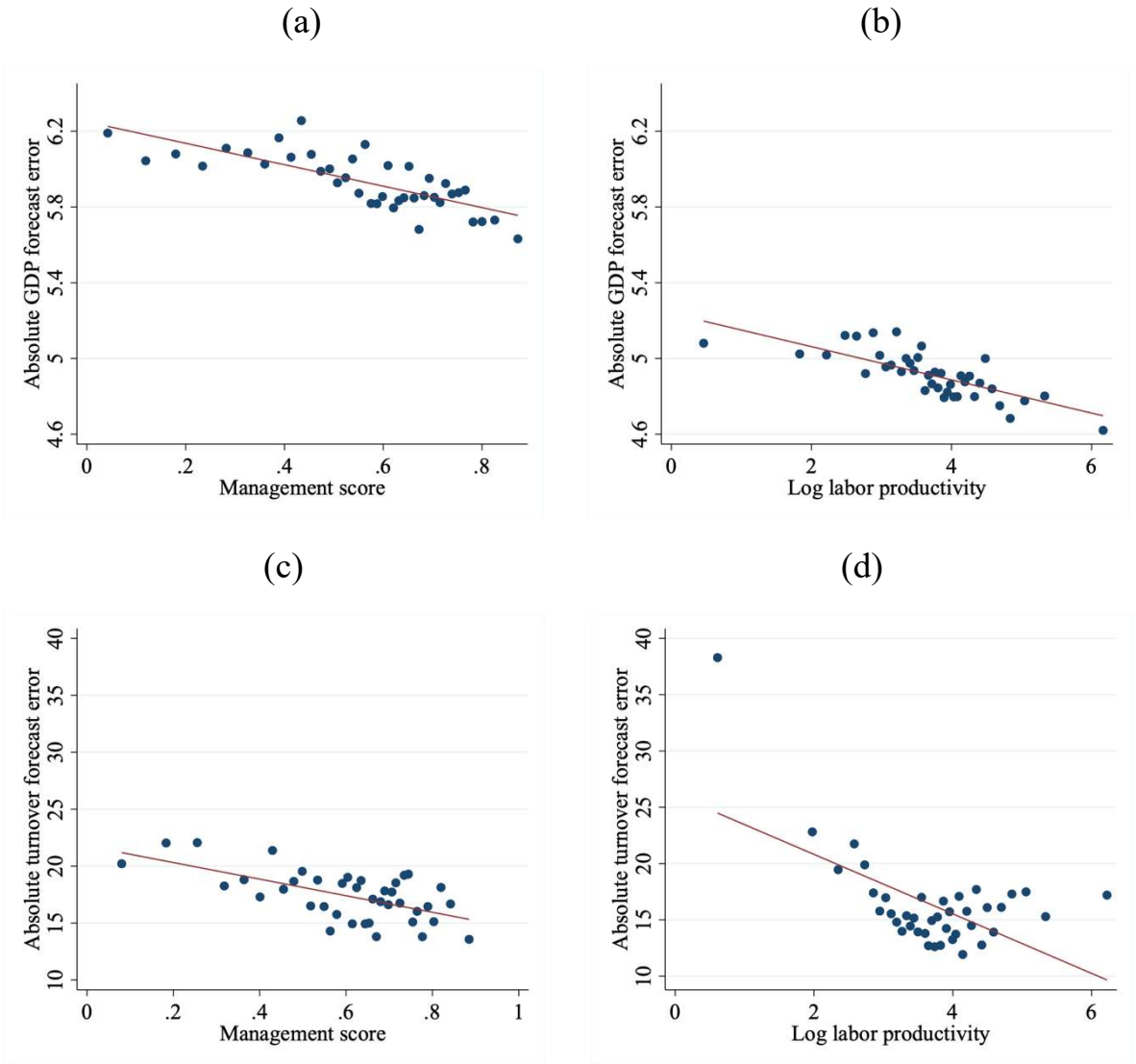
Notes: Estimation by OLS with standard errors (clustered by firm) in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. The dependent variable is the log subjective uncertainty regarding the forecast over turnover in columns (1)-(3) and over GDP in the final column (see text for details). For turnover uncertainty, we exclude firms reporting zero turnover in both MES and ABS from the analysis. Firm employment and age are from the ABS. Other controls include ownership status (foreign owned, family owned not run, family owned and run) and the share of managers with a college degree. Industry fixed effects are two-digit SIC codes. Location fixed effects are the 9 NUTS1 regions. Survey year fixed effects and an indicator for multi-site are also included.

Table 4: Forecast Errors and Uncertainty Over Forecasts with Productivity

Dependent Variable	(1) GDP Forecast Errors	(2) GDP Forecast Errors	(3) Turnover Forecast Errors	(4) Turnover Forecast Errors	(5) GDP Uncertainty	(6) GDP Uncertainty	(7) Turnover Uncertainty	(8) Turnover Uncertainty
Log GVA per worker	-0.087***	-0.057***	-2.608***	-2.799***	-0.013***	-0.013***	-0.015	-0.051***
	(0.0136)	(0.0159)	(0.3800)	(0.4525)	(0.0036)	(0.0042)	(0.0110)	(0.0131)
Management score		-0.194**		-5.811***		-0.007		-0.153***
		(0.0854)		(1.9466)		(0.0216)		(0.0513)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Location FE	No	Yes	No	Yes	No	Yes	No	Yes
Other Controls	No	Yes	No	Yes	No	Yes	No	Yes
Year & Missing FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13500	13500	8706	8706	12662	12662	12980	12980
R^2	0.830	0.834	0.023	0.070	0.073	0.088	0.027	0.145

Notes: Estimation by OLS with standard errors (clustered by firm) in parentheses.. *p < 0.10, **p < 0.05, ***p < 0.01. The dependent variable is the average of the absolute value of the difference between actual and expected growth rates in columns (1)-(4) and the log subjective uncertainty over forecasts in columns (5)-(8). For 2016 forecast errors, we do this for 2016-2017 and also 2016-2018 (and re-weight the regression if the firm error is available in both years so that each firm is only counted once). For 2019 forecast errors, we do this for 2019 – 2020 and also 2019-2021 (and re-weight the regression if the firm error is available in both years so that each firm is only counted once). We exclude firms from reporting zero turnover in both MES and ABS from the analysis. Firm employment and age are from the ABS. Other controls include the log employment and log age, ownership status (foreign owned, family owned not run, family owned and run), the share of managers with a college degree. In columns (3)-(4), five-year turnover volatility is included. Industry fixed effects are two-digit SIC codes. Location fixed effects are the 9 NUTS1 regions. Survey year fixed effects and an indicator for multi-site are also included.

Figure 1: Forecast Errors in GDP and Turnover, Management and Productivity



Notes: The figures show the relationships between absolute GDP forecast error and absolute turnover forecast error , respectively, and management score and log labor productivity. This is shown for the pooled sample of MES2017 and MES2020. Differences in the magnitude of absolute GDP forecast errors between panels (a) and (b) and the absolute turnover forecast errors in panels (c) and (d) arise because of the loss of approximately 6,000 observations when linking the MES to the Annual Business Survey. Descriptive statistics detailing sample sizes are provided in the online Appendix Table A1. The horizontal axes are the mean values of management score and log labor productivity, respectively. Data points are winsorized (top and bottom 1%) and grouped into 40 equal-sized bins.

Online Appendix

Section A: Survey Design and Data Description

This section provides foundational information on the survey instrument, variable construction, and overall descriptive statistics of the sample.

Survey Design, Sample, and Variable Construction

The MES is the largest ever survey on management capabilities in the UK covering both manufacturing and non-manufacturing firms; one of the most extensive management surveys in the world. Moreover, the MES collects expectations data at the business level, building on the US Management and Organizational Practices Survey (MOPS) and the Atlanta Fed Survey of Business Uncertainty (SBU) and the UK Decision Maker Panel. The MES survey attempts to measure three aspects of firms' management practices: (1) monitoring - how well does the firm monitor its operations and use this information for continuous improvement (e.g. effectively collecting and using key performance indicators)? (2) targets - are the firm's targets stretching, tracked and appropriately reviewed? (3) incentives - is the firm promoting and rewarding employees based on performance, managing employee under-performance, making careful hiring decisions and providing adequate training opportunities? Based on the response to each question, we retrieve the management score for each firm using an identical methodology to the US MOPS, which facilitates international comparisons.

