Firm performance and macro forecast accuracy

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1. Introduction

There has been a longstanding interest in the importance of firm expectations for business outcomes. For example, Keynes (1936) talked about animal spirits to highlight the importance of (potentially irrational) expectations, while Tobin’s Q-theory of investment (Tobin, 1982) hinges on firms’ future expectations of demand. More recently, almost all stochastic models of firm dynamics assume forward looking agents who develop beliefs about future micro and macroeconomic conditions. Central – and still outstanding – questions in this literature include: how much do these forecasts matter for realized economic outcomes, under what circumstances, and to what extent does their level and accuracy vary across firms?\textsuperscript{1}

This paper investigates these questions by matching data on firms’ forecasts of GDP growth from the Japanese Annual Survey of Corporate Behavior (ASCB) to company accounting data. This survey was conducted by the Economic and Social Research Institute within the Cabinet Office over the period 1989–2015 and achieved a response rate of about 50\% from all firms publicly listed at major stock exchanges in Japan, generating a panel sample on around 1000 firms per year. The survey asks firms for quantitative estimates of future GDP growth and appears to be of relatively high quality – for example, the typical respondent was in management, planning or strategy departments.

Analyzing these data, we find three main results. First, firms’ GDP forecasts are positively and significantly associated with their subsequent input choices, such as investment and employment, as well as sales growth, even after controlling for year and firm fixed effects. Second, forecast accuracy appears to be tightly related to profitability and productivity (TFPR). Prior year forecast accuracy has significant predictive power for firm performance, even after controlling for time and firm fixed effects, as well as longer-run forecast accuracy. This is true both for over-optimistic firms (positive forecast errors) as

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\textsuperscript{1} See, for example, classic works including Abel and Blanchard (1986); Caballero (1997); Chirinko (1993); Nickell (1978); or Dixit and Pindyck (1994).

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well as over-pessimistic ones (negative forecast errors). We provide a simple model of firm input choice in the face of uncertainty and costly adjustment that rationalizes each of these findings – larger forecast errors lead to a greater over/under accumulation of inputs and lower profitability and the interaction of pricing effects with costs of adjustment can generate a negative effect of forecast errors (of either sign) on measured productivity. For all of these results, we find the empirical relationships are strongest in firms whose performance is more sensitive to the state of the business cycle.

Finally, we find significant variation in forecast quality across firms. We measure forecast quality in two ways, first in comparison with professional forecasters’ forecasts and second in comparison with the actual realizations of GDP growth rates. While comparison with realizations is a natural measure of forecast accuracy, it reflects unavoidable forecast errors (e.g. through not being able to predict natural disasters), and so is likely to be a noisy measure of forecast quality. Therefore, we mainly use comparisons with professional forecasts, which are likely to be the best available “real-time” forecasts at the time of the survey. We find that larger and more cyclically sensitive firms have forecasts most similar to professionals, presumably because their returns from accuracy are largest. Interestingly, we also see that more productive, older, and bank-owned firms tend to have forecasts closer to professionals, suggesting that experience, management ability, and governance may also play an important role in making better forecasts. The results are similar when we measure firms’ forecast accuracy alternatively by the distance to realizations.

Our work connects to several branches of literature. First is the literature on macroeconomics and firm forecasts. Macroeconomic theories have long shown that explicitly incorporating heterogeneous beliefs can help explain important features of economic dynamics (for example, Lucas, 1972, and Mankiw and Reis, 2002). More recently, David et al. (2016) provide and estimate a model in which imperfect information at the firm-level lowers aggregate productivity through resource misallocation. In addition, a growing number of studies have demonstrated that forecasts of economic agents have a key role in driving business cycles (Beaudry and Portier, 2004; Ilut and Schneider, 2014; Schmitt-Grohe and Uribe, 2012).

Second, this paper builds on a growing empirical literature investigating expectations formation. Mankiw et al. (2003) analyze consumers’ inflation forecasts and find larger disagreements among the general public compared to professional forecasters. Studies examining the patterns of macroeconomic forecasts have found that they tend to be consistent with models featuring information rigidity and belief updating (Carroll, 2003; Coibion and Gorodnichenko, 2012, 2015; Coibion et al., 2018). Coibion et al. (2018) document substantial heterogeneity in firms’ macroeconomic forecasts in a firm survey in New Zealand and find that firms facing higher competition are more accurate than others. Bachmann and Elstner (2015) and Massenot and Pettinichhi (2018) use a German manufacturing survey that asks about predictions of own-firm performance and find that at most one third of firms systematically over- or under-predict their performance, and that the degree of forecasting errors are smaller for larger and older firms. Several studies have documented US firm executives’ underpredictions of future aggregate stock market volatility and of their own sales growth (Barrera, 2018; Ben-David et al., 2013). Bloom et al. (2018) use US Census data and find more productive and better managed firms have improved forecast accuracy. Chen et al. (2018) use Japanese multinational firms’ sales forecasts and find superior export forecast accuracy for firms with experience in the destination markets. Using the same firm survey in Japan as in this study, Kaihatsu and Shiraki (2016) examine heterogeneity in firms’ inflation forecasts, and Koga and Kato (2017) document systematic patterns of optimism and pessimism in firms’ industry demand forecasts.

We argue that our analysis of firms’ forecasts of an important common outcome – GDP growth – is valuable for measuring forecasting ability across firms. Most datasets collect forecast information about own-firm performance (e.g. own sales), which makes it hard to say if, for example, larger firms are better at forecasting their own sales, or if their own sales are more stable and so easier to forecast. Since we analyze forecasts of a common variable (GDP growth), the second source of variation is not present. In addition, using forecasts of GDP growth enables us to compare firms’ forecasts with professional forecasts. This provides us with a rare opportunity to evaluate firms’ forecasts against benchmark forecasts that are not influenced by unforeseeable shocks. Finally, a critical aspect of our data supporting the use of GDP growth forecasts is that our sample is mostly composed of large firms whose sales growth tends to be highly correlated with GDP growth, suggesting they have strong incentives to form accurate GDP growth forecasts.

Several recent studies provide evidence related to ours about the relationship between firms’ expectations and firm outcomes. Gennaioli et al. (2015) examine the rationality of CFOs’ expectations and show that investment plans and realizations are well explained by expectations of earnings growth. In a related effort, Massenot and Pettinichchi (2018) use a German survey data containing firms’ qualitative assessments of their business conditions and show that over-optimistic firms subsequently report lower profits and over-pessimistic firms higher profits. Our study is unique in that we use a long panel of firms’ quantitative GDP forecasts matched with their accounting data, which enables us to quantitatively examine the relationship between firms’ forecasts and their input choices and performance.

Finally, our study is closely related to the literature on management and productivity. Growing empirical evidence suggests that managers’ abilities and practices are important determinants of firm productivity and other measures of performance (for example, Bertrand and Schoar, 2003, and Bloom and Van Reenen, 2007). In this paper, we view forecast ability as one component of management ability.

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2 For example, the median employment size is 1084 employees in our sample. A simple pooled regression of firms’ annual sales growth rates on Japan’s annual GDP growth rate yields an estimated coefficient of 2.02 (with standard error 0.04).
The paper is organized as follows. Section 2 lays out a simple theory of firm dynamics in the face of uncertainty to guide our empirical investigation. Section 3 describes the data. Section 4 presents our main findings on firm forecasts and performance and Section 5 reports results on forecast quality by firm characteristics. Section 6 provides concluding remarks.

