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Firm Performance and Macro Forecast Accuracy

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Firm Performance and Macro Forecast Accuracy*

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Abstract

Ever since Keyenes' famous quote about animal spirits, there has been an interest in linking firms' expectations and actions. But the empirical evidence on this is scarce because of the lack of firm panel data on expectations and outcomes. In this paper, we combine a unique survey of Japanese firms' GDP forecasts with their accounting data for 27 years for over 1,000 large Japanese firms. We find four main results. First, we find that firms' GDP forecasts are positively and significantly associated with firms' input choices, such as investment and employment, and with firm's sales, even after controlling for year and firm fixed effects. These results are stronger for cyclical firms, suggesting a firm's input decision is particularly dependent on its manager's forecasts when its demand is more sensitive to the macro economy. Second, both optimistic and pessimistic forecast errors lower profitability because it is costly to have too much or too little capacity. Third, while over optimistic forecasts lower measured productivity, over pessimistic forecasts do not tend to have an impact on productivity. Finally, larger and more cyclical firms make more accurate forecasts, presumably reflecting the higher return from accurate forecasts. More productive, older, and bank owned firms also make more accurate forecasts, suggesting that forecasting ability is also linked to management ability, experience and governance. Collectively, this highlights the importance of firms' forecasting ability for micro and macro performance.

Keywords: Forecast, investment, employment, productivity

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1 Introduction

There is a long interest in the importance of firm expectations on business outcomes. Keynes (1936) talked about animal spirits to highlight the importance of (potentially irrational) expectations, while Tobin's Q model of investment hinges on firms' future expectations of demand. More recently, almost all stochastic models of firms assume forward looking agents, who develop beliefs about future micro and macro outcomes. But a central question in this literature is how much these forecasts really matter, in which circumstances, and how much their level and accuracy vary across firms.[1]

In this paper, we used the Japanese Annual Survey of Corporate Behavior (ASCB) on firms forecasts for GDP growth from 1989–2015, matched to their accounting data. This survey was run by the Economic and Social Research Institute (ESRI) within the Cabinet Office, and achieved about a 40% response rate from all publicly listed firms in Japan, generating a panel sample of around 1,000 firms. The survey asks about future GDP growth and appears to be reasonably high quality - the typical respondent was in management, planning or strategy departments.

Analyzing this data, we find four main results. First, we find that firms' GDP forecasts are positively and significantly associated with firms' input choices, such as investment and employment, and with firm's sales, even after controlling for year and firm fixed effects. As predicted, the effects are strongest in firms whose performance are cyclically sensitive to GDP growth. Secondly, forecast accuracy appears to be tightly related to profitability. Prior year forecast accuracy has a significant predictive power for profits, even after controlling for longer-run forecast accuracy (so prior year accuracy is particularly important) and firm fixed effects. This is true both for over optimistic (positive) forecast errors as well as over pessimistic (negative) forecast errors, very much as any simple model of firm forecasting would predict.

Third, measured productivity (TFPR) is negatively impacted by excessively optimistic forecasts, while we do not find the effect of excessively pessimistic forecasts. One natural explanation is that firms that over invest and hire increase output, which reduces prices and capacity utilization, and so does measured TFP (since firm-level prices and capacity are not observed). In reverse, over-pessimistic forecasts lead to lower output, so they increase prices and utilization, which would lead

[1] See, for example, classic works including Nickell (1978), Abel and Blanchard (1986), Caballero (1997), Chirinko (1993) or Dixit and Pindyck (1994).

to an increase in measured TFP. On the other hand, both over- optimistic and pessimistic forecasts may reduce TFP if for example making changes to plans takes up managerial time.

Finally, larger and more cyclical firms have more accurate forecasts, presumably because their returns from accuracy are large. Interestingly, we also see that more productive and older firms and firms with higher stock share of banks are more accurate than the others, suggesting experience, management ability, and governance may also play an important role in forecast accuracy.

This work connects to a number of literatures. First is the literature on macroeconomics and firm forecasts. Macroeconomic theories have long shown that departing from rational expectation hypothesis and employing models of agents having heterogeneous beliefs can explain important dynamics of economic features (for example, Lucas 1972; Mankiw and Reis 2002). More recently, David, Hopenhayn, and Venkateswaran (2016) provide and estimate a model in which firms' information frictions lower aggregate productivity through resource misallocation, and they show that the estimated loss of productivity ranges from 7 to 10% in India and 4% in United States. In addition, growing number of studies have demonstrated that forecasts of economic agents have a key role in driving business cycles (Beaudry and Portier 2004; Schmitt- Grohé and Uribe 2012; Ilut and Schneider 2014).