The MES 2017 was dispatched in July 2017, about one year after the 'Brexit' referendum in June 2016 on whether to leave the EU. There was considerable uncertainty about whether Brexit would actually occur, and if so when and what form it would take. After several rounds of negotiations with the EU side, Brexit was delayed. These facts resulted in high-level uncertainty and made it difficult for UK firms to make accurate forecasts about future economic conditions both at the macro and micro levels. The MES2020 was collected from November 2020 until May 2021 during the Covid-19 pandemic and two national lockdowns when there was considerable uncertainty about macro and micro-outcomes.

Survey Questions

The MES was conducted by the ONS, in partnership with the Economic Statistics Centre of Excellence (ESCoE). The first wave of the survey was sent in July 2017 to approximately 25,000 firms and covered both the production and services industries. It was a voluntary survey of firms with ten or more employees, with the same sampling frame as the Annual Business Survey (ABS) for 2016, allowing us to match data on value added, employment, output and investment. In November 2020, a second wave of the survey was sent to approximately 50,000 firms drawing from the UK Inter-Departmental Business Register (IDBR) together with a booster sample from the MES first wave.

The MES collects data on management practices (12 questions), decentralization (4 questions), business characteristics (4 questions), and forecasts (10 questions). The forecasting questions ask firms to forecast next year's growth rate of real GDP using a bin structure reproduced in Figure 1, with the bins taken from a Bank of England survey question sent to professional forecasters to enable an evaluation of firms' forecasts against those from professionals. As shown in Figure 1, the bins (points used for expectations) are: -4% or less (-5%), -3% to -2% (-2.5%), -1% (-1%), 0% (0%), 1% (1%), 2% to 3 % (2.5%) and 4% or more (5%). Firms were also asked to forecast their own sales one year ahead and two years ahead using a blank "five-

bin" scale with five scenarios about their own future outcomes alongside probabilities (Figure 2). Granting them this degree of freedom is important because firm-level outcomes are widely dispersed across firms.

Sample

The MES survey was a voluntary survey on a sample of 25,006 firms in 2017 (the total response rate was 38.7%) and 50,712 firms in 2020 (the total response rate was 24%).[1] For our analysis, we require firms to have no more than two question non-responses out of the 12 management practice questions and positive employment, leaving us with an analysis sample of 20,169 firms with management scores.

Variable Construction

We define profit as gross value added minus labor costs. For our capital stock series, we apply the perpetual inventory method, starting from the firm's initial level of capital stock to generate a subsequent series of capital stock using the firm-level investment data from the ABS (2008-2016) and industry-level deflators. We use a capital depreciation rate of 12%. Initial capital stock is calculated by assuming that the firm is in steady state, so the initial investment rate is divided by the depreciation rate plus the steady state growth rate (assumed to be a three-year moving average of the GDP growth rate).

[1] For more information on response rates and firm characteristics, see: https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/labourproductivity/articles/experimentaldataonthemanagementpracticesofmanufacturingbusinessesingreatbritain/2018-04-06 https://www.ons.gov.uk/economy/economicoutputandproductivity/productivitymeasures/articles/managementpracticesingreatbritain/2016to2020

Table A1: Descriptive Statistics

Variables	Number of observations	Mean	Median	Standard deviation
Panel A: Management				
Management score	20169	0.554	0.593	0.199
Employment (IDBR)	20169	194.3	54	759.5
Age	20169	18.789	22	8.304
Log GVA per worker	14075	3.674	3.740	1.017
Share of managers with a college degree	19908	0.382	0.350	0.347
Family owned but not run	20130	0.181	0.000	0.385
Family owned and run	20130	0.428	0.000	0.495
Foreign owned	20169	0.120	0.000	0.325
Profit per worker	14802	25.032	10.846	58.059
Survival	20169	0.917	1	0.276
Employment growth (survey year to 2022)	9353	-0.329	-0.012	0.840
Profit per worker growth (survey year to 2022)	6399	0.0383	0.0750	3.699
Panel B: Expectations (shown as percentage)				
Macro forecasts				
GDP growth forecast (2017 – 2018)	7756	0.096	0	1.047
GDP growth forecast (2020 – 2021)	12412	-1.037	-0.925	2.054
Absolute GDP forecast error	19546	5.936	7.150	3.845
GDP uncertainty	18267	0.574	0.645	0.386
Micro forecasts – one year ahead				
Turnover growth forecast	18487	-7.219	0.000	38.890
Realized turnover growth	8535	-3.855	0.442	32.530
Turnover forecast error	8533	0.256	0.010	26.966
Absolute turnover forecast error	8533	13.769	5.782	25.118
Micro forecasts – two year ahead				
Turnover growth forecast	18508	-2.922	0.204	45.065
Realized turnover growth	5774	5.400	6.936	37.945
Turnover forecast error	5774	4.604	4.618	0.389
Absolute turnover forecast error	5774	22.358	12.193	33.045
Absolute turnover forecast error (averaged)	9069	17.397	8.859	26.696
Turnover uncertainty	18422	1.927	2.018	1.022

Notes: These are descriptives from the data MES and ABS pooled for 2017 and 2020. Details in text. Panel A is the cleaned sample for management analysis. Panel B focuses on the subsample which has expectations information. To construct micro forecast errors, we need realized outcomes from the ABS which is why the

samples are smaller. All variables in Panel B are winsorized at the top and bottom 1% of the distribution. Uncertainty measures are in logarithm

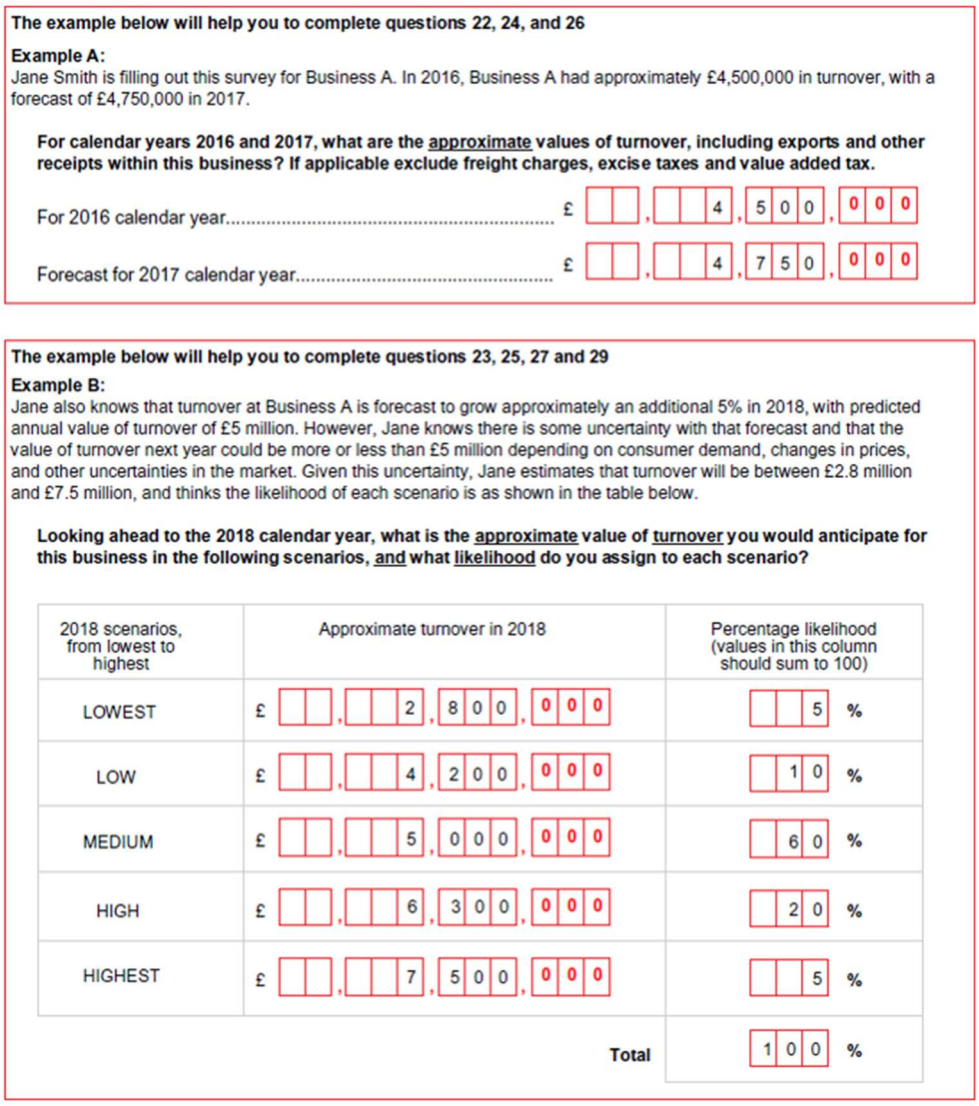
Figure A1: MES Questionnaire on Macro Growth Expectations

30. Please indicate what likelihood you would attach to the possible 2018 rates of UK economic growth (real growth rate of Gross Domestic Product) below.
Gross Domestic Product (GDP) is the main measure of the size of the UK economy, based on the value of goods and services produced during a given period.