2. The model

This section outlines a parsimonious model of firm input choice under uncertainty. The framework provides sharp guidance on the relationship between firm expectations, i.e., optimism/pessimism, input choices, and outcomes, e.g., measured TFP and profitability. We use these results to guide our empirical investigations below. All derivations not explicitly shown are in the Appendix.

2.1. Predictions under imperfect information

A continuum of firms, indexed by i, produce differentiated goods using capital (K_t) and labor (N_t) according to a constant returns to scale Cobb–Douglas production function:

\[ Y_{it} = K_{it}^{\alpha} N_{it}^{1-\alpha}. \]

Demand for each good takes a standard constant elasticity of demand form

\[ Q_{it} = A_{it}^\sigma P_{it}^{-\sigma}, \]

where \( A_{it} \) represents a demand shifter, \( P_{it} \) is the price of the good, and \( \sigma > 1 \) denotes the (absolute value of the) elasticity of demand. Firm revenues are then given by

\[ P_{it} Y_{it} = A_{it} K_{it}^{\hat{\alpha}} N_{it}^{\hat{\beta}}, \]

where

\[ \hat{\alpha} = \alpha - \frac{\sigma - 1}{\sigma}, \quad \hat{\beta} = (1 - \alpha) - \frac{\sigma - 1}{\sigma}, \quad \hat{\alpha} + \hat{\beta} = \frac{\sigma - 1}{\sigma}. \]

Input markets work as follows. In each period, the firm can purchase capital at a price normalized to one and hires labor in a competitive labor market at wage \( W_t \). The firm produces, accrues revenues, and sells its undepreciated capital at the end of the period. Capital depreciates at rate \( \delta \). The firm discounts time at rate \( \beta \).

We assume, first, that the firm chooses capital and labor to maximize profits under imperfect information regarding the fundamental \( A_{it} \) and that there is no further adjustment of inputs after its true value is realized. Specifically, the firm solves

\[ \max_{K_{it}, N_{it}} \Pi_{it} = \mathbb{E}_{it}[A_{it}] K_{it}^{\hat{\alpha}} N_{it}^{\hat{\beta}} - R K_{it} - W_t N_{it}. \]  

(1)

where \( R = 1 - \beta (1 - \delta) \) is the user cost of capital.\(^3\) Fundamentals, \( A_{it} \), and expectations are jointly log-normally distributed. Without loss of generality, we normalize the unconditional mean of \( A_{it} \) to one.

We can derive the following expressions for the optimal choices of capital and labor

\[ K_{it} = C_{1t} \mathbb{E}_{it}[A_{it}]^{\sigma}, \]

\[ N_{it} = C_{2t} \mathbb{E}_{it}[A_{it}]^{\sigma}, \]  

(2)

where \( C_{1t} \) and \( C_{2t} \) are time varying terms that are common across firms, which reflect the wage and cost of capital. Expression (2) shows that the firm’s input choices are monotonically increasing in its expectations of fundamentals. Revenues and profits are given by

\[ P_{it} Y_{it} = C_{3t} A_{it} \mathbb{E}_{it}[A_{it}]^{\sigma-1} \]  

(3)

\[ \Pi_{it} = C_{3t} \left( A_{it} \mathbb{E}_{it}[A_{it}]^{\sigma-1} - \frac{\sigma - 1}{\sigma} \mathbb{E}_{it}[A_{it}]^{\sigma} \right). \]  

(4)

where \( C_{3t} \) is constant across firms. Expression (3) shows that, conditional on the realization of fundamentals, the firm’s revenues are increasing in its expectations. We can use expression (4) to prove that profits are decreasing in the absolute value of the forecast error. In other words, profits are maximized where \( \mathbb{E}_{it}[A_{it}] = A_{it} \) and are declining in the difference between expected and realized fundamentals. Finally, measured productivity is calculated as revenues divided by inputs taken to the powers of their respective elasticities in production. Importantly, this is a measure of revenue-based productivity, i.e., TFPR, rather than quantity-based productivity (TFPQ). We can derive TFPR as

\[ TFPR_{it} = C_{4t} \left( \frac{\mathbb{E}_{it}[A_{it}]}{A_{it}} \right)^{-1}. \]  

(5)

\(^3\) This setup is equivalent to one with a rental market for capital where the rental rate is equal to \( R \).
where $C_d$ is again a constant across firms. In other words, TFPR varies inversely with the firm’s forecast error, which is the term in parentheses (the ratio of expected fundamentals to actual). Intuitively, when the firm is overly optimistic, it over-accumulates inputs relative to the optimal level under full information, reducing the marginal revenue productivity of those inputs. The opposite occurs when the firm is overly pessimistic. We can summarize the key predictions of this simple framework as follows:

**Prediction 1:** Input choices are increasing in the firm’s expectations.

**Prediction 2:** Revenues are increasing in the firm’s expectations.

**Prediction 3:** Profits are decreasing in the absolute value of the forecast error.

**Prediction 4:** TFPR is decreasing in the forecast error.

2.2. Predictions with additional adjustment and disruption costs

Next, we extend the environment to allow the firm to further adjust its input choices after the realization of the fundamental, but where these latter adjustments are subject to disruption costs that reduce output. To obtain clear analytical results, we focus on a special case with only one input, which we call capital, but can alternatively be thought of as a composite input. The key result from this extension is that TFPR is no longer necessarily decreasing in the forecast error for pessimistic firms – while optimistic firms are still predicted to have lower TFPR, because of the disruption cost, pessimistic firms can have lower TFPR as well, reversing the implied sign for these firms from the simpler model.\(^4\)

There are two stages within each period. In the first, the firm forms expectations and chooses a level of capital, $K_{it}^0$, paying only the explicit cost of new capital. In the second stage, the firm observes the realization of the fundamental and can re-adjust its stock of capital. To perform this additional adjustment, the firm must pay the explicit cost of any new capital as well as the additional disruption costs. We assume that these costs take the form

$$
\Phi(K_{it}, K_{it}^0) = \frac{\xi}{2} \left( \frac{K_{it}}{K_{it}^0} - 1 \right)^2, \quad \xi \in (0, \infty),
$$

where $K_{it}$ denotes the final amount of capital used in production and $\xi$ captures the severity of the cost. Similar specifications are commonly used to describe settings where firms find it harder to work efficiently with excessive or inadequate inputs.\(^5\)

With these assumptions, the output of the firm is given by:

$$
Y_{it} = K_{it} - \Phi(K_{it}, K_{it}^0).
$$

We set up and solve the firm’s problem in the Appendix. The firm’s final choice of capital is given by

$$
K_{it} = C_d \left[ A_{it}^{\phi_1} \right]^{\phi_2} [A_{it}]^{\phi_2}.
$$

where

$$
\phi_1 = \frac{\sigma}{1 + \sigma \xi}, \quad \phi_2 = \frac{\sigma \xi}{1 + \sigma \xi}.
$$

Capital now depends both on the firm’s initial expectations, as well as the realization of the fundamental, with weights determined by the exponents $\phi_1$ and $\phi_2$. If the disruption cost, $\xi$, approaches infinity, $\phi_1$ approaches zero and $\phi_2$ one, i.e., the firm will not adjust to the realization of the shock and capital is only determined by initial expectations, as in the simpler model above. If $\xi$ approaches zero, the firm can respond fully to the true fundamental, e.g., $\phi_2$ goes to zero.