Secondly, this paper is built on a growing empirical literature examining the process of expectation formations by various agents. Mankiw, Reis, and Wolfers (2003) analyze consumers' inflation forecasts and find larger disagreements among general public compared to professional forecasters. Empirical studies examining the patterns of macroeconomic forecasts by various economic agents have found that the estimated patterns are consistent with models with information rigidity (Carroll 2003; Coibion and Gorodnichenko 2012, 2015). Coibion, Gorodnichenko, and Kumar (2015) document a large heterogeneity in firms' macroeconomic forecasts in a firm survey in New Zealand and find that firms with higher incentive to predict (e.g. facing higher competitions) are more accurate. Bachmann and Elstner (2015) use a German manufacturing survey that asked about predictions about own firm's performance and find that at most one third of firms are over- or under-predicting their performance, and the degree of forecasting errors are smaller for larger firms. Bloom et al. (2017) use US Census data and find that larger and older firms tend to provide more concise forecasts that are more highly correlated with past behavior. Using the same firm survey in Japan as in this study, Shiraki and Kaihatsu (2016) examine the heterogeneity of firms' inflation forecasts, and Koga and Kato (2017) document systematic pattern of optimism and pessimism of industry demand forecasts by firms. We argue that our analysis of firms forecasts for a common important outcome - GDP growth - is valuable for measuring forecasting ability across firms.[2]

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

In what is following, section 2 explains the data, section 3 discusses our main results on forecast and firm performance, section 4 shows results on forecast quality by firm characteristics, and section 5 provides concluding remarks.

2 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 during the period from 1989 to 2015, as individual firm identifiers are available only after 1989. In each year, the survey questionnaire was sent to all listed firms at the Tokyo and Nagoya Stock Exchange that consist of approximately 2500 firms. Among them around 40% of firms respond to the survey (see Appendix Figure A1 for the number of responses in each year). The survey is conducted annually between mid-December and mid-January. Respondents are required to answer business outlook for the real economic growth rates and industry demand, and their business plans regarding investment, employment, and pricing. The items we use are forecasts of real economic growth rate of Japan in the following fiscal year that starts from April.

The questions were phrased the following way (see Appendix Figure A2 for the corresponding part of the questionnaire):

> 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

[2] Most datasets collect forecast information about the manager's own firm or industry performance, which makes it hard to say if - for example - larger firms are better at forecasting their own sales, or their own sales is more stable so easier to forecast. Since we analyze the forecasts on a common object - GDP growth - the second source of variation is not present.

real growth rates of demand in your industry for FY 2017, the next 3 years (average of FY 2017-2019) and the next 5 years (average of FY 2017-2011).

To reduce the effects of outliers, we winsorized the forecast variable by replacing the variable with more than $\pm 3\sigma$ with $\pm 3\sigma$, where σ is the standard deviation. The left hand side of Figure 1 shows the distribution of "firm i 's forecasts for fiscal year $t+1$ real economic growth rate answered in fiscal year t" (denote by $f_{it}(t+1)$ hereafter) after winsorizing. The right hand side of Figure 1 shows the distribution of the absolute value of forecast errors in each year, namely $|e_{it-1}(t)| \equiv |f_{it-1}(t) - g(t)|$, where $g(t)$ is the realized GDP growth rate of the year t.[3]

While the survey does not specify positions of respondents, 66% of the respondents belong to departments responsible for corporate planning and strategy, management, and CEO office (see Appendix Table A1). The rest of the answers are from departments of finance (12%), general affairs (12 %), and IR and public relations (7%).

As initial checks of the survey data, in Figure 2, we plot time-series of the mean of $f_{it}(t+1)$ and $g(t)$. The two lines roughly correspond in terms of ranges, implying that the forecasts for next year tend to reflect the realization of the growth rates in the current year. Mean of the forecasts tend to be correlated more with the contemporaneous GDP growth than with the targeted GDP growth.[4] In Figure 3, we show the yearly average of the absolute forecast errors, $|e_{it-1}(t)|$. The same figure also plots annual daily stock volatility based on TOPIX and the average of monthly Economic and Policy Uncertainty Index for Japan (see Baker, Bloom, and Davis 2016) for each fiscal year.[5] All time series are standardized by the year-level observations. The three lines share the peaks around mid 1990s, 2000, and 2007, suggesting forecast errors correspond to standard measures of macro uncertainty.

We match the responses in the survey with other data at the firm level. We use the Development Bank of Japan's "Financial data of Listed Firms" (DBJ data hereafter) to capture financial conditions of firms, and Nikkei Needs Financial Quest for information on stock price, firm age, and ownership structure. In addition to firm data, we use "Consensus Forecasts" published by Consensus Economics to compare firm forecasts with professional forecasts. For our baseline specification,

[3]In this study, we assume that the survey respondents interpreted "the real economic growth rate" as the real GDP growth rate.

[4]Also see the binned scatter plots in the Appendix Figure A3 and time series regression results in the Appendix Table A4.

[5]`http://www.policyuncertainty.com`

we use their forecasts made in December about Japan's real GDP growth rate of the next calendar year. As for actual values of Japan's real GDP growth, we use the GDP estimates of FY 1990–FY 2015 from the Cabinet Office in June 2016. Appendix Table A2 shows the basic sample statistics for our main variables. To mitigate the effect of outliers, we winsorize 1 % of samples in each tail in respect to sales growth and employment growth, and TFP growth. We also exclude firms that responded to the survey for less than three times in ASCB during the period of the study.

It is possible that the response rates to the ASCB are correlated with certain firm characteristics. Indeed, a probit model estimation of response rates using the sample of DBJ data shows that firms with higher TFP, larger employment size, and older firms were more likely to have responded to the survey (see Appendix Table A3 for the results). The magnitude of the response differences is small - for example, a 10% increase in productivity or size induces a 2% and 0.2% increase in the response rate respectively (on a 40% bases). Nevertheless, this sample selection might potentially bias our results, so we also re-estimated our main equations by weighting samples by inverse of response rates as robustness checks. The main qualitative results are unchanged.