UK Economic Growth in 2018		Percentage likelihood (values in this column should sum to 100)
Strong decline	-4% or less	2 % 1138
Moderate decline	-2% to -3%	5 % 1139
Slight decline	-1%	10 % 1140
No change	0%	30 % 1141
Slight increase	1%	40 % 1142
Moderate increase	2% to 3%	10 % 1143
Strong increase	4% or more	3 % 1144
	Total	100 %

Notes: This is the macro growth expectations question from the MES 2017

Figure A2: MES Questionnaire on Micro Growth Expectations



The example below will help you to complete questions 22, 24, and 26

Example A:
Jane Smith is filling out this survey for Business A. In 2016, Business A had approximately £4,500,000 in turnover, with a forecast of £4,750,000 in 2017.

For calendar years 2016 and 2017, what are the approximate values of turnover, including exports and other receipts within this business? If applicable exclude freight charges, excise taxes and value added tax.

For 2016 calendar year..... £ , , 4 , 5 0 0 , 0 0 0

Forecast for 2017 calendar year..... £ , , 4 , 7 5 0 , 0 0 0

The example below will help you to complete questions 23, 25, 27 and 29

Example B:
Jane also knows that turnover at Business A is forecast to grow approximately an additional 5% in 2018, with predicted annual value of turnover of £5 million. However, Jane knows there is some uncertainty with that forecast and that the value of turnover next year could be more or less than £5 million depending on consumer demand, changes in prices, and other uncertainties in the market. Given this uncertainty, Jane estimates that turnover will be between £2.8 million and £7.5 million, and thinks the likelihood of each scenario is as shown in the table below.

Looking ahead to the 2018 calendar year, what is the approximate value of turnover you would anticipate for this business in the following scenarios, and what likelihood do you assign to each scenario?

2018 scenarios, from lowest to highest	Approximate turnover in 2018	Percentage likelihood (values in this column should sum to 100)
LOWEST	£ , , 2 , 8 0 0 , 0 0 0	5 %
LOW	£ , , 4 , 2 0 0 , 0 0 0	1 0 %
MEDIUM	£ , , 5 , 0 0 0 , 0 0 0	6 0 %
HIGH	£ , , 6 , 3 0 0 , 0 0 0	2 0 %
HIGHEST	£ , , 7 , 5 0 0 , 0 0 0	5 %
	Total	1 0 0 %

Notes: This is the micro growth expectations question from the MES 2017.