We can then derive the following expression for TFPR:

$$
TFPR_{it} = C_d \left( 1 + \xi \right) Z_{it}^{-\xi \phi_1 (1 - \phi_1)} - \frac{\xi}{2} Z_{it}^{-\xi \phi_1 (1 - \phi_1) - 2 \phi_1} - \frac{\xi}{2} Z_{it}^{-\xi \phi_1 (1 - \phi_1)} \right)^{\phi_1}. \tag{6}
$$

where $Z_{it} \propto \frac{X_{it} \Phi_{it}}{A_{it}}$ captures the firm’s forecast error. Similar to Eq. (5), expression (6) shows that even in this more complicated setting, TFPR depends only on the firm’s forecast error. We can use expression (6) to prove that TFPR is strictly decreasing in the forecast error when $Z_{it} > 1$, i.e., when the firm is overly optimistic. However, there is a value of $Z_{it}$, $\hat{Z} < 1$ such that TFPR is increasing in $Z_{it}$ when $Z_{it} < \hat{Z}$. In other words, larger (absolute) forecast errors reduce TFPR for (sufficiently) pessimistic firms as well.

Intuitively, there are two effects of forecast errors on TFPR: the first is the same as in the simpler environment above – optimistic firms over-accumulate inputs relative to actual fundamentals, reducing the measured productivity of those inputs.

\(^4\) In the Appendix, we show that the logic of this case extends to a setting where we explicitly model labor separately from capital. Specifically, we show that when capital and labor are chosen simultaneously and subject to the same cost functions, labor is linear in capital, i.e., $N_t = \eta_t K_t$, where $\eta_t$ is a function of period t wages, and can be substituted out, leading to a production function that is linear in capital, which is the example here. For other cases, we can no longer analytically characterize the sign of the derivative of TFPR with respect to the forecast error, but simulations show similar patterns to the ones here.

\(^5\) One reason may be fixed costs of operations and diminishing returns to scale – see, for example, Bartelsman et al. (2013).

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The opposite occurs for pessimistic firms, which together lead to a universal negative relationship between TFPR and forecast errors. The second effect comes from the disruption costs – the larger the firm’s forecast error, the greater will be its within period adjustment and so the larger the disruption cost to output. These costs will reduce measured TFPR, since output will be lower for the same level of inputs. This holds whether the firm is optimistic or pessimistic. Notice that for optimistic firms, the two effects work in the same direction, i.e., they both serve to reduce measured TFPR. Thus, for these firms, TFPR is unambiguously decreasing in the forecast error. For pessimistic firms, the two effects work in opposite directions – the first increases TFPR, the second reduces it. For sufficiently pessimistic firms, the second effect dominates. We summarize this result in the following prediction:

**Prediction 5:** When the firm can adjust its input choices upon realization of the fundamental but subject to disruption costs, TFPR is decreasing in the forecast error for optimistic firms and for (sufficiently) pessimistic firms.

3. Data

The survey data we use is the Annual Survey of Corporate Behavior (ASCB hereafter) conducted by the Economic and Social Research Institute in the Cabinet Office of Japan. We use data over the period 1989–2015, as individual firm identifiers are available only after 1989. In each year, the survey questionnaire was sent to all listed firms on the Tokyo and Nagoya Stock Exchanges. This consists of about 2200 firms on average during these years. Of them, 53% on average responded to the survey each year (see Appendix Fig. A.1 for the number of responses in each year). The survey is conducted annually between mid-December and mid-January. Respondents are required to answer questions regarding their business outlook for GDP and industry demand, and their business plans for investment and employment. The forecasts are made for multiple horizons. The main variable we use is the forecast of real GDP growth rate in Japan in the upcoming fiscal year that starts from April. For example, the questions asked in December 2004 were phrased the following way:

Please enter a figure up to one decimal place in each of the boxes below as your rough forecast of Japan’s nominal and real economic growth rates and the nominal and real growth rates of demand in your industry for FY 2005, the next 3 years (average of FY 2005–2007) and the next 5 years (average of FY 2005–2009).

A potential concern in this survey measure is whether the answers truly reflect the firms’ forecasts of future macroeconomic growth that are used for their decision making. We conduct several checks for this issue. First, while the survey does not obtain positions of respondents, it collects information on the respondent’s department since 2006. This reveals that 66% of the respondents belong to departments responsible for corporate planning and strategy, general management, and CEO office (see Appendix Table A.1 for details). The rest of the answers are from departments of finance (12%), general affairs (12%), and IR and public relations (7%). Second, we find that annual sales growth rates of the firms in our sample are strongly positively correlated with realized Japanese GDP growth, suggesting that the sample of firms in this study, which consists of relatively larger firms in Japan, would have incentives to obtain accurate GDP growth forecasts. Third, looking at the autocorrelations of forecasts and forecast errors with and without firm fixed effects, it is neither the case that the firms are repeating the same forecasts over and over, nor that they are answering with the current year GDP growth rate (for the results, see Appendix Table A.2). Fourth, we find significant variation in GDP expectations across firms above and beyond the variation in firms’ forecasts of their own performance, suggesting that firms are not simply using information about their own plans to form their GDP forecasts (see Appendix Table A.3). Fifth, on average, the GDP forecasts provided by firms align well with that of professional forecasters over time (see Appendix Fig. A.4). These observations suggest that most of the respondents provide meaningful values that, on average, roughly follow professionals’ forecasts. Even so, there may be some outliers that provide unrealistic forecasts that could affect our analysis. Thus, in order to reduce the potential effects of outliers, we exclude observations that make extreme GDP growth forecasts (1% of the sample in each tail). In the following section, we further test and confirm that firms’ input choices are indeed significantly correlated with their macro forecasts even after controlling for firm and year fixed effects.

The left hand side of Fig. 1 shows the distribution of “firm i’s forecast for fiscal year t + 1 real economic growth rate answered in fiscal year t” (denote by $f_{i,t}(t + 1)$ hereafter). The right hand side of Fig. 1 shows the distribution of the absolute value of forecast errors in each year, namely $|e_{i,t-1}(t)| = |f_{i,t-1}(t) − g(t)|$, where $g(t)$ is the realized GDP growth rate of the year $t$.

As additional checks of the survey data, in Fig. 2 we plot time-series of the means of $f_{i,t}(t + 1)$ and $g(t)$. The two lines roughly correspond in terms of ranges, implying that the forecasts for the following year tend to reflect the realization of the growth rate in the current year. The mean of the forecasts tend to be more correlated with contemporaneous GDP growth than with the targeted GDP growth. In Fig. 3, we show the yearly average of the “absolute value of forecast errors in each year”, namely $|e_{i,t-1}(t)| = |f_{i,t-1}(t) − g(t)|$. The same figure also plots annual daily stock volatility based on Tokyo Stock Price Index (TOPIX) and the average of the monthly Economic and Policy Uncertainty Index for Japan (see

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6 Appendix Fig. A.2 shows the corresponding part of the questionnaire

7 Appendix Fig. A.3 shows this by a binned scatter plot.

8 In this study, we assume that the survey respondents interpreted “the real economic growth rate” as the real GDP growth rate.

9 Also see the binned scatter plots in Appendix Fig. A.5.

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Fig. 1. Forecasts and forecast errors.
Notes: Left figure shows the histogram of fiscal year $t$ GDP growth rate forecasts answered by firm $i$ in fiscal year $t-1$ in the ASCB, for the entire sample periods. The vertical line shows the average of realized GDP growth rates during the period. The right figure shows the histogram of the absolute values of forecast errors, the forecasts less their realized values. Both forecasts and forecast errors are measured in percentage. Both forecasted and realized GDP series are in real terms.