On calculating firm-level TFP, we assume Cobb-Douglas production function in which TFP is derived as follows: $TFP_{it} = LnY_{it} - S^L_{jt}LnL_{it} - S^K_{jt}LnK_{it} - S^M_{jt}LnM_{it}$, where S^k_{jt} represents cost share of factor k for industry j in year t, and Y_{it}, L_{it}, K_{it}, and M_{it} denote gross output, labor, capital, and other intermediate inputs of firm i in fiscal year t, respectively.[6] Due to data availability, we assume that cost share is the same across firms in the same industry.[7] Cost share for each industry is 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 output industry-level deflator from JIP database. Labor input is calculated as a product of number of workers and average hours worked. Capital is defined as tangible asset excluding land, and computed using the perpetual inventory method. Data source for gross output and factors is described in the Appendix in detail.

In order to measure cyclicality of firms with respect to Japanese macro economy, we estimate

[6] Investment hereafter refers to investment in physical assets such as machinery, vehicles, buildings, and structures. Due to limited data availability, the data are on a non-consolidated basis. For calculating real investment and 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 stocks: 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 Producer Price Index.

[7] Using industry-level cost share is a standard way in the literature (for example, Foster, Haltiwanger, and Syverson (2008)).

the degree to which the firm's stock prices react to a surprise in quarterly GDP announcements. In each quarter, at pre-specified date and time, the Cabinet Office announces a quarterly real GDP estimate for the preceding quarter for the first time. We estimate the following regression:

$$Ln\left(\frac{p_{it}^a}{p_{it}^b}\right) = \beta_i LnGDP_t + \sum_{k=1}^{3} \phi_k LnGDP_{t-k} + \phi_q FC_{t-1} + F_i + F_y + F_q + u_{it}. \tag{1}$$

p_{it}^a and p_{it}^b are the average of three business days' closing prices before the announcement and after the announcement including the announcement date, respectively. $LnGDP_t$ is logarithm of quarterly real GDP preliminary earliest announcement (seasonality unadjusted). The rest of the terms in the equation control as much as possible for the pre-announcement information set that would affect general trends of stock prices. This set includes logarithm of GDP in preceding three quarters, and the average of forecasts about GDP growth rate of the following calendar year by professional forecasters made in the last 90 days before the announcement at t. The coefficient of the professional forecast ϕ_q is allowed to differ by quarters due to the fact that the professional forecasts are always about coming calendar year. Firm fixed effects F_i, fiscal year fixed effects F_y, and quarter fixed effects F_q are also controlled. β_i is firm i specific response to the announced GDP, which is a measure of firm cyclicality for our study. In practice, β_i is estimated as the coefficient on the dummy variable for firm i interacted with $LnGDP_t$. The estimated coefficients of β_i is distributed around a mean of 0.12 with standard deviation 0.14 (see Figure 4 for the resulting distribution),[8] which means that, for example, the average firm sees an 1.2% larger increase in stock prices when the announced quarterly GDP was higher than the common expectation by 10%.

3 Forecasts and firm performance

In this section, we empirically investigate a possibility that firms' GDP forecasts influence their input choices and firm performance.

[8]For the possibility of outliers' existence in the estimates of β_i, we winsorized the variable by replacing observations with the value of more than $\mu \pm 3\sigma$ with $\mu \pm 3\sigma$, where μ and σ are the mean and standard deviation, respectively. While we winsorize 1 % of samples in each tail for other variables such as employment growth, here we take a larger range for winsorizing due to standard errors of the estimates. The above statistics are for the distribution after winsorizing.

3.1 Firm input choices and sales

First, we estimate the following empirical equation:

$$Y_{it} = \beta f_{it-1}(t) + u_i + u_t + \eta_{it}. \quad (2)$$

where Y_{it} is either growth of employment, investment, or sales of firm i from fiscal year $t-1$ to t measured by the difference in logarithm.[9] $f_{it-1}(t)$ is the forecast of GDP growth rate in fiscal year t answered by firm i in year $t-1$. We include firm fixed effects and year fixed effects in the equation as denoted by u_i and u_t, respectively. These fixed effects control for unobserved time-invariant characteristics of the firms as well as effects of macroeconomic shocks that are common to all firms.

A primarily purpose of estimating equation (2) is to test the quality of the survey. Since the survey targeted all stock listed firms, the firms in the sample are relatively large firms. Because of this, there is a possibility that the respondent's forecast does not reflect the forecast that is actually used for the company's decision making. If the firms' survey responses reflect future beliefs of managers, which are actually used for their decision making, then we would expect to see a positive association between the firms' forecasts and their input choices.

Panel A of Figure 5 graphically shows the relationship of equation (2) by binned scatterplots. The horizontal axis shows residual values of $f_{i,t-1}(t)$ after regressing them on year fixed effects and firm fixed effects. The residual values are grouped into equal-sized 15 bins, and for each bin, the vertical axis shows the mean of residual values of Y_{it} after regressing them on year fixed effects and firm fixed effects. The results suggest clear positive associations between firm's reported forecasts and their input choices and resulting outputs.