Figure A3: Distribution of Signed GDP Forecast Errors

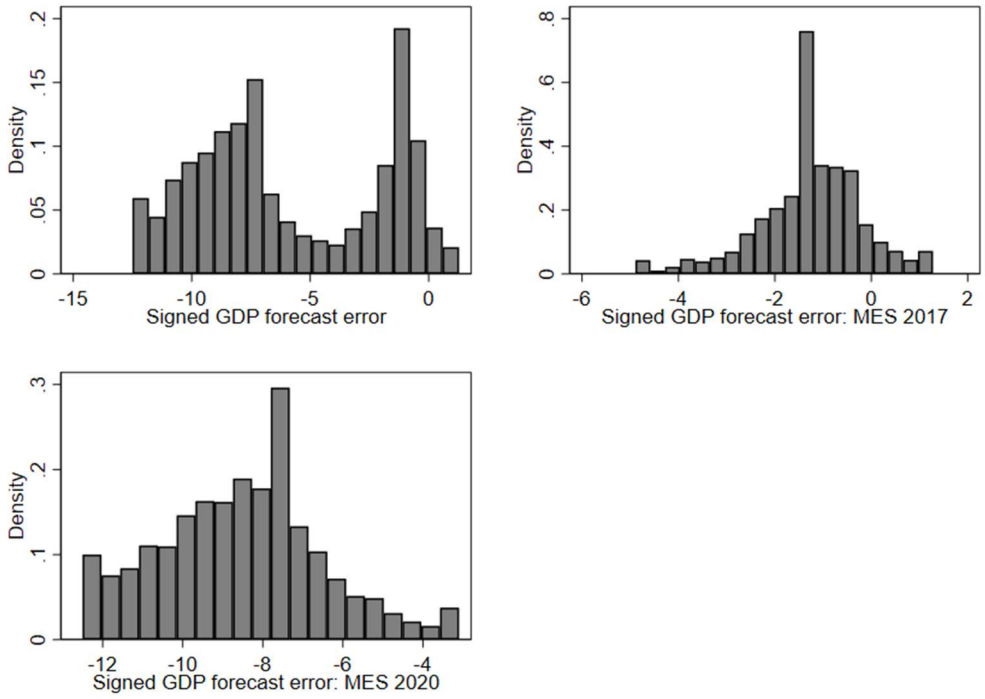


Figure A4: Distribution of Signed Turnover Forecast Errors

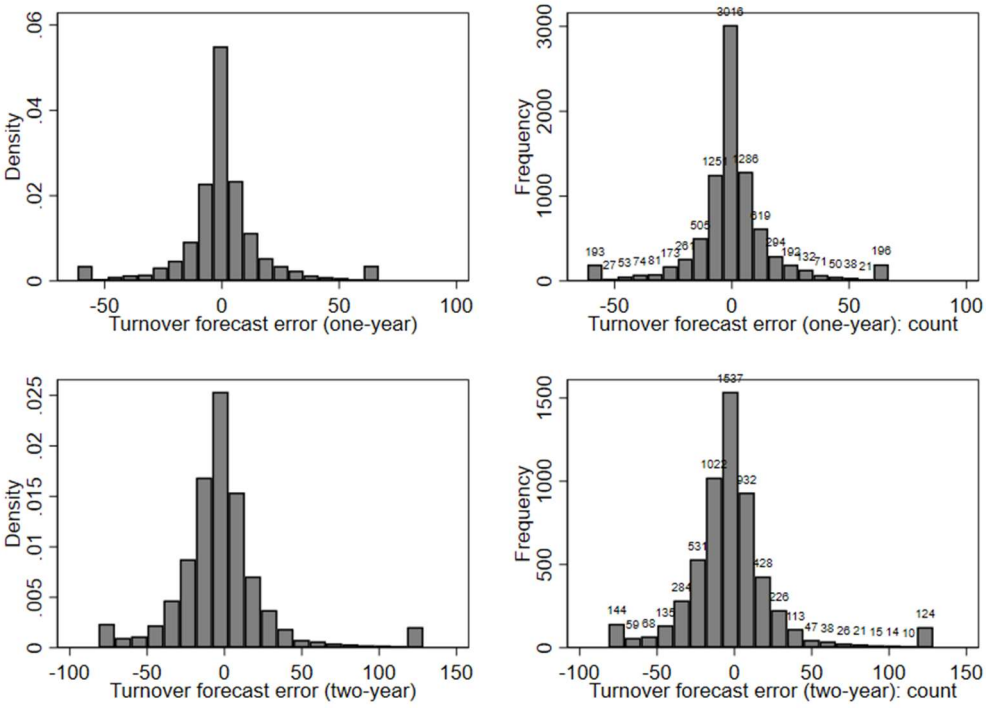


Figure A5: Distribution of Log Employment

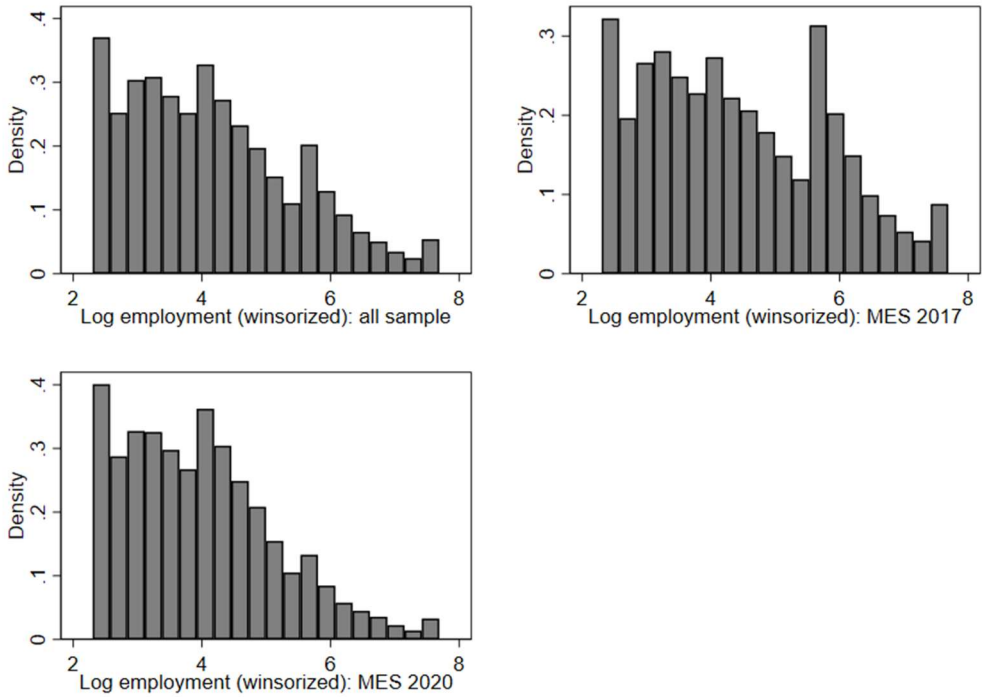
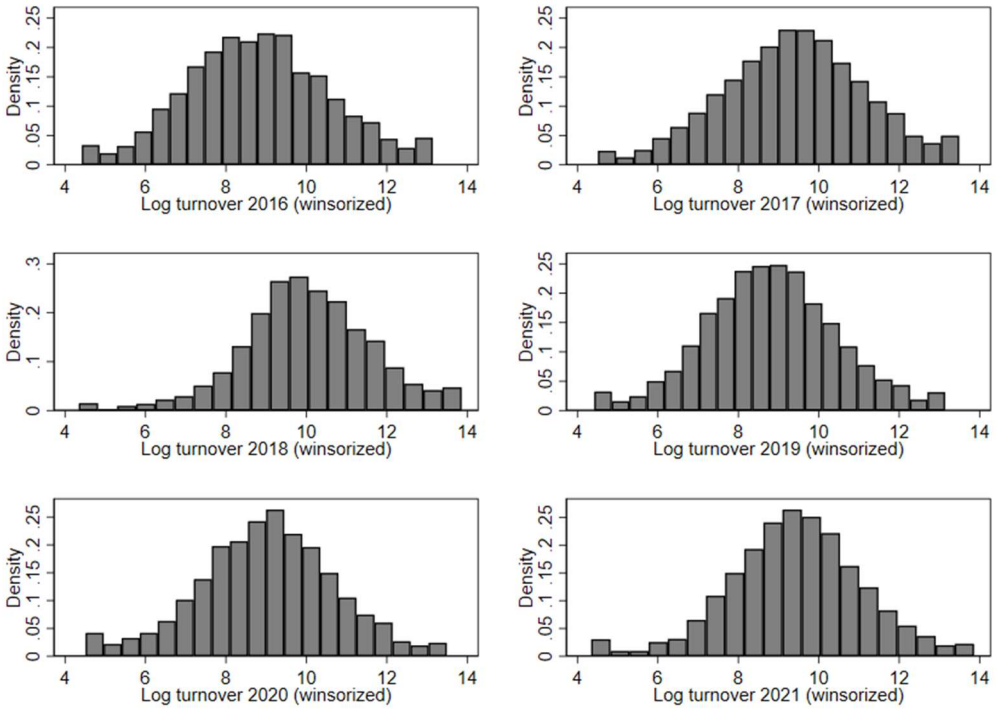


Figure A6: Distribution of Log Turnover



Section B: Core Management Score Analysis

This section details the characteristics of the management score, its drivers, and its relationship to firm performance and data quality.

Table B1: Management Scores by Broad Industry

	Employment: 10-49		Employment: 50-99		Employment: 100-249		Employment: 250+		All	
	Mean	Share	Mean	Share	Mean	Share	Mean	Share	Mean	Share
Manufacturing	0.46	9.28	0.57	4.72	0.62	3.56	0.70	2.68	0.55	20.23
Construction	0.44	4.60	0.55	1.78	0.62	1.05	0.65	0.73	0.50	8.16
Retail, distribution, hotels and restaurants	0.47	10.35	0.59	3.95	0.64	2.43	0.71	3.72	0.56	20.45
Transport, storage and communication	0.49	4.84	0.56	1.94	0.62	1.40	0.70	1.33	0.55	9.52
Business services	0.51	8.79	0.58	3.73	0.61	3.05	0.65	3.74	0.57	19.30
Real estate and others	0.48	8.83	0.57	4.23	0.61	3.57	0.66	5.71	0.57	22.34
Total	0.48	46.69	0.57	20.34	0.62	15.07	0.68	17.90	0.55	100

Notes: Mean shows the average management score for the firms in the industry and employment size categories. Share describes the share of firms in the industry and employment size categories out of the full sample.

Table B2: "Drivers" of Management Scores

Dependent Variable	**Management Score**						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	All	All	All	All	Employment 10-49	Employment 50-249	Employment 250+
Log employment	0.059***	0.059***	0.053***	0.054***	0.094***	0.052***	0.019***
	(0.0011)	(0.0012)	(0.0012)	(0.0012)	(0.0045)	(0.0044)	(0.0031)
Family owned but not run			-0.007*	0.001	-0.004	0.003	-0.008
			(0.0038)	(0.0037)	(0.0063)	(0.0055)	(0.0068)
Family owned and run			-0.025***	-0.015***	-0.004	-0.023***	-0.034***
			(0.0033)	(0.0032)	(0.0052)	(0.0049)	(0.0066)
Foreign owned			0.049***	0.039***	0.050***	0.039***	0.028***
			(0.0038)	(0.0037)	(0.0083)	(0.0054)	(0.0061)
Log age				-0.004*	-0.018***	-0.003	0.016***
				(0.0023)	(0.0033)	(0.0040)	(0.0043)
Share of managers with a college degree				0.109***	0.113***	0.102***	0.070***
				(0.0045)	(0.0063)	(0.0074)	(0.0105)
Industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Year & Missing FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20169	20169	20169	20169	9416	7142	3611
R^2	0.183	0.223	0.234	0.262	0.154	0.149	0.194

Notes: Estimation by OLS with clustered standard errors by firms in parentheses. Management score is the unweighted average of the score for each of the 12 questions, with scores on a scale of 0 to 1 for each question, where 0 was the least and 1 the most structured management practice. Firm employment is from the ABS. "Foreign Owned" is a dummy for whether the firm is an affiliate of a non-UK firm. "Family owned and run" is a firm owned by a family and run by a family member; "Family owned but not run" is a dummy for a firm which is family owned but whose CEO is a non-family member (a firm which is not owned by a family is the omitted base) from MES. Age is the date from the date of incorporation reported in the ABS. We include the share of managers with a college degree as an additional control variable. Industry fixed effects are two-digit SIC codes. Location fixed effects are the 9 NUTS1 regions. Survey year fixed effects and an indicator for multi-site are also included. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B3: Firm Performance (Productivity and Profits) and Management Score

Dependent variable	**Log (Gross Value Added per worker)**							**Profit Per Worker**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	All	All	All	All	Employ-ment 10-49	Employ-ment 50-249	Employ-ment 250+	All
Management score	0.805*** (0.0478)	0.826*** (0.0439)	0.749*** (0.0467)	0.697*** (0.0471)	0.734*** (0.0662)	0.588*** (0.0770)	0.745*** (0.1383)	17.747*** (2.7324)
Log employment			-0.077*** (0.0081)	-0.075*** (0.0082)	-0.032 (0.0275)	-0.157*** (0.0275)	-0.035 (0.0212)	-4.817*** (0.4749)
Log capital per worker			0.127*** (0.0063)	0.124*** (0.0063)	0.122*** (0.0112)	0.113*** (0.0093)	0.146*** (0.0134)	5.748*** (0.4506)
Log age			0.079*** (0.0151)	0.079*** (0.0151)	0.081*** (0.0216)	0.084*** (0.0268)	0.070** (0.0329)	0.324 (0.8075)
Industry FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year & Missing FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14075	14075	14075	14075	5850	4994	3231	14802
R^2	0.024	0.270	0.319	0.322	0.285	0.352	0.417	0.128