Baker et al. (2016) for each fiscal year. The three series are normalized to mean 0 and standard deviation 1. The series share the peaks around the mid 1990s, 2000, and 2007, suggesting that periods with larger forecast errors correspond to those with larger macro uncertainty.
In addition to the forecasts of GDP growth rates, the survey asks about the firm’s forecasts of its investment and employment growth over the next three years. The respondents were asked to mark one of several bins containing 5% intervals, for example, “5–10%”. We use the median values of these intervals to construct variables representing investment and employment growth forecasts.\(^\text{11}\)

We match the responses in the survey with a number of other datasets at the firm level. We use the Development Bank of Japan’s Financial Data of Listed Firms (DBJ data hereafter) to capture the financial conditions of firms, and Nikkei Needs Financial Quest for information on stock price, firm age, and ownership structure. In addition to the firm-level data, we use “Consensus Forecasts” published by Consensus Economics to compare firm forecasts with professional forecasts. In our baseline specification, we use professional forecasts made in December about Japan’s real GDP growth rate of the next calendar year. As for the actual values of Japan’s real GDP growth, we use the GDP estimates of FY 1990–FY 2015 from the Cabinet Office as of June 2016.

It is possible that the response rates to the ASCB are correlated with certain firm characteristics. Indeed, a logit model estimation of response rates using the sample of DBJ data shows that larger and older firms were more likely to have responded to the survey (see Appendix Table A.4 for the results). The magnitude of the response differences are small – for example, a 10% increase in sales size induces a 0.4% increase in the response rate. Nevertheless, this sample selection might potentially bias our results, so we also re-estimate our main equations by weighting samples by inverse of response rates as robustness checks and find qualitatively the same results.

To calculate firm-level TFP, we follow Syverson (2011) and assume a Cobb–Douglas production function in which TFP is derived as follows: $\text{TFP}_j = \ln(Y_j) - S_{jk} \ln(L_j) - S_{jk} \ln(K_j) - S_{jk} \ln(M_j)$, where $S_{jk}$ represents cost share of factor $k$ for industry $j$ in year $t$, and $Y_j, L_j, K_j$, and $M_j$ denote gross output measured by sales revenue, labor, capital, and intermediate inputs of firm $i$ in year $t$, respectively.\(^\text{12}\) Cost shares are defined at the industry level to reduce the impact of firm-level measurement error, as is standard in the literature. The cost shares for each industry are obtained from the Japan Industrial Productivity Database 2015 (JIP database hereafter) published by Research Institute of Economy, Trade, and Industry. Gross output is defined as sales divided by the industry-level output deflator from the JIP database. Labor input is calculated as the product of the number of workers and average hours worked in the industry. Capital is defined as tangible assets excluding land and is computed using the perpetual inventory method. Data source for gross output and factors is described

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\(^\text{11}\) Fig. A.6 in the Appendix shows this part of the questionnaire. The questionnaire asks for the firm’s hiring and investment plans worldwide (including Japan). Two extreme forecasts, “25% or more” and “−25% or less”, are represented by 30% and −30%.

\(^\text{12}\) Investment hereafter refers to investment in physical assets such as machinery, vehicles, buildings, and structures. For calculating real investment and the capital stock, we first divide nominal gross investment by the corresponding price indices, and then apply the perpetual inventory method to three types of capital: buildings and structures; machinery and equipment; and vessels and vehicles, following Hayashi and Inoue (1991). For price indices, we use the Bank of Japan’s Corporate Goods Index.

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in detail in the Appendix. Appendix Table A.5 shows the basic sample statistics for our main variables. To mitigate the effect of outliers, we winsorize the 1% tails of investment, employment, and sales growth.

In order to measure the cyclicity of firms with respect to the Japanese macro economy, we estimate the degree of sensitivity of firms’ quarterly sales growth to quarterly GDP growth at the industry level. Specifically, we estimate the following regression:

$$DLn(Sales_{ijt}) = \beta_1 DLn(GDP_t) + F_t + F_q + Year_t + \epsilon_{it}$$

where $DLn(Sales_{ijt})$ is the quarterly sales growth of firm $i$ in industry $j$ from April 2004 to June 2016 and $DLn(GDP_t)$ is the growth of quarterly real GDP from the Cabinet Office as of June 2016. Firm fixed effects, $F_t$, quarter fixed effects (to control for seasonality), $F_q$ (for $q = 1, 2, 3$), and a linear time trend are controlled. The specification allows the coefficients $\beta_j$ to vary across 27 industries, defined by the first 2-digits of securities codes that customary reflect the firm’s industry (throughout the analysis, we exclude finance and banking sectors). The estimates of $\beta_j$ have a median of 0.7 (mean of 1.4) with a standard deviation of about 4, which implies large variation across industries. To verify our estimates, we have also estimated industry-level cyclicity measures for these industries (matched with SIC codes) following the same methodology using data on US publicly listed firms from Compustat. There is a strong positive correlation between the measures (see Appendix Table A.6). As a further robustness check, we have estimated the degree to which the firm’s stock price reacts to a surprise in quarterly GDP announcements and used those estimates as an alternative measure of cyclicity (see Appendix for details and results).

4. Forecasts and firm performance

In this section, we investigate the relationships between firms’ GDP forecasts, their input choices and subsequent performance.

4.1. Firm input choices and sales

First, we estimate the following empirical equation:

$$Y_{it} = \rho f_{i,t-1}(t) + \gamma_i + \lambda_t + \eta_{it}$$

where $Y_{it}$ is the growth rate in either employment, investment, or sales of firm $i$ from fiscal year $t-1$ to fiscal year $t$. $f_{i,t-1}(t)$ is the forecast of GDP growth rate in fiscal year $t$ answered by firm $i$ in year $t-1$. We include firm fixed effects ($\gamma_i$) to control for unobserved time-invariant characteristics of the firms. We also control for realizations of macro economic shocks by controlling for year fixed effects ($\lambda_t$). Since some firms responded to the survey sporadically over the 25 year period, making identification of within-firm effects more difficult, we further limit our sample to observations that have non-missing GDP forecasts in the last two consecutive years (i.e. both $f_{i,t-1}(t)$ and $f_{i,t-2}(t-1)$ are observed) for the analysis in this section.

A primary purpose of estimating Eq. (8) is to test the quality of the survey. Since the survey targeted all stock-exchange listed firms, the sample is made up primarily of large firms. Because of this, there is a possibility that the respondent’s forecast does not reflect the forecast actually used for the company’s decision making. But if the firm’s survey response does reflect the beliefs of the firm’s managers, then we would expect to see a positive association between a firm’s forecasts and its input choices such as investment and employment.

The specification of a one-year lag between forecasts and outcomes is considered to be reasonable for the following reasons. First, Japanese firms commonly adjust their employment levels by hiring fresh college graduates. Interviews and employment offers for hiring these workers in year $t$ are most concentrated around the period from April to June of year $t-1$ due to customs of the Japanese freshen labor market. Similarly, it is natural to assume that firms need to make arrangements (e.g. financing) at least a year prior for raising investment in year $t$.

Fig. 4 illustrates the relationship of Eq. (8) by binned scatterplots. The horizontal axis shows the residual values of $f_{i,t-1}(t)$ after extracting year and firm fixed effects. The values are grouped into equal-sized 15 bins, and for each bin, the vertical axis shows the mean values of $Y_{it}$ again after extracting year and firm fixed effects. The figure reveals a clear positive association between firms’ reported forecasts and their input choices and resulting output.

Table 1 reports the OLS estimates of Eq. (8). Columns (1) and (2) estimate the equations for employment and investment growth including year and firm fixed effects. The estimated coefficients on the forecast are positive and statistically

---

13 Since the quarterly sales data is available only since 2004, we do not have large enough sample per each firm to estimate firm specific coefficients.