Table 1 shows the estimates for the equation (2) by OLS. Column (1) and (3) estimate the equations for employment and investment growth including year fixed effects and 30 sector fixed effects, and column (2) and (4) show the estimates including year fixed effects and firm fixed effects. The estimated coefficients of forecast are positive and statistically significant. The estimates suggest that having 1 percent higher GDP growth forecast is associated with around 0.2 percentage points higher employment growth rate and around 2.5 percentage points higher investment growth rate on

[9] Investment growth is calculated by adding value 1 to the value of investment, (i.e. $Ln(investment_{it} + 1) - Ln(investment_{it-1} + 1)$) because around 3% of total observations took the value 0 for investment. The unit of investment is 1 million JPY, and the minimum positive value is 12.86 (million JPY).

average.[10] Considering the fact that the average employment and investment growth rates in this period were around −1.8 and −4.5 percentage points, respectively, the effects of forecast seem to be economically large. The last two columns estimate equation (2) for sales growth. The estimate coefficients suggest that having 1 percent higher GDP growth rate forecast predicts an increase of sales growth by around 0.3 percentage points.

Overall, the results suggest that firm's reported forecasts are positively and significantly correlated with its input choice and sales. One rationalization of these results is the standard dynamic model of firms where firms decide input mix of period t in period $t-1$ based on its expectations for demand in period t.

This standard model would also imply that firms whose performance are more cyclical (sensitive to the macro economy) would be more responsive to their GDP growth rates. We explore this possibility by dividing the sample into high and low cyclicality firms using the firm cyclicality measure (as described in the data section). Table 2 shows the results. Columns (1), (3), and (5) show the estimates for firms with the cyclicality measures above the median, and the rest of the columns show the results for the other firms We find that more cyclical firms see a tighter correlation between GDP forecasts and their sales, employment, and investment.[11]

3.2 Profit and productivity

Next, we explore the relationships between firms' forecast errors and performance by estimating the following equation:

$$V_{it} = \theta |e_{it-1}(t)| + v_i + v_t + \omega_{it}. \tag{3}$$

where V_{it} is either profit or TFP of firm i in fiscal year t. $|e_{it-1}(t)|$ is the absolute value of firm i's forecast error that is defined by $e_{it-1}(t) = f_{it-1}(t) - g_t$, in which g_t is the realized GDP growth rate in fiscal year t. We control for time-invariant firm characteristics and macro-level shocks by including firm fixed effects (v_i) and year fixed effects (v_t).

Panel B of Figure 5 graphically illustrates the results by binned scatterplots. As for the upper two figures, the horizontal axis shows residual values of $|e_{it-1}(t)|$ after regressing them on year

[10] If we look at R&D, we get similar significant results. For example, in a specification like column (4) for Ln(1+R&D) with firm fixed-effects, the coefficient (and standard error) on forecast is 0.014 (0.060).

[11] Alternative specification to test the differences in the coefficients of forecasts by cyclicality is to include an interaction terms of cyclicality and forecasts in equation (2). Table A5 in the appendix shows the results, which are qualitatively similar to the results in Table 2.

fixed effects and firm fixed effects. As before, the residual values are grouped into equal-sized 15 bins, and the vertical axis plots the mean of residual values of V_{it} for each bin, after regressing them on year fixed effects and firm fixed effects. The results suggest that firms' absolute forecast errors are negatively associated with their profit and productivity, even after controlling for firm and year fixed effects. In the lower two figures, we change only the horizontal axis to the raw value of forecasts (i.e. $e_{it-1}(t)$) without residualizing this variable in order to provide clearer images of the relationship between raw forecast errors and firm performance. The figures show higher values of profit and TFP around zero forecast error. In particular, as for profit (left figure), the relationship appears to be symmetric around zero. As for TFP, the positive forecast errors appear to be associated with lower TFP, while the relationship in the negative part of forecast errors is less clear.

Table 3 shows the regression estimates of the equation (3). Column (1) reports the results for profit. The estimated coefficient is negative and statistically significant at 1 percent significance level. The estimate implies a sizable effect of forecast error on profit: having 1 percent higher or lower GDP growth rate forecast tends to lower the level of profit by around 8 percent.[12] Column (2) shows the result for TFP. The coefficient estimate of absolute forecast error is negative and statistically significant at 5 percent level. The result implies that having 1 percent absolute forecast error is associated with 0.54 percent lower TFP.[13] We also examined robustness against possible sampling selection effects by estimating the equation (3) by weighting observations by inverse of response rates. The results of this exercise produce very similar results as in the main specification (Table A6 in the Appendix show the results).[14] While we show the results for the level of TFP, we observe qualitatively the same results when we regress the growth rate of TFP (i.e. the first difference in the logarithm of TFP) on absolute forecast errors (the estimated coefficient is -0.0037 and the standard error is 0.0012).

Our results on profit can be interpreted according to standard dynamic models of firms. That is, firms' profit would be maximized when firms make investment with perfect foresight of future

[12]This magnitude is measured by the relative size of the coefficient to the mean of the dependent variable (i.e., 0.8 / 9.82=0.08)

[13]The way of calculation is the same as footnote 12.

[14]Additionally, we examined a different specification using a squared loss function (i.e. $e^2_{it-1}(t)$) in stead of using the absolute loss function. The results are shown in the Table A7 in the Appendix. We find that profit is still negatively and significantly associated with the squared error, while the coefficient of squared error for TFP is insignificantly estimated. This result might be due to the offsetting two possible mechanisms for the influence of forecasts on TFP as discussed in the following.

productivity and demand. Profit declines when firms over- or under- invest by mis-forecasting.