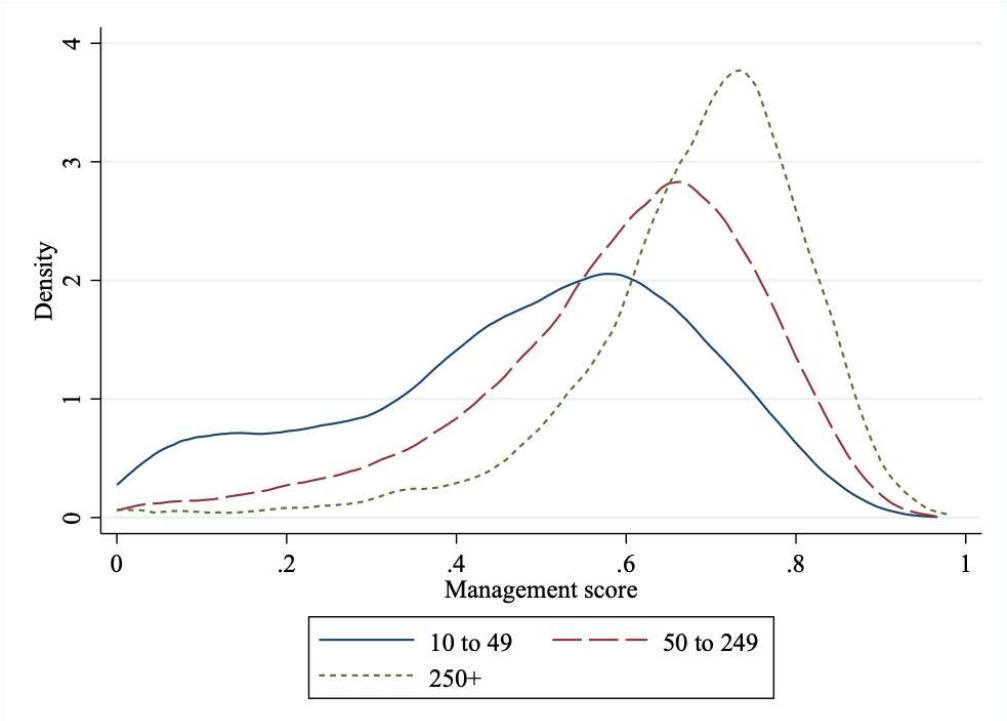
Notes: Estimation by OLS with clustered standard errors by firms in parentheses. Dependent variable is log gross value added per worker in columns (1) - (7); profits per worker, winsorized with top and bottom 1%, in column (8). Employment and capital constructed from the ABS. Other controls include ownership status (foreign owned, family owned not run, family owned and run) and the share of managers with a college degree. Industry fixed effects are two-digit SIC codes. Location fixed effects are the 9 NUTS1 regions. Survey year fixed effects and an indicator for multi-site are also included. See Table 1 notes and text for more details. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B4: Correlations Between "Usable Response" Dummy and Control Variables

	(1) GDP	(2) GDP	(3) Turnover	(4) Turnover	(5) Employment	(6) Employment
Management score	0.033***	0.045***	0.096***	0.142***	0.234***	0.254***
	(0.0071)	(0.0077)	(0.0114)	(0.0126)	(0.0137)	(0.0150)
Log GVA per worker		-0.001		-0.001		0.005
		(0.0022)		(0.0029)		(0.0033)
Log employment		-0.003**		-0.003*		0.005**
		(0.0014)		(0.0020)		(0.0024)
Log age		0.004*		0.020***		0.010***
		(0.0022)		(0.0034)		(0.0038)
Industry FE	No	Yes	No	Yes	No	Yes
Location FE	No	Yes	No	Yes	No	Yes
Other Controls	No	Yes	No	Yes	No	Yes
Year & Missing FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20169	20169	20169	20169	20169	20169
R^2	0.053	0.067	0.005	0.051	0.021	0.057

Notes: In all columns the dependent variable is a "usable response" dummy (see text) for the relevant question. Estimation by OLS with robust standard errors in parentheses. Management score is the unweighted average of the score for each of the 12 questions, with scores on a scale of 0 to 1 for each question, where 0 was the least and 1 the most structured management practice. Firm employment is from the ABS in 2016. Other controls include ownership status (foreign owned, family owned not run, family owned and run) and the share of managers with a college degree. Industry dummies are two-digit, location dummies are the 9 NUTS1 regions and "Other Controls" includes dummies for the month when the survey was returned, time spent on the survey, multi-site dummy and reporting accuracy indicator (difference between 2016 employment as reported in ABS and MES). * p < 0.10, ** p < 0.05, *** p < 0.01.

Figure B1: Firm Size and the Management Score Distribution



Notes: This figure shows the distribution of management score for the pooled sample of MES2017 and MES2020. Each curve corresponds to the kernel density of firms in each employment size category.

Section C: Forecasts, Errors, and Subsequent Performance

This section explores the relationships between management, forecast levels, forecast errors, and subsequent real firm outcomes.

Table C1: Management and GDP Growth Forecasts (Levels)

	Expected GDP Growth		
	(1)	(2)	(3)
Management score	0.566***	0.512***	0.297***
	(0.0672)	(0.0690)	(0.0756)
Log employment			0.079***
			(0.0126)
Log age			-0.034*
			(0.0200)
Industry FE	No	Yes	Yes
Location FE	No	Yes	Yes
Other Controls	No	No	Yes
Year & Missing FE	Yes	Yes	Yes
19546	19546	19546	19546
0.091	0.092	0.102	0.105

Notes: In all regressions the dependent variable is the expected real GDP growth. Estimation by OLS with robust standard errors in parentheses. Management score is the unweighted average of the score for each of the 12 questions, with scores on a scale of 0 to 1 for each question, where 0 was the least and 1 the most structured management practice. Firm employment is from the ABS in 2016. Age is calculated from the date of incorporation recorded in the ABS. We include ownership status (foreign owned, family owned not run, family owned and run) and the share of managers with a college degree as additional control variables. Industry dummies are two-digit, location dummies are the 9 NUTS1 regions and "Other Controls" includes dummies for the month when the survey was returned, time spent on the survey, multi-site dummy and reporting accuracy indicator (difference between 2016 employment as reported in ABS and MES). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table C2: Management and Firm-level Turnover Growth Forecast (One-year, Levels)

	One-year Turnover Forecast		
	(1)	(2)	(3)
Management score	3.785**	3.489**	2.273
	(1.6958)	(1.7291)	(1.9312)
Log employment			0.741**
			(0.2961)
Log age			-7.526***
			(0.6515)
Industry FE	No	Yes	Yes
Location FE	No	Yes	Yes
Other Controls	No	No	Yes
Year & Missing FE	Yes	Yes	Yes
Observations	18487	18487	18487
R^2	0.065	0.127	0.141

Notes: The dependent variable is expected turnover in 2017. Estimation by OLS with robust standard errors in parentheses. Management score is the unweighted average of the score for each of the 12 questions, with scores on a scale of 0 to 1 for each question, where 0 was the least and 1 the most structured management practice. Firm employment is from the ABS in 2016. Age is calculated from the date of incorporation recorded in the ABS. We include ownership status (foreign owned, family owned not run, family owned and run) and the share of managers with a college degree as additional control variables. Industry dummies are two-digit, location dummies are the 9 NUTS1 regions and "Other Controls" includes dummies for the month when the survey was returned, time spent on the survey, multi-site dummy and reporting accuracy indicator (difference between 2016 employment as reported in ABS and MES). * p < 0.10, ** p < 0.05, *** p < 0.01.

Table C3: Management and Firm-level Turnover Growth Forecast (Two-year, Levels)

	Two-year Turnover Forecast		
	(1)	(2)	(3)
Management score	11.566***	10.968***	7.480***
	(2.0252)	(2.1040)	(2.2835)
Log employment			1.931***
			(0.3619)
Log age			-11.200***
			(0.7699)
Industry FE	No	Yes	Yes
Location FE	No	Yes	Yes
Other Controls	No	No	Yes
Year & Missing FE	Yes	Yes	Yes
Observations	18508	18508	18508
R^2	0.032	0.058	0.083

Notes: The dependent variable is expected 2018 turnover. We exclude firms reporting zero turnover in both MES and ABS from the analysis. Estimation by OLS with robust standard errors in parentheses. Management score is the unweighted average of the score for each of the 12 questions, with scores on a scale of 0 to 1 for each question, where 0 was the least and 1 the most structured management practice. Firm employment is from the ABS in 2016. Age is calculated from the date of incorporation recorded in the ABS. We include ownership status (foreign owned, family owned not run, family owned and run) and the share of managers with a college degree as additional control variables. Industry dummies are two-digit, location dummies are the 9 NUTS1 regions and "Other Controls" includes dummies for the month when the survey was returned, time spent on the survey, multi-site dummy and reporting accuracy indicator (difference between 2016 employment as reported in ABS and MES). * p < 0.10, ** p < 0.05, *** p < 0.01.