14 Only 2% of the sample had zero investment values, which were dropped when we estimate the equation for investment growth. As a robustness check, we employed an alternative measure of investment growth by adding value 1 (i.e. $ln(investment_{t} + 1) - ln(\text{investment}_{t-1} + 1)$) and found that the qualitative results were unchanged.

15 Interestingly, not controlling for year fixed effects result in larger estimates of $\rho$ for employment, investment, and sales growth than the ones in the baseline specification shown below. Assuming that forecasts and realizations of aggregate shocks are positively correlated, this result is consistent with our model in Section 2.2 where firms can make costly readjustments of inputs after observing the realizations of the shocks. This point highlights the importance of controlling for the realizations of the shocks in order to separately examine the effect of forecasts.

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Examining R&D expenditures yields similar results. For example, in a specification analogous to column (4) with firm fixed-effects, the coefficient (and standard error) on ln(1+R&D) is 1.03 (0.42).
respectively, suggesting that the coefficients are economically large, presumably reflecting the importance of aggregate economic conditions for employment and investment in large Japanese firms.\(^\text{17}\)

Column (3) estimates Eq. (8) for sales growth. The estimated coefficient suggests that a 1 percentage point higher GDP growth rate forecast predicts an increase in sales growth rate of 0.4 percentage points. Overall, the results imply that firms’ reported forecasts of GDP growth are significantly correlated with their input choices as implied by the baseline model (Prediction 1).

A natural conjecture is that macro forecasts affect firms’ realized inputs by influencing their initial plans for hiring and investment. Using the data on the firms’ forecasts of own-investment and employment, we find evidence consistent with this hypothesis. Specifically, in columns (4) and (5), we regress firms’ forecasts of investment and employment growth for the next three years on its GDP growth forecast for the next year, which are all answered in year \(t - 1\). The estimated coefficients are large, positive, and significant at the 1% level, implying that a 1 percentage point change in the GDP growth rate forecast corresponds to a 0.2 and 0.4 percentage point change in expected employment and investment growth, respectively. We then examine the relationship between forecasts and realizations of employment and investment growths. In columns (6) and (7), the dependent variables are the realized growth rate in employment and investment over the corresponding three years, i.e., from year \(t - 1\) to \(t + 2\). The results show that the input growth forecasts are highly significantly correlated with their realization even after controlling for firm and year fixed effects.

One concern is that these results may reflect unobserved firm-specific shocks that affect both macro forecasts and outcomes or, relatedly, that given the persistence in outcome variables, forecasts may not have predictive power above and beyond the information in lagged outcomes. We find that additionally controlling for lagged outcomes (i.e., employment growth, investment growth, and sales growth) in columns (1)-(3), respectively, does not alter the qualitative results. Moreover, controlling for lagged forecasts of GDP growth \((f_{t-2} (t - 1))\) produces the same qualitative results.\(^\text{18}\) Still, these findings do not exclude the possibility that there are unobserved shocks affecting both macro forecasts and outcomes, which suggests a degree of caution in interpreting our results as causal evidence.

4.2. Profit and productivity

Next, we explore the relationship between firms’ forecast errors and realized performance by estimating the following equation:

\[
V_t = \theta |e_{t-1}(t)| + \gamma_1 + \lambda_t + \omega_{it}
\]

where \(V_t\) is either profit or measured TFP of firm \(i\) in year \(t\). \(|e_{t-1}(t)|\) is the absolute value of firm \(i\)’s GDP growth forecast error defined as \(e_{t-1}(t) = f_{t-1}(t) - g_r\), where \(g_r\) is the realized GDP growth rate in fiscal year \(t\). We control for time-invariant firm characteristics and realizations of macro-level shocks by including firm fixed effect \((\gamma_1)\) and year fixed effect \((\lambda_t)\). As before, we limit our sample to observations with non-missing forecasts in the last two consecutive years.

Fig. 5 illustrates the results by binned scatter plots. In the upper two figures, the horizontal axis shows residual values of \(|e_{t-1}(t)|\) after extracting year and firm fixed effects. As before, the values are grouped into equal-sized 15 bins, and the vertical axis plots the mean of \(V_t\) in each bin, after extracting year and firm fixed effects. The results show negative relationships between forecast errors and profit and productivity. In the lower two figures, we divide the observations by over- and under- forecast errors. That is, the \(x\)-axis is the residual values of over-forecast errors \((|e_{t-1}(t)| \cdot 1(e_{t-1}(t) > 0)\) after regressing on year and firm fixed effects and adding the mean if the forecast error is positive \((e_{t-1}(t) > 0);\) otherwise, the \(x\)-axis is residual values of under-forecast error \((|e_{t-1}(t)| \cdot 1(e_{t-1}(t) < 0))\) after regressing on year and firm fixed effects and adding the mean. The figures show higher values of profit and TFP around the locations where the raw value of error is close to zero. In particular, the relationships appear to be roughly symmetric around zero, i.e., profits and productivity are highest when forecast errors are lowest in absolute value and decrease as the forecast error grows in either direction.

Table 2 shows the OLS estimates for regressions of Eq. (9). Column (1) reports the results for profit. The estimated coefficient is negative and statistically significant at the 1% significance level. The size of the coefficient is economically large: for example, having a 1 percentage point higher or lower GDP growth rate forecast error predicts a decline in profitability of about 856 million Japanese Yen, which is equivalent to around 8 million USD.\(^\text{19}\) Column (2) shows the result for TFP. The coefficient estimate on the absolute forecast error is negative and statistically significant at 1% level. The result implies that a 1 percentage point higher forecast error (in absolute value) is associated with a 0.66% lower level of measured TFP.

We also examined the robustness of these findings against possible sampling selection effects by employing two alternative specifications and found similar results as in the main specification (see Appendix Table A.8): (1) estimating Eq. (9) by weighting observations by the inverse of response rates and (2) including the outliers of growth forecasts, i.e., the 1% tails.

\(^\text{17}\) Annual average investment declined an average of 2.4% per year (43% cumulative) among the firms in our sample. This is consistent with falling average investment for all Japanese firms over this period. For example, data from the Financial Statements Statistics of Corporations by Industry from the Ministry of Finance show an average annual decline in average firm investment of 2.3% (42% cumulative) across all firms and 2.8% (48% cumulative) for large firms in particular (capital greater than 10 billion Yen).

\(^\text{18}\) These results are shown in Appendix Table A.7.

\(^\text{19}\) Note that the standard deviation of forecast errors in the sample is 1.12%. The average exchange rate during 1989–2018 is used.

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Fig. 5. Binscatter plots for profit and TFP.

Notes: The figures show the relationship between forecast errors ($\epsilon_{t-1}(t)$, measured in percentage) and firm's profit and TFP by binned scatterplots. In the upper figures, the x-axis shows residual values of absolute forecast errors ($|\epsilon_{t-1}(t)|$) after repressing on year fixed effects and firm fixed effects and adding the mean. In the lower figures, the x-axis is residual values of absolute positive forecast errors ($|\epsilon_{t-1}(t)(+)|$) after repressing on year fixed effects and firm fixed effects and adding the mean if the forecast error is positive ($\epsilon_{t-1}(t) > 0$); otherwise, the x-axis is residual values of absolute negative forecast errors ($|\epsilon_{t-1}(t)(-)|$) after repressing on year fixed effects and firm fixed effects and adding the mean. In both upper and lower figures, the y-axis shows the average of the residual value of $V_i$ (either profit or TFP) for each equal-sized 15 bins (30 bins for lower figure) of x-axis. The unit of profit is billion Japanese Yen. Sample is restricted to observations with non-missing GDP forecasts in the last two consecutive years (that is, $f_{t-1}(t)$ and $f_{t-2}(t-1)$ are observed).