The results on TFP are less trivial to interpret as there are two possible mechanisms. One mechanism is "true TFP" effects, whereby having too few or too many inputs reduces TFP. Firms may find it harder to work efficiently with excessive or inadequate inputs. For example, one can think of management time as a part of production input provided by firm managers (for example, Lucas 1978). Forecast mistakes would require making changes to plans, which would take up management time and would reduce "true TFP".[15] This would lead to lower TFP for both positive and negative forecast errors. Another mechanism would be around "measurement errors" in TFP, which would lead to a negative correlation between TFP and raw forecast errors. One measurement error mechanism could arise from capacity. If firms with too many inputs reduce capacity utilization (e.g. hours or capital use), since capacity utilization is unobserved, it will show up as lower TFP. Another measurement story is around prices. Note that we observe industry prices but not firm prices. Therefore, when firms are over optimistic and produce large quantity, their prices may be lowered, and this will cut imputed output.

To examine this hypothesis, we estimate the same equation (3) by allowing the coefficients of pessimistic errors ($|e_{it-1}(t)| \cdot 1\{e_{it-1}(t) < 0\}$) and optimistic errors ($|e_{it-1}(t)| \cdot 1\{e_{it-1}(t) > 0\}$) to differ. Columns (3) and (4) of Table 3 estimate such equations for profit and TFP. For profits, the results are consistent with the hypothesis above: both pessimistic and optimistic errors are negatively and significantly related with profit. For TFP, the negative and significant coefficient estimate of optimistic errors is consistent with both the "true TFP" and "measurement errors" stories. The coefficient of pessimistic error is estimated to be insignificant, which is consistent with some combination of these effects since they push in opposite directions.[16]

An alternative explanation of the results in Table 3 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 may be 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 five years preceding year $t-1$ (i.e. $t-2, ..., t-6$). Our intuition behind this

[15] Another explanation of this may be to consider fixed costs of operations and diminishing returns to scale (see, for example, Bartelsman, Haltiwanger, and Scarpetta (2013)).

[16] The results are qualitatively the same when we use the growth of TFP (the coefficient of positive forecast error is -0.0047 (s.d. = 0.0015) and the coefficient of negative forecast error is -0.0023 (s.d. = 0.0018)).

test is as follows. Manager's ability and its effect on firm performance are considered to persist for relatively long periods. Therefore, historical average of past forecast errors is likely to be the more accurate proxy of firm's managerial ability than the prior year forecast error. Hence, if forecast errors proxy for managers' ability, then its long-run effect of historical average should dominate short-run effect.

To test the above hypothesis, column (5) and (6) of Table 3 show the results of adding historical average of forecast errors. Overall, only the coefficients of the one-year lagged forecast errors are negatively and significantly estimated in equations including firm fixed effects. The coefficients of historical average of forecast errors are insignificantly estimated with large standard errors.[17] A possible interpretation is that the one-year lagged forecast errors are more important in explaining profit and productivity than firm's managerial ability.[18]

4 Forecast quality by firm characteristics

In this section, we identify the types of firms whose forecast errors tend to be more accurate. Contrary to the analysis in the previous section where we employ within-firm variations in forecast errors by including firm fixed effects, we focus on across-firm variations in firm characteristics in this section.

To this end, we measure firm's forecast quality in two alternative ways. One measure is its difference from realization. As its natural counterpart in data, we use $|e_{it}(t+1)|$, which is, as defined in the previous section, the absolute value of firm i's forecast error made in year t. Table 4 shows the results of regressing $|e_{it}(t+1)|$ on various contemporaneous firm characteristics in year t. All of the estimated equations include year fixed effects and 30 sector fixed effects.

First, the results show that the coefficients of the log of employment size are negative and statistically significant, implying that firm size is a strong predictor of lower forecast errors. This evidence is consistent with Bachmann and Elstner (2015) who find similar evidence for firms' forecasts about own production performance in German firm data.[19] Secondly, we examine whether

[17]We also tested similar specification where the historical average of forecast errors include the forecast made in period $t-1$ dating back to the forecast made in $t-5$. The qualitative results are similar with this specification.

[18]An alternative test of this is to examine the relationship between a firm's forecast and contemporaneous firm performance (i.e. regressing profit and TFP in year t on forecast error $f_{i,t}(t+1)$). In this specification, we find insignificant correlations (see Appendix Table A8 for the results).

[19]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 on larger firms' forecast accuracy on own

more productive firms make more accurate forecasts. Column (2) and (3) show the results of regressing forecast errors on the firm's average TFP in the preceding three years, measuring historical productivity of the firm. The estimated coefficients of historical TFP are negative and statistically significant, and the coefficient remains after controlling for the firm size. This result implies firm productivity - and probably in particular management ability - can be an important determinant of forecast accuracy.

Third, we test whether firm age matters for forecast errors. Column (4) and (5) indicate that older firms tend to make smaller absolute errors, even after controlling for the firm size. This result suggests longer business experience may help firms make accurate forecasts. Fourth, we test the hypothesis that firms whose performance are responsive to the macro economy have higher incentive to predict accurately due to larger cost of misforecasting and make more accurate forecasts. The results show in column (6) and (7) test are consistent with this hypothesis: firms with higher cyclicality index tend to make more accurate forecasts. The results are consistent with the evidence shown by Coibion, Gorodnichenko, and Kumar (2015) that firms with higher incentive to predict (due to facing higher competitions) make more accurate forecasts than the others among New Zealand firms.