Section D: Robustness I - Alternative Specifications

Table D1: Regressions with Squared Forecast Errors

	(1) GDP	(2) GDP	(3) GDP	(4) Turnover	(5) Turnover	(6) Turnover
Management score	-7.243***	-6.495***	-3.426***	-648.673***	-660.494***	-937.692***
	(1.0688)	(1.1012)	(1.2139)	(248.6936)	(254.6712)	(285.4304)
Log employment			-0.603***			107.690**
			(0.2290)			(51.3363)
Foreign ownership			-1.796***			-126.587
			(0.6534)			(95.7470)
Family owned not run			-0.039			46.435
			(0.6181)			(123.5212)
Family owned and run			0.431			-295.831***
			(0.5108)			(91.8499)
Log age			0.529*			-220.051***
			(0.3131)			(78.6475)
Share of managers with a college degree			-0.496			236.881
			(0.6886)			(147.7815)
Firm turnover 5-year volatility			1.271			2263.032***
			(1.5856)			(462.0472)
Industry Dummies	No	Yes	Yes	No	Yes	Yes
Location Dummies	No	Yes	Yes	No	Yes	Yes
Missing Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Used for Average	No	No	No	Yes	Yes	Yes
Observations	19546	19546	19546	9069	9069	9069
R^2	0.624	0.628	0.629	0.008	0.040	0.056

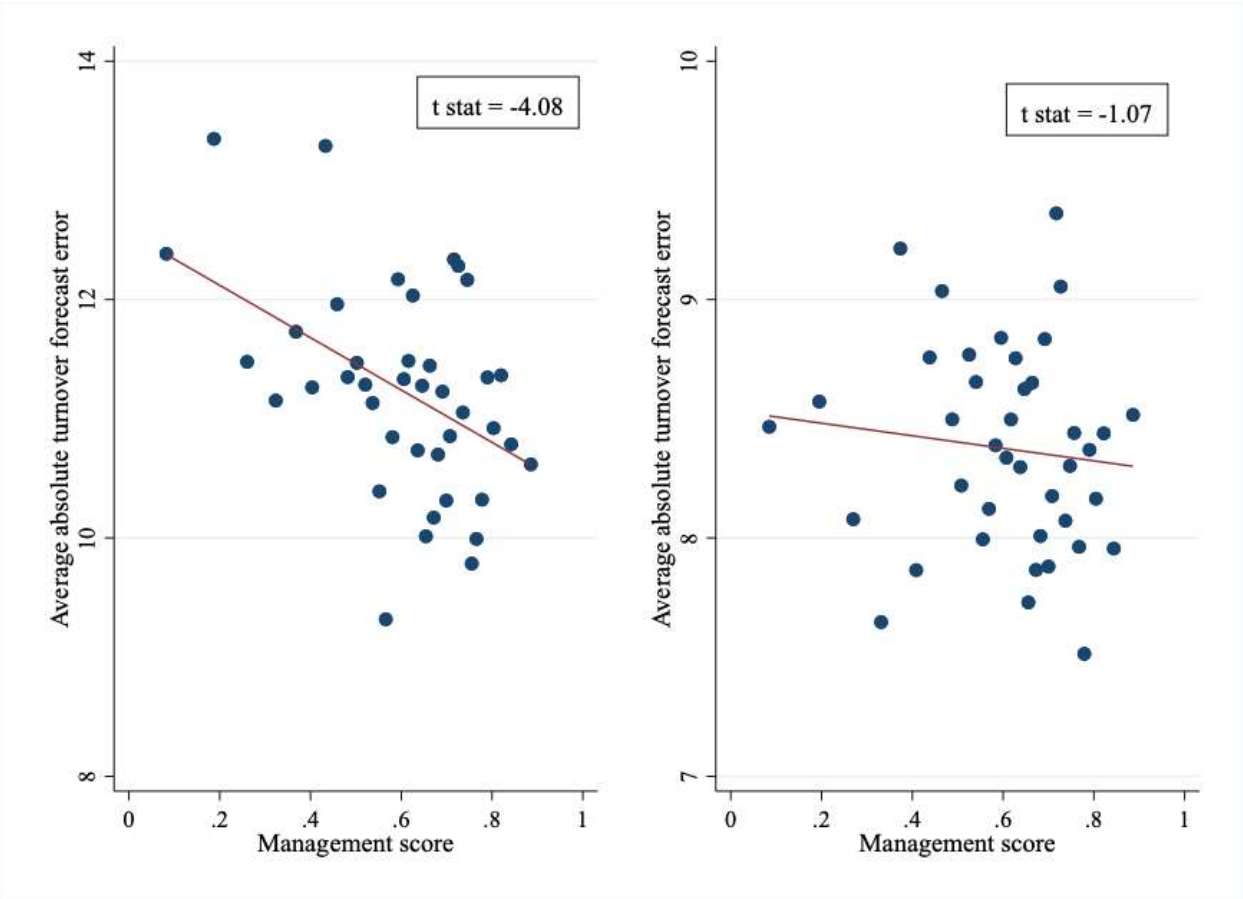
Standard errors in parentheses
Forecast error = actual - expected; with weights (used for squared only)
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table D2: Regressions with Squared Forecast Errors with Productivity

	(1) GDP forecast error	(2) GDP forecast error	(3) GDP forecast error	(4) Turnover forecast error	(5) Turnover forecast error	(6) Turnover forecast error
Log GVA per worker	-1.333***	-0.886***	-0.826***	-316.090***	-360.505***	-346.453***
	(0.2053)	(0.2430)	(0.2456)	(54.4221)	(64.1288)	(64.5402)
Log employment		-1.129***	-1.015***		2.966	29.855
		(0.1931)	(0.2069)		(40.5328)	(43.5960)
Foreign ownership		-1.969***	-1.899***		14.884	36.363
		(0.6868)	(0.6888)		(90.8900)	(90.1281)
Family owned not run		-0.172	-0.173		151.786	152.532
		(0.6849)	(0.6850)		(116.2688)	(116.2382)
Family owned and run		-0.162	-0.199		-200.574**	-216.148***
		(0.5286)	(0.5286)		(80.9238)	(81.7133)
Log age		0.483	0.450		-232.894***	-238.422***
		(0.3193)	(0.3205)		(68.6172)	(68.7480)
Share of managers with a college degree		-0.898	-0.721		166.785	213.403
		(0.7313)	(0.7400)		(133.9883)	(136.3052)
Management score			-2.116			-603.752**
			(1.3322)			(278.1927)
Firm turnover 5-year volatility					851.990***	843.284***
					(308.6671)	(309.5373)
Industry Dummies	No	Yes	Yes	No	Yes	Yes
Location Dummies	No	Yes	Yes	No	Yes	Yes
Missing Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Used for Average	No	No	No	Yes	Yes	Yes
Observations	13500	13500	13500	8706	8706	8706
R^2	0.690	0.694	0.694	0.018	0.049	0.050

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure D1: Sensitivity of Turnover Forecast Error to Trimming Outliers



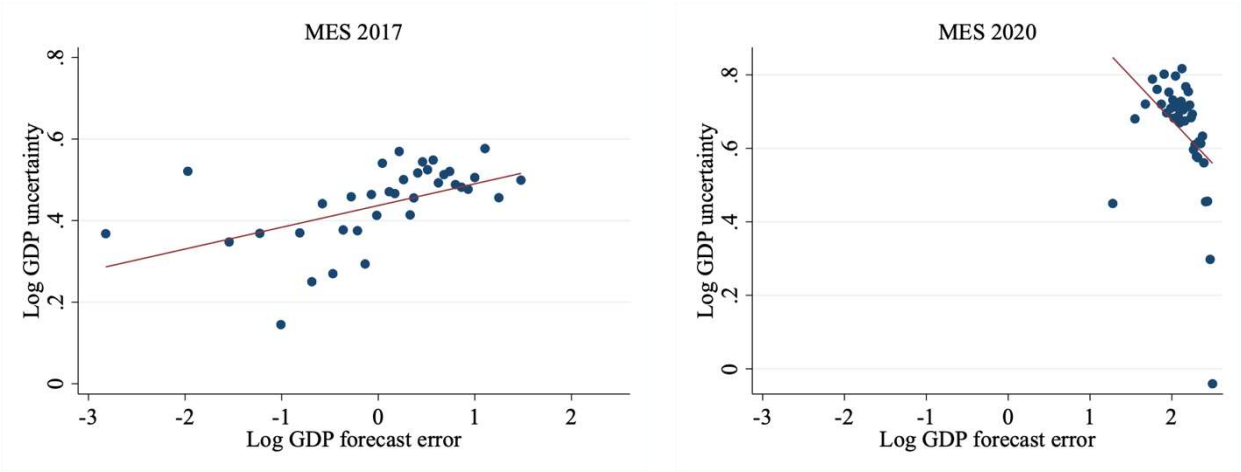
Notes: Both panels show the relationship between turnover forecast errors and management scores. Panel A trims the sample with forecast errors equal or greater than 50% and Panel B trims the sample with forecast errors equal or greater than 25%. Horizontal axes show the level of the forecast error in absolute value. The values are winsorized with top and bottom 1% and grouped into 40 equal-sized bins. Vertical axes are the mean values of management score. The box in both panels shows t statistics.