Table 2 GDP forecast errors and firm performance.

<table>
<thead>
<tr>
<th>(1) Profit</th>
<th>(2) TFP</th>
<th>(3) Profit</th>
<th>(4) TFP</th>
<th>(5) Profit</th>
<th>(6) TFP</th>
<th>(7) Profit</th>
<th>(8) TFP</th>
</tr>
</thead>
<tbody>
<tr>
<td>$</td>
<td>\epsilon_{t-1}(t)</td>
<td>$</td>
<td>$-85.60^{**}$</td>
<td>$-85.60^{**}$</td>
<td>$-92.39^{**}$</td>
<td>$-92.39^{**}$</td>
<td>$48.82$</td>
</tr>
<tr>
<td>$\epsilon_{t-1}(t)(+)$</td>
<td>$33.73$</td>
<td>$33.73$</td>
<td>$104.49^{**}$</td>
<td>$104.49^{**}$</td>
<td>$(48.07)$</td>
<td>$48.07$</td>
<td>$(0.40)$</td>
</tr>
<tr>
<td>$\epsilon_{t-1}(t)(-)$</td>
<td>$-62.80^{**}$</td>
<td>$-62.80^{**}$</td>
<td>$-52.52^{**}$</td>
<td>$-52.52^{**}$</td>
<td>$26.32$</td>
<td>$26.32$</td>
<td>$(0.23)$</td>
</tr>
<tr>
<td>$\frac{1}{T} \sum_{i=1}^{T}</td>
<td>\epsilon_{t-1}(t)</td>
<td>$</td>
<td>$-25.73$</td>
<td>$-25.73$</td>
<td>$-92.92^{*}$</td>
<td>$-92.92^{*}$</td>
<td>$85.08$</td>
</tr>
<tr>
<td>$</td>
<td>\epsilon_{t-1}(t+1)</td>
<td>$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>$-19.09$</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Firm FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>15,410</td>
<td>12,479</td>
<td>15,410</td>
<td>12,479</td>
<td>9624</td>
<td>7821</td>
<td>14,170</td>
</tr>
<tr>
<td>N firms</td>
<td>2086</td>
<td>1737</td>
<td>2086</td>
<td>1737</td>
<td>1526</td>
<td>1264</td>
<td>1966</td>
</tr>
</tbody>
</table>

Notes: $|\epsilon_{t-1}(t)|$ is a measure of forecast error defined by the absolute value of difference between firm i's forecast of GDP growth in fiscal year $t$ answered in year $t-1$ and the realized GDP growth in fiscal year $t$. $|\epsilon_{t-1}(t+1)|$ is measured in percentage, $\epsilon_{t-1}(t)(+)=|\epsilon_{t-1}(t)|$ if $|\epsilon_{t-1}(t)| > 0$ and $\epsilon_{t-1}(t)(-) = |\epsilon_{t-1}(t)| + 1$ if $|\epsilon_{t-1}(t)| < 0$, where $\epsilon_{t-1}(t)$ is a measure of forecast error defined by the firm's forecast of GDP growth in fiscal year $t$ answered in year $t-1$ minus the realized GDP growth in fiscal year $t$. Profit and TFP are the measures of fiscal year $t$. Unit of profit is billion JPY. $\frac{1}{T} \sum_{i=1}^{T} |\epsilon_{t-1}(t)|$ is the average absolute forecast errors of firm i in the 3 years preceding to the year $t-1$. Sample is restricted to observations with non-missing GDP forecasts in the last two consecutive years (that is, $f_{t-1}(t)$ and $f_{t-2}(t-1)$ are observed). Driscoll–Kraay standard errors with lag 4 are shown in the parentheses.

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of the sample. Also, we observe qualitatively the same results when we regress the growth rate of TFP instead of the level of TFP on absolute forecast errors (the estimated coefficient is \(-0.53\) and the standard error is 0.16). Further, we have estimated specifications excluding Japanese multinational firms, defined as firms that produce more than 50% of their total production value abroad and controlling for lagged outcomes (i.e. lagged sales growth). In both cases, the qualitative results go through. Finally, it is worth noting that our data includes the period of Japan’s “lost decade”, i.e. the period of declining growth that started suddenly in the early 1990s.21 Focusing on the period from 2000 to 2015 yields qualitatively similar results as the baseline, suggesting that our findings are not specific to the early part of this period (see Appendix Table A.8).

Next, we estimate the same equation, (9), but allowing the coefficients of under-forecast error \([|\varepsilon_{t-1}(t)| \cdot 1(\varepsilon_{t-1}(t) < 0)\] and over-forecast error \([|\varepsilon_{t-1}(t)| \cdot 1(\varepsilon_{t-1}(t) > 0)\] to differ. Columns (3) and (4) of Table 2 estimate such equations for profit and TFP. The results indicate that both pessimistic and optimistic errors are negatively and significantly related with profit and productivity in the subsequent year.

Our results on profit are consistent with Prediction 3 derived based on a standard dynamic model of firms. That is, firms’ performance would be maximized when firms choose inputs with more accurate information about its future conditions. Further, our results on TFP are consistent with Prediction 5 obtained from a model where firms can adjust their initial input choices subject to disruption costs: the interaction of the pricing effects from having too few or too many inputs with larger disruption costs leads to lower measured productivity for both optimistic and pessimistic firms. Thus, both profit and productivity decline when firms over- or under- invest by mis-forecasting future productivity growth.

An alternative explanation of the results is not that forecast errors shape performance, but that both forecast errors and performance are correlated with some firm-level unobservable like management quality. Firms with high-ability managers are more capable of making accurate forecasts, while such high-ability managers are more likely to employ high-performing management practices. To explore this possibility, we add in the estimation equation a historical average of the firm’s forecast errors for the three years preceding the year \(t - 1\) (i.e. \(t - 2, t - 3, t - 4\)). Our intuition behind this test is as follows. Manager’s ability and its effect on firm performance are considered to persist for relatively long periods. Therefore, the historical average of past forecast errors is likely to be a more accurate proxy of the firm’s managerial ability than the prior year forecast error. Hence, if forecast errors proxy for managers’ ability, then the long-run effect of the historical average should dominate the short-run effect. To test this hypothesis, columns (5) and (6) of Table 2 show the results of adding the historical average of forecast errors. Overall, the coefficients are both negative, but the negative coefficients of 1 year lagged forecast errors stay large and significant while the longer-run average is either insignificant (profits) or only weakly significant (TFP). Finally, in columns (7) and (8), we also estimate the specification where the forecast errors are those of the next year \((|\varepsilon_{t+1}(t)|)\) rather than the current year \((|\varepsilon_{t-1}(t)|)\) and find insignificant results, suggesting against a basic reverse causality mechanism.22

4.3. Results by firm cyclicality and export status

It is reasonable to expect that firms whose performance is more sensitive to the macro economy would be more responsive to their expectations of future GDP growth rates. We explore this possibility by dividing the sample into high and low cyclicality firms using the industry cyclicality measure described in the data section. In addition, since firms selling in foreign markets may be less affected by Japanese GDP growth, we further divide the sample into exporting and non-exporting firms.24 Table 3 shows the results. Columns (1), (4), (7), and (10) show the estimates for non-exporting firms with an above-median industry cyclicality index, columns (2), (5), (8), and (11) show the results for non-exporting firms with a below-median cyclicality index and the remaining columns show the results for exporting firms. Overall, we find strong evidence that non-exporting and more cyclically sensitive firms exhibit a tighter correlation between GDP forecasts and outcomes than other firms.