Finally, we examine differences in forecast accuracy by firms' ownership types. We use the names of the top 30th largest stock owners of each firm to construct the measures of the total stock share owned by banks and financial institutions (we call this as "bank share" hereafter).[20] As shown in Column (8) and (9), the coefficients of bank share are negative and statistically significant. This result remains qualitatively similar in the last column where we include all variables in one regression. These results suggest that governance may also play an important role in forecast accuracy. Historically speaking, Japanese banks tended to be heavily involved in management and business planning of their client firms in the post-war period (Hoshi and Kashap 2001). Therefore, given that banks are likely to have professional forecasters,[21] it is not surprising that bank share predicts firms' forecast accuracies.

We have also tested several other specifications. When we change the specification of forecast

performance may be because larger firms have more predictable sales due to better monitoring and targeting. Our result is more striking since we still find that larger firms are more accurate in absence of such a mechanism.

[20]The information of the stock share is limited to the period after 2004. Therefore, the number of observations using the bank share is reduced.

[21]Most of the professional forecasters in the Consensus Forecast are banks and financial institutions.

errors to the squared loss function (i.e. $e_{it}^2(t+1)$), the results are qualitatively the same as in the above (see Appendix Table A10 for the results). We also tested robustness against possible sampling selection effects by weighting observations by inverse of response rates, and found qualitatively the same results (see Appendix Table A11 for the results). Lastly, we alternatively used real-time GDP estimates as a measure of realized GDP growth rates. In particular, instead of using the revised estimates as of year 2016, we used an early report of GDP published in June of the following fiscal year.[22] The results are similar to the baseline results except that the coefficients of historical TFP and cyclicality are statistically insignificant for the specification with real-time estimates (see Appendix Table A12 for the results). This difference may be due to noises of the early estimates as such estimates are based on primitive set of data.

The negative association between forecast errors and firm size appear to be mainly driven by across-firms variation. That is, when we include firm fixed effects, the coefficients of firm size and TFP become small and insignificant (see Appendix Table A9 for the results). Nevertheless, we still find that bank share is negatively associated with forecast errors even after controlling for firm fixed effects.

The other way to measure the forecast quality is to take its difference from the average forecasts of professional forecasters. The idea behind construction of this measure is that professionals' forecasts are likely to be the best available forecasts in each period of time.[23] Hence, it should strip out unavoidable forecast errors - for example, due to disasters like the Tohoku earthquakes - and try to measure firms' deviations from best-practice forecasts.

To start this analysis, we first examine whether professional forecasts from the Consensus Forecasts data are more accurate than firms' forecast on average. Time-trends of professional forecasts' mean and firm forecasts' mean look quite similar (see Appendix Figure A4 Panel A). We regressed forecasts and forecast errors on a dummy variable indicating professional forecasters using dataset pooling both professional and firm forecasts.[24] We find that professional forecasts are on average marginally more optimistic and make smaller absolute errors than firm forecasts although the difference is statistically insignificant. However, we find that squared forecast errors (i.e. $e_{it}^2(t+1)$)

[22]The series by periods of publication is summarized and provided by Yasuyuki Komaki (`http://www.eco.nihon-u.ac.jp/eco_kyouin/komaki/RealTimeData-091121.html`).

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

[24]There were in total 635 professional forecasts in the observed period.

are significantly smaller for professional forecasts. The results indicate that professional forecasts tend to make fewer extreme forecast errors than firms.[25]

Table 5 shows the results of regressing the absolute value of distance to the mean of professional forecasts on firm characteristics. The results are similar to those in Table 4 in terms of the signs of the coefficients, although the levels of statistical significance vary when we control for firm size. Overall, as before, firm size, productivity, age, cyclicality, and bank share predict firms having forecasts closer to professional forecasters. Interestingly, in column (8), 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 0.336 and 0.130, respectively).[26] Some of the firms might not have looked at the professional forecasts in December yet at the time when they filled in the survey form because the survey was answered between mid-December to mid-January. Therefore, as a robustness check, we also tested an alternative specification using the professional forecasts in November. The results are qualitatively the same as the baseline specification (see Table A13 in the Appendix).

5 Concluding remarks

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

In this paper, we used the Japanese Annual Survey of Corporate Behavior (ASCB) on firms forecasts for GDP growth from 1989–2015, matched to their accounting data. We find four main results. First, we find that firms' GDP forecasts are positively associated with firms' input choices such as investment, employment, and output. As predicted, we find the strongest effects for firms whose performance are cyclically sensitive to GDP growth. Secondly, forecast accuracy is strongly