Section E: Results by Survey Wave

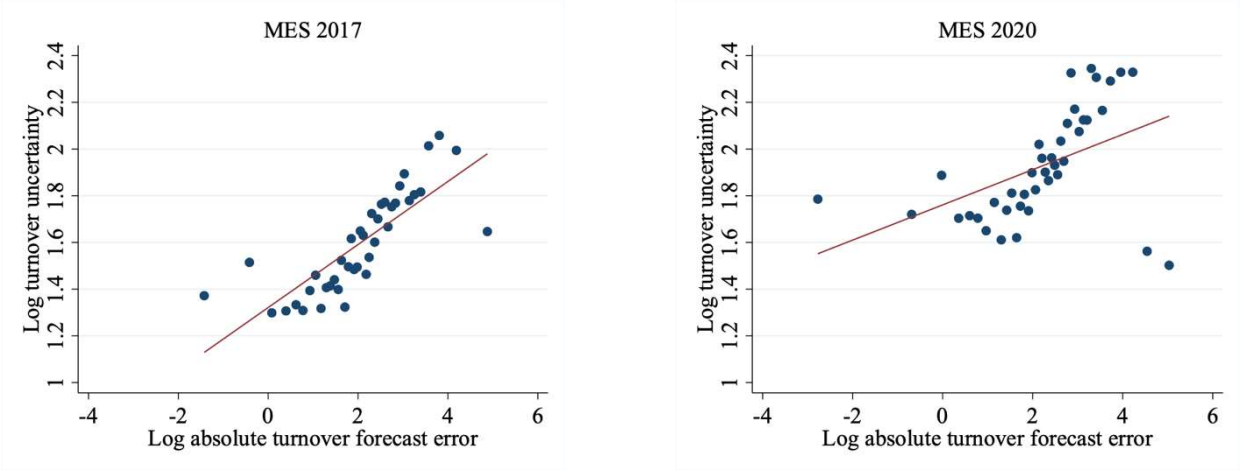
This final section presents key relationships disaggregated by the MES 2017 and MES 2020 survey waves.

Figure E1: Forecast Errors and Uncertainty (Separate Waves)

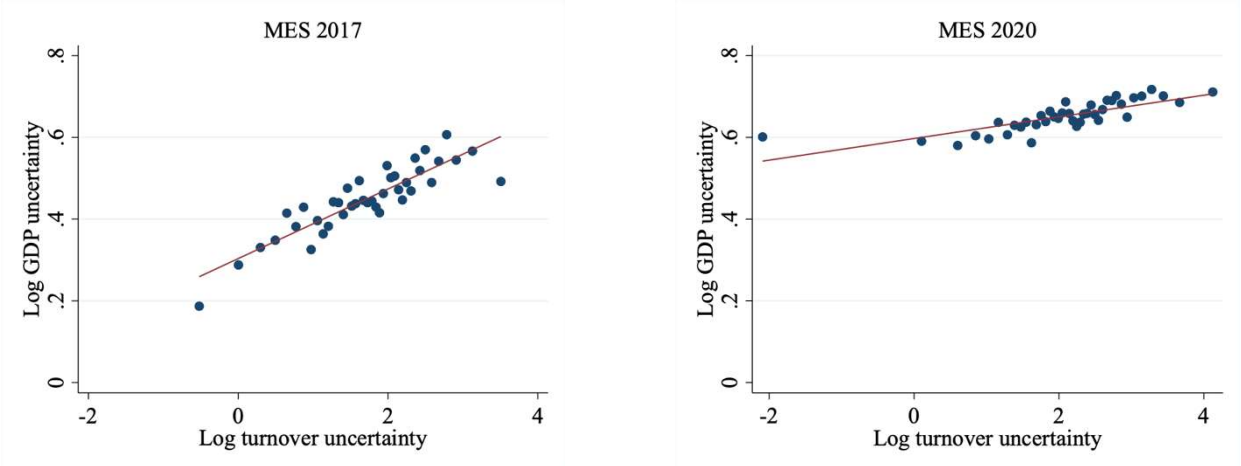
(a) GDP uncertainty vs. forecast error



(b) Turnover uncertainty vs. forecast error



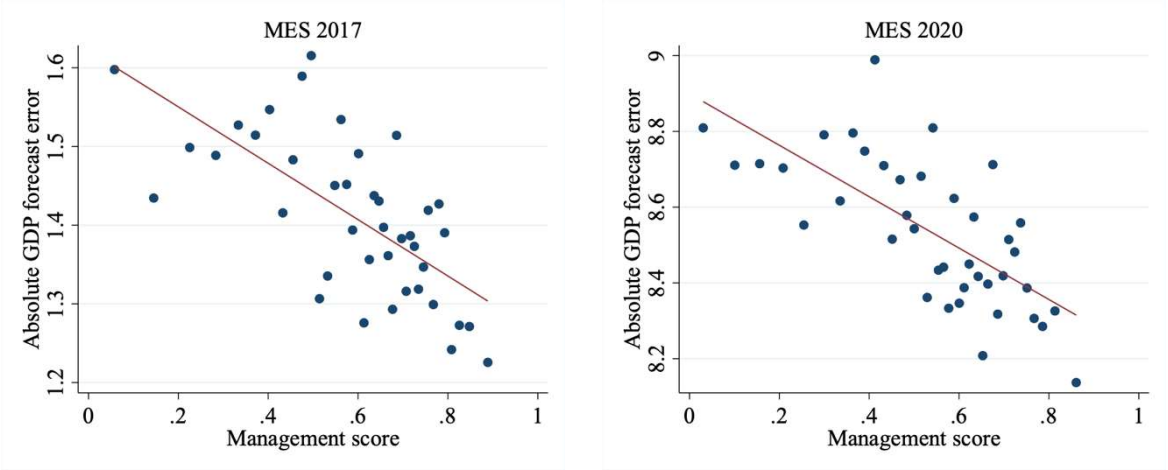
(c) GDP uncertainty vs. turnover uncertainty



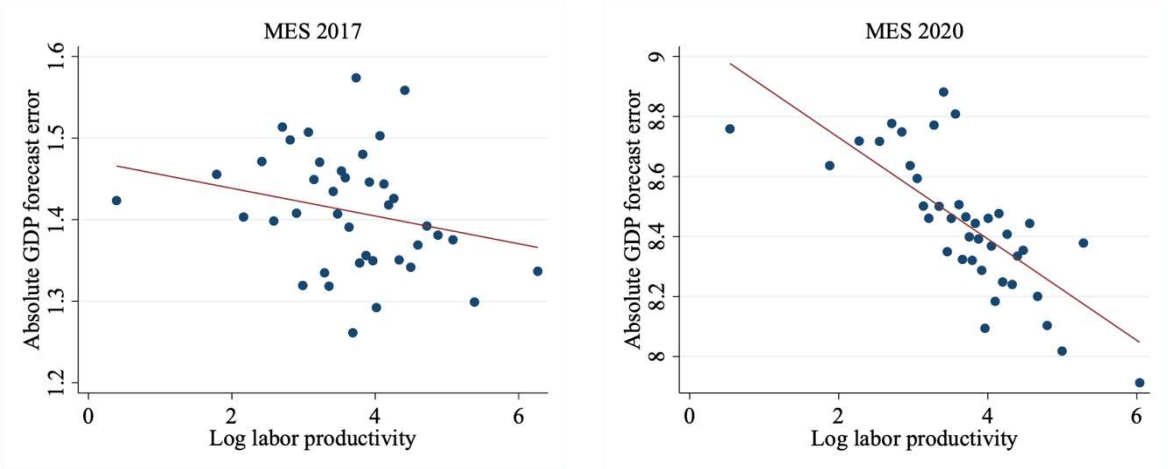
Notes: The figures show the relationship between log GDP forecast errors and log GDP uncertainty, log average turnover forecast errors and log turnover uncertainty, and log GDP uncertainty and log turnover uncertainty, respectively. This is shown for MES2017 and MES2020 separately. Data points are winsorized (top and bottom 1%) and grouped into 40 equal-sized bins.