As a robustness check, we have also used an alternative cyclicality measure to divide the sample and find similar results. Specifically, for each firm, we estimate the degree to which the firm’s stock price reacts to a surprise in quarterly GDP announcements. Table A.9 in the appendix shows these results, which are qualitatively the same as the results in Table 3.

20 Additionally, we examined a different specification using a squared loss function (i.e. \((\varepsilon_{t-1}(t))^2\)) rather than using the absolute loss function. The results are shown in the Appendix Table A.8. We find that both profits and TFP are still negatively and significantly associated with the squared error (although TFP is somewhat more weakly significant, i.e. at the 10% level, possibly due to the offsetting effects of the two possible mechanisms through which forecasts may affect TFP discussed in the theory section).
21 This feature of the economy may explain some characteristics of firms’ macro forecasts in our data. For example, as shown in Fig. 1, average firms’ GDP growth forecasts are over-optimistic compared to the realizations for all years in 1991-1994. This might be because many firms initially did not expect the period of slow growth to last so long.
22 Results are similar when we use profit divided by sales as an alternative measure of profitability. For example, using this as a dependent variable in the specification of column (3) of Table 2, we find point estimates (standard errors) on positive and negative forecast errors of \(-0.14 (0.07)\) and \(-0.32 (0.12)\), respectively.
23 We also examined similar specifications using two-year ahead forecast errors, \((|\varepsilon_{t+2}(t+1)|)\), and find insignificant results.
24 There is a question in ASCB asked only to exporting firms. We identify exporting companies based on whether the firm answered this question.

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Table 3

GDP forecasts and firm performance by export status and cyclicity.

<table>
<thead>
<tr>
<th>Export status Cyclicity</th>
<th>(1) D ln(Emp)</th>
<th>(2) D ln(Emp)</th>
<th>(3) D ln(Emp)</th>
<th>(4) D ln(lnv)</th>
<th>(5) D ln(lnv)</th>
<th>(6) D ln(lnv)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-exporter High</td>
<td>0.63**</td>
<td>0.30</td>
<td>0.10</td>
<td>5.49**</td>
<td>0.95</td>
<td>2.76</td>
</tr>
<tr>
<td></td>
<td>(0.13)</td>
<td>(0.11)</td>
<td>(0.06)</td>
<td>(2.61)</td>
<td>(1.87)</td>
<td>(2.43)</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Firm FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>3789</td>
<td>5052</td>
<td>6568</td>
<td>3721</td>
<td>4691</td>
<td>6525</td>
</tr>
<tr>
<td>N firms</td>
<td>818</td>
<td>770</td>
<td>1061</td>
<td>806</td>
<td>742</td>
<td>1052</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Export status Cyclicity</th>
<th>(7) Profit</th>
<th>(8) Profit</th>
<th>(9) Profit</th>
<th>(10) TFP</th>
<th>(11) TFP</th>
<th>(12) TFP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-exporter High</td>
<td>−13.180**</td>
<td>−78.42</td>
<td>−49.51**</td>
<td>−1.14**</td>
<td>−0.47</td>
<td>−0.74*</td>
</tr>
<tr>
<td></td>
<td>(51.06)</td>
<td>(75.40)</td>
<td>(24.32)</td>
<td>(0.38)</td>
<td>(0.34)</td>
<td>(0.40)</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Firm FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>3790</td>
<td>5052</td>
<td>6568</td>
<td>2890</td>
<td>3877</td>
<td>5712</td>
</tr>
<tr>
<td>N firms</td>
<td>819</td>
<td>770</td>
<td>1061</td>
<td>650</td>
<td>618</td>
<td>946</td>
</tr>
</tbody>
</table>

Notes: The sample is divided into exporting and non-exporting firms and into high and low cyclicity firms. Cyclicity is measured by the association of sales growth with GDP growth at industry level as described in Section 3 (Log Quarterly sales growthy = δy Log Quarterly GDP growth, + f + q, + year, where industries are indexed by j, firms by t. Using quarterly data from 2004Q1 to 2016Q1, q, is quarter fixed effects indicating one of the four quarters.) Firms in high cyclicity sample have cyclicity above the median. f is firm t’s forecast of GDP growth in fiscal year t answered in year t − 1. |e| is a measure of forecast error defined by the absolute value of difference between firm’s forecast of GDP growth in fiscal year t answered in year t − 1 and the realized GDP growth in fiscal year t. D ln(Emp) = ln(employment) − ln(employment, t − 1), D ln(lnv) = ln(investment) − ln(investment, t − 1). Profit and TFP are the measures of fiscal year t. Unit of profit is billion JPY. Sample is restricted to observations with non-missing GDP forecasts in the last two consecutive years (that is, and are observed); Driscoll–Kraay standard errors with lag 4 are shown in the parentheses.

5. Forecast quality by firm characteristics

In this section, we identify the types of firms that make better forecasts. In particular, we examine the determinants of firm forecast quality measured in two alternative ways. One way to measure forecast quality is to take its difference from the average forecasts of professional forecasters. The idea behind this measure is that professionals’ forecasts are likely to be the best available forecasts in each period of time and hence should strip out unavoidable forecast errors – for example, due to disasters like the Tohoku earthquakes – and capture firms’ deviations from best-practice forecasts.

To begin this analysis, we first examine whether professional forecasts from the Consensus Forecasts data are typically more accurate than firms’ forecasts. Time-trends of average professional forecasts and firm forecasts look quite similar (see Appendix Fig. A.4). To more systematically examine the differences, we regressed forecasts and forecast errors on a dummy variable indicating professional forecasters using a pooled dataset that includes both professional and firm forecasts. We find that professional forecasters make smaller absolute errors than firms, although the difference is statistically insignificant. However, we find that squared forecast errors (i.e., (e(t + 1))^2) are significantly smaller for professional forecasts, suggesting that professional forecasters tend to make fewer extreme forecast errors.

Which types of firms have forecasts closer to those of professional forecasters? Contrary to the previous section where we employ within-firm variation by including firm fixed effects, here we focus on across-firm variation in firm characteristics and forecasts. To do so, we calculate and use the averages of all variables at the firm level. Then we regress the firm’s average distance to the mean of professional forecasts over the sample period ([ep(t + T)]) on various average firm characteristics. We report the results in Table 4. All of the estimated equations include sector fixed effects except for the equations including industry cyclicity.

First, the results show that the coefficients on firm size, measured by employment, are negative and statistically significant, suggesting that size is a strong predictor of smaller forecast errors. This result is consistent with Bachmann and Elstner (2015) and Bloom et al. (2018), who find similar evidence for firms’ forecasts and forecast uncertainty about

25 There is a large empirical literature on the accuracy of professional forecasts. Among them, for example, Keane and Runkle (1990) support the rationality of professional forecasts using panel data.

26 There were in total 635 professional forecasts in the sample period.

27 Distributions of the forecast errors by professionals and firms show that firms’ forecast errors have longer tails (see Appendix Fig. A.7).

28 One issue is that some firms are observed in periods with relatively higher uncertainty than are others. To control for this, we rescale the distance from the mean of professional forecasts to be 0 and standard deviation 100 in each year before taking the firm-level averages. In all regressions, firms are weighted by the number of year-observations in the original data to reflect heterogeneity in the accuracy of observations across firms.