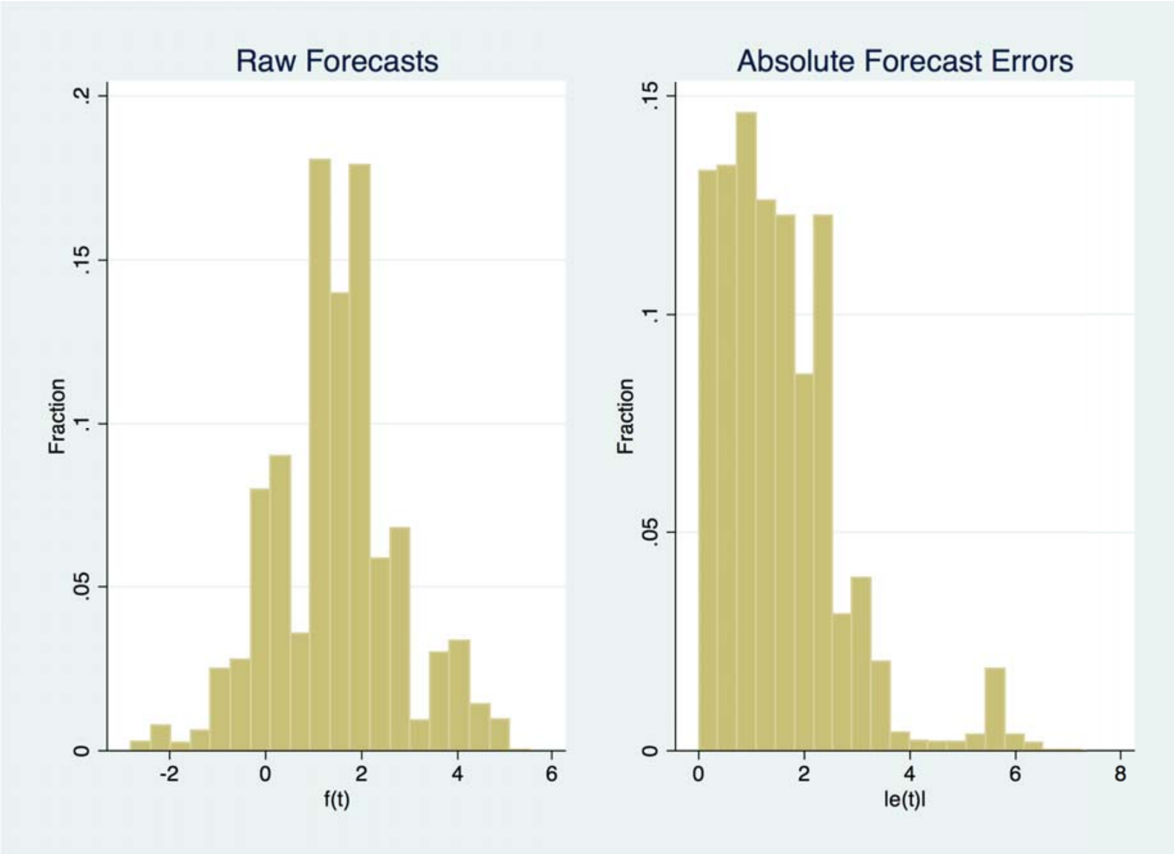
[25] Distributions of the forecast errors by professionals and firms show that firms' forecast errors have longer tails (see Appendix Figure A4 Panel B).

[26] Family owned share is calculated as the total share owned by the top 30 shareholders whose family names are the same as the firm's representative.

related with profitability. Making a higher forecast error for the following year significantly predicts lower profits in that year. As any simple model of firm forecasting would predict, we find both over optimistic forecast errors as well as over pessimistic forecast errors are related with lower profit.

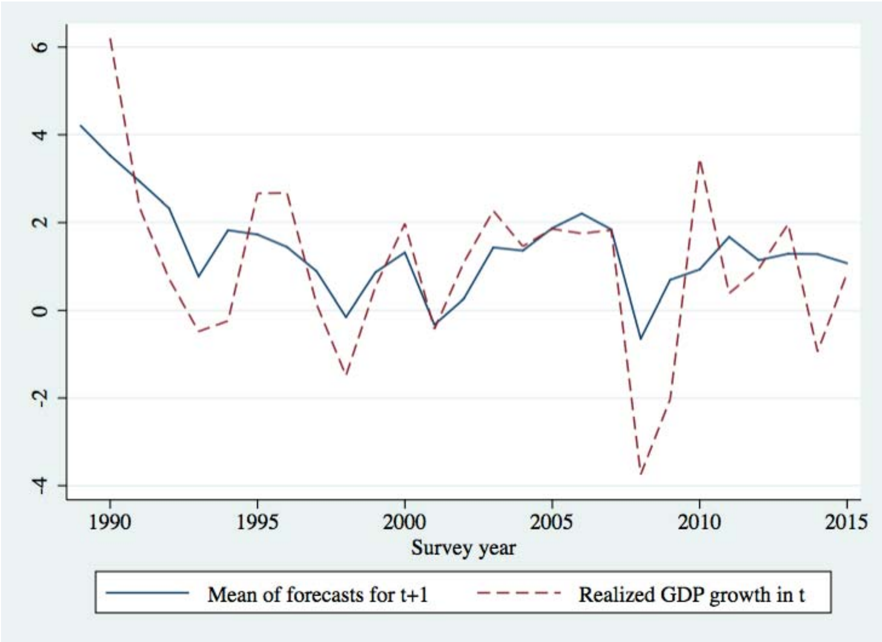
Third, we find that measured productivity is negatively associated with excessively optimistic forecasts, while no effect was found for excessively pessimistic forecasts. This can be partly explained by a capacity utilization model where firms with optimistic forecast over invest, resulting in lower measured TFP since utilization is unmeasured. In contrast, over-pessimistic forecasts lead to lower output and higher utilization, and thus to higher measured TFP, offsetting any direct negative TFP effects of forecast errors. Finally, we find that larger and more cyclical firms have the most accurate forecasts, presumably because their returns from accuracy are the largest. Interestingly, we also see more productive, older, and bank owned firms are also more accurate, suggesting experience, management ability, and corporate governance may also play an important role in forecast accuracy.