Figure E2: GDP Forecast Errors vs. Firm Characteristics (Separate Waves)

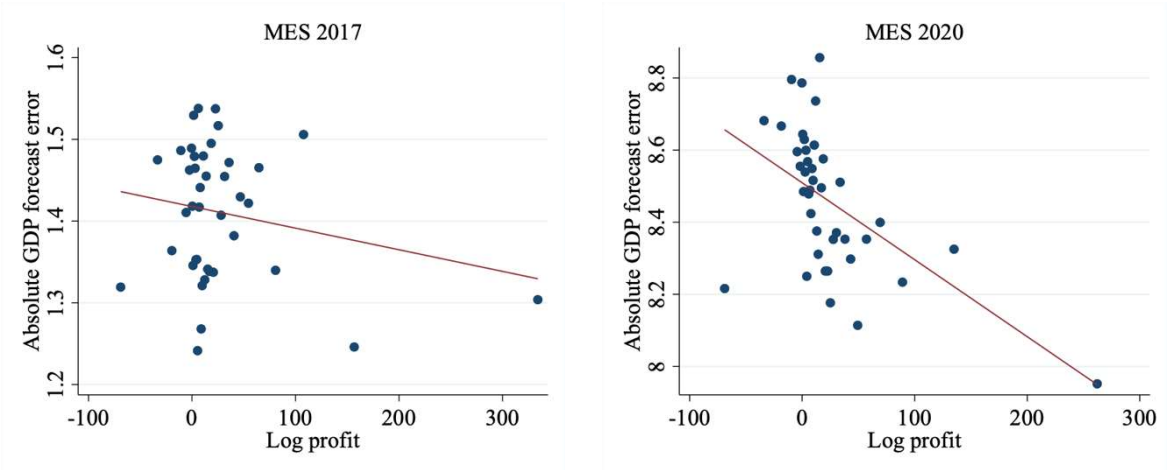
(a) GDP forecast errors vs. management score



(b) GDP forecast errors vs. productivity



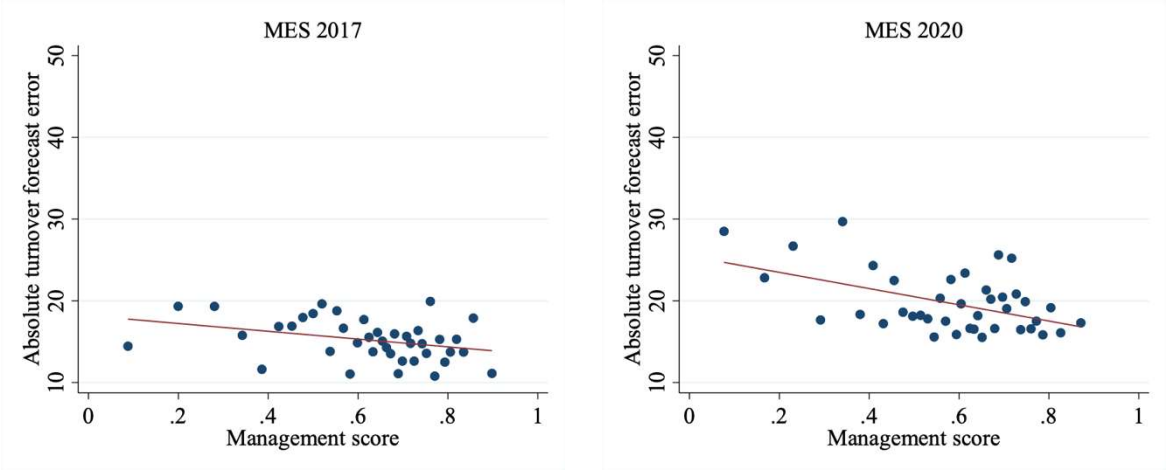
(c) GDP forecast errors vs. profits



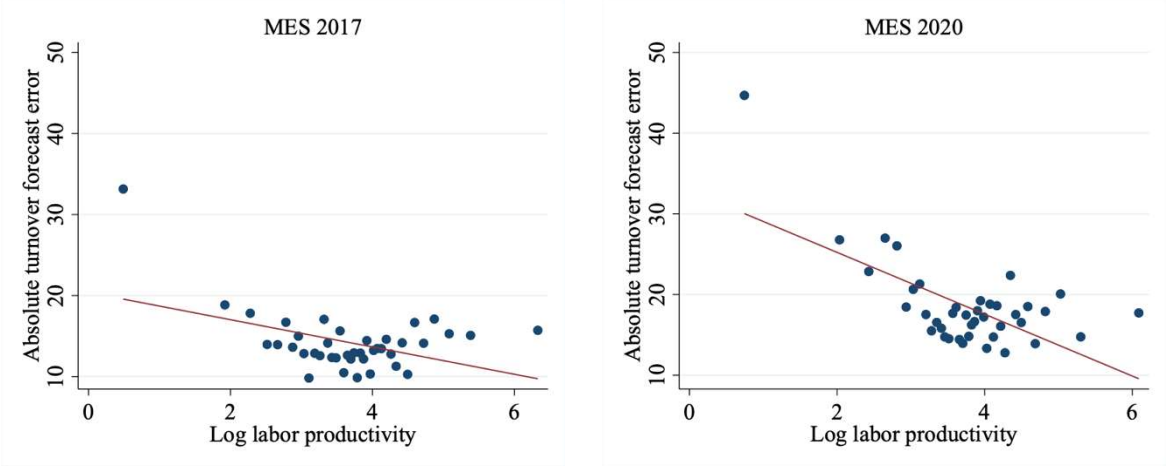
Notes: The figures show the relationships between absolute GDP forecast error and management score, log labor productivity, and log profit, respectively. This is shown for MES2017 and MES2020 separately. Horizontal axes are the mean values of management score, labor productivity, and profit, respectively. Data points are winsorized (top and bottom 1%) and grouped into 40 equal-sized bins.

Figure E3: Micro Turnover Forecast Errors vs. Firm Characteristics (Separate Waves)

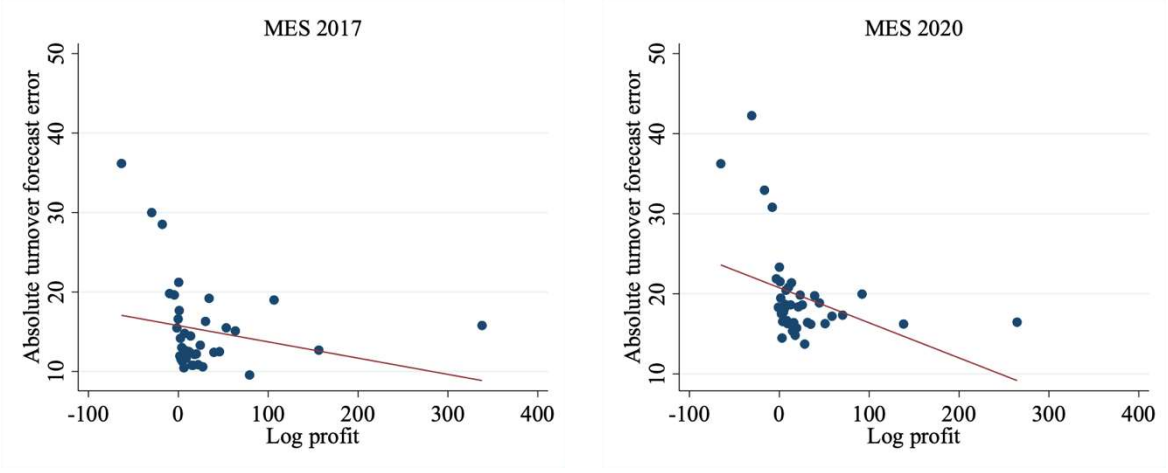
(a) Turnover forecast errors vs. management score



(b) Turnover forecast errors vs. productivity



(c) Turnover forecast errors vs. profits



Notes: The figures show the relationships between average absolute turnover forecast error and management score, log labor productivity, and log profit, respectively. This is shown for MES2017 and MES2020 separately. Horizontal axes are the mean values of management score, labor productivity, and profit, respectively. Data points are winsorized (top and bottom 1%) and grouped into 40 equal-sized bins.