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own-performance in German and US data. Second, we examine whether more productive firms make more accurate forecasts. Column (2) adds firms’ average TFP as an explanatory variable and shows that the coefficient on TFP is negative and statistically significant, even after controlling for size. This result suggests that firm productivity is an important determinant of forecast accuracy.

Third, we test whether firm age matters for forecast accuracy. Column (3) indicates that older firms tend to make smaller absolute errors, even after controlling for size. This result suggests that more extensive business experience may help firms make accurate forecasts, or alternatively, that firms that have superior forecasting ability tend to survive longer. Fourth, we test the hypothesis that firms whose performance are responsive to the state of the macro economy have a greater incentive to predict accurately due to larger costs of misforecasting and therefore make more accurate forecasts. In column (4), we regress the distance to professional forecasts on the logarithm of industry cyclicality (measured in absolute value). The result is consistent with this hypothesis: firms with higher cyclicality (either pro or counter) tend to make more accurate forecasts. The results are consistent with the evidence shown by Cobian et al. (2018) that firms with greater incentives to predict inflation (due to facing higher competition) make more accurate forecasts than others.

Finally, we examine differences in forecast accuracy by firms’ ownership types. We use the names of the top 25 stock owners of each firm to construct measures of stock shares owned by banks and financial institutions ("bank share"). As shown in column (5), the coefficient on bank share is negative and statistically significant. These results suggest that governance may also play an important role in forecast accuracy. Historically, Japanese banks have tended to be heavily involved in management and business planning for their client firms in the post-war period (Hoshi and Kashyap, 2001). Therefore, given that banks are likely to have professional forecasters, it is not surprising that banks’ share predicts firms’ forecast accuracy. Interestingly, if we split out the non-bank share into family owned and non-family owned, we find family owned have significantly larger gaps versus professional forecasters (point estimate and standard errors are 0.345 and 0.196, respectively). Overall, these results remain qualitatively similar in the last two columns where we include all variables with and without industry fixed effects.

An alternative measure of forecast quality is its raw difference from realization. As its natural counterpart in data, we use $|ε_i(t+1)|$, the absolute value of firm $i$’s forecast error made in year $t$ defined by $|F_{i,t}(t+1) - g_{t+1}|$, in which $g_{t+1}$ is the realized GDP growth rate in fiscal year $t + 1$. Table 5 shows the results of regressing firm-level average absolute forecast errors $|ε_i(t+1)|$ on the various firm-level average characteristics. The results are similar to the ones from above in terms of the signs of the coefficients, although the levels of statistical significance vary. Overall, as before, firm size, productivity, age, cyclicality, and bank ownership share predict firms having forecasts closer to the realizations. As another robustness check,

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29 One important difference from their results is that in our case we are evaluating firms’ forecasts on a common outcome – GDP – rather than the firm’s own performance. Prior results may be because larger firms have more predictable sales. In this sense, our result may be more telling since we find that larger firms are more accurate even for a common outcome like GDP growth.

30 We take the logarithm because the absolute value of the industry cyclicality measure has a skewed distribution.

31 Most of the professional forecasters in the Consensus Forecast are banks and financial institutions.

32 Family owned share is calculated as the total share owned by the top 25 shareholders whose family names are the same as the firm’s representative.

33 As a robustness check we also try restricting the sample to respondents in either management, strategy, or planning departments, and the results remain qualitatively the same.

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Table 4: Forecast accuracy with respect to professional forecasts.

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\text{Ln(Ownership)}$</td>
<td>$-11.36^{***}$</td>
<td>$-12.08^{***}$</td>
<td>$-10.40^{***}$</td>
<td>$-10.81^{***}$</td>
<td>$-9.38^{***}$</td>
<td>$-9.61^{***}$</td>
</tr>
<tr>
<td>(0.72)</td>
<td>(0.78)</td>
<td>(0.88)</td>
<td>(0.65)</td>
<td>(0.93)</td>
<td>(1.07)</td>
<td>(0.96)</td>
</tr>
<tr>
<td>TFP</td>
<td>$-8.83^{***}$</td>
<td>$-8.28^{**}$</td>
<td>$-8.28^{**}$</td>
<td>$-8.28^{**}$</td>
<td>$-6.95^{**}$</td>
<td>(3.31)</td>
</tr>
<tr>
<td>Firm age</td>
<td>$-0.17^{***}$</td>
<td>$-0.15^{**}$</td>
<td>$-0.17^{**}$</td>
<td>$-0.36$</td>
<td>(0.05)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>$\text{Ln}(\text{Cyclicality})$</td>
<td>$-0.76^{*}$</td>
<td>$-0.76^{*}$</td>
<td>$-0.76^{*}$</td>
<td>$-0.76^{*}$</td>
<td>(0.36)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>Banks share</td>
<td>$-64.64^{***}$</td>
<td>$-42.92^{***}$</td>
<td>$-52.34^{***}$</td>
<td>$-52.34^{***}$</td>
<td>$-52.34^{***}$</td>
<td>(14.13)</td>
</tr>
<tr>
<td>Sector FEs</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>2770</td>
<td>2275</td>
<td>1919</td>
<td>1800</td>
<td>1424</td>
<td>1424</td>
</tr>
</tbody>
</table>

Notes: All variables are averaged at the firm level. Firms are weighted by the number of year-observations in the original data. In the original data, $|F_{i,t}(t+1)|$ is a measure of forecast error defined by the absolute value of difference between firm $i$’s forecast for GDP growth in fiscal year $t + 1$ answered in the December of year $t$ and the average forecasts by professionals in the December of year $t$. $|F_{i,t}(t+1)|$ are rescaled to mean 0 and standard deviation 100 in each year before taking the average. The firm-average TFP is rescaled to mean 0 at sector level. Cyclicality is measured by the association of sales growth with GDP growth at industry level as described in Section 3, and taken the logarithm after converted to the absolute value. Bank share is defined by the stock share owned banks and other financial institutions among the firm’s top 30 stock holders. Robust standard errors are estimated.

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we also tested an alternative specification using the professional forecasts in November (rather than December) in case firms had not examined the latest professional forecasts, and the results are very similar (see Table A.10 in the Appendix).

6. Concluding remarks

Economists have long been interested in how firms' expectations affect business outcomes. For example, most recent stochastic models of firm dynamics assume forward looking firm managers. Key questions are to what extent do these firms' forecasts matter for their input choices and performance and what are the factors that explain heterogeneity in forecast accuracy across firms. However, micro-level evidence on these questions has been hard to come by due to a lack of firm-level panel data tracking both firms' forecasts and performance.

This paper matches panel data on firms' forecasts of GDP growth from the Japanese Annual Survey of Corporate Behavior (ASCB) to company accounting data to provide new evidence on these questions. We find three main results. First, firms’ GDP forecasts are positively associated with their input choices, such as investment and employment, as well as output. Second, forecast accuracy is strongly related to profitability and productivity – a higher forecast error (of either sign) significantly predicts a sizable reduction in profit and productivity. We show that a simple model of firm input choice under uncertainty and costly adjustment can rationalize these findings. For all of these empirical results, we find the strongest effects for firms whose performance is more sensitive to the state of the business cycle. Finally, we find that larger and more cyclically sensitive firms have the most reasonable forecasts, presumably because their returns from accuracy are the largest. We also see that more productive, older, and bank owned firms tend to make forecasts similar to professionals, suggesting that experience, management ability, and governance may also play an important role in forecast quality.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2019.02.008.
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