Figure 1: Distribution of Forecasts



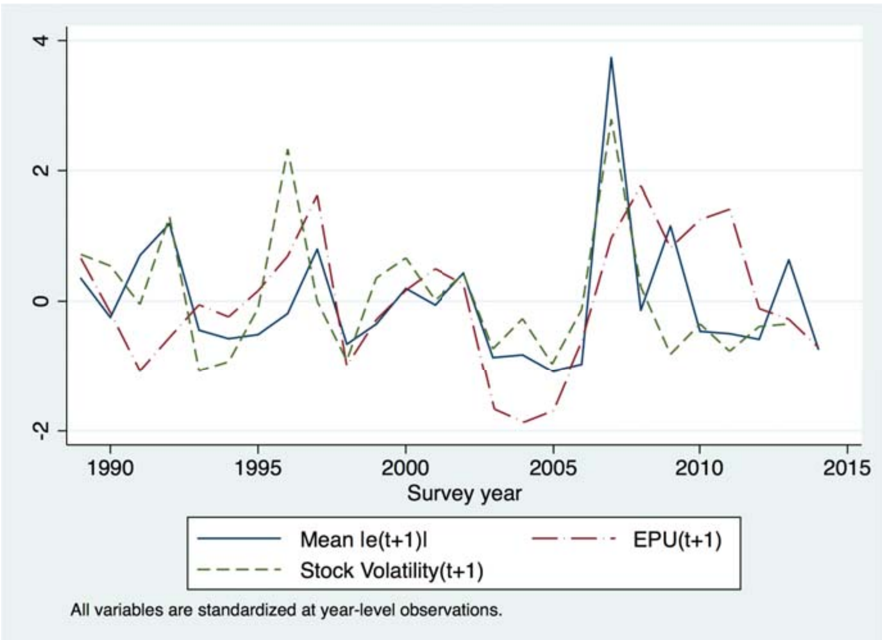
Notes: Left figure shows the histogram of $f_{it-1}(t)$, forecast of fiscal year t economic growth rate answered by firm i in fiscal year $t-1$ in the ASCB, for the entire sample periods. The right figure shows the histogram of $|e_{it-1}(t)|$, the absolute forecast errors which are the absolute values of the forecasts less their realized values.

Figure 2: Forecasts and realized GDP growth



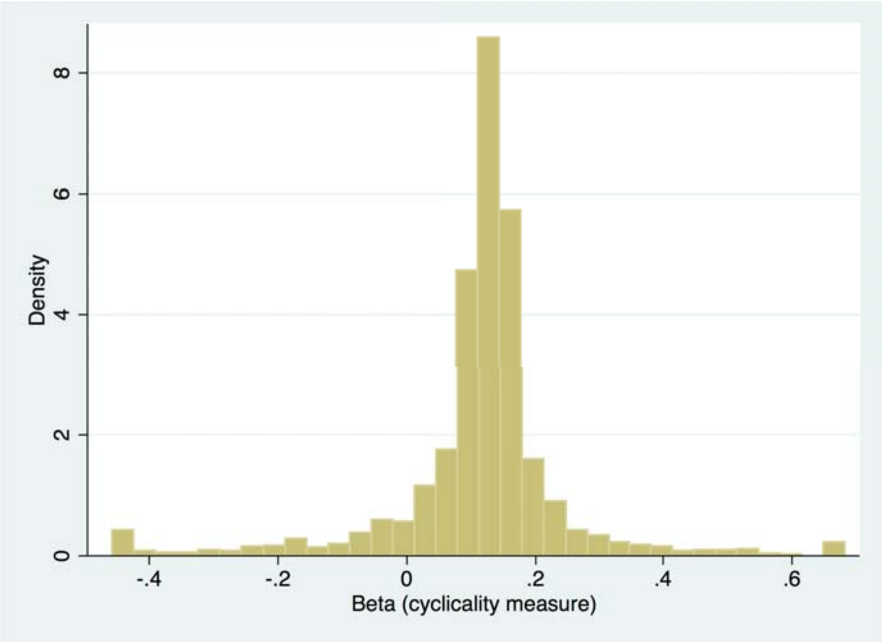
Notes: The horizontal axis indicates fiscal year (t). The solid line shows the average of $f_{it}(t+1)$, the forecast of fiscal year GDP growth rate in $t+1$ answered by firm i in fiscal year t in the ASCB. The dashed line shows the realized GDP growth rate in fiscal year t.

Figure 3: Second moments of forecasts



Notes: The horizontal axis indicates fiscal year (t). The solid line shows the average of $|e_{it}(t+1)|$, the absolute forecast error of fiscal year GDP growth rate in $t+1$ made by firm i in fiscal year t in the ASCB. The dashed line shows the Japanese stock volatility based on TOPIX in fiscal year t. The long-short dashed line is the average of monthly Economic and Policy Uncertainty Index in Japan (Baker, Bloom, and Davis 2016). All variables are standardized to mean 0 and standard deviation 1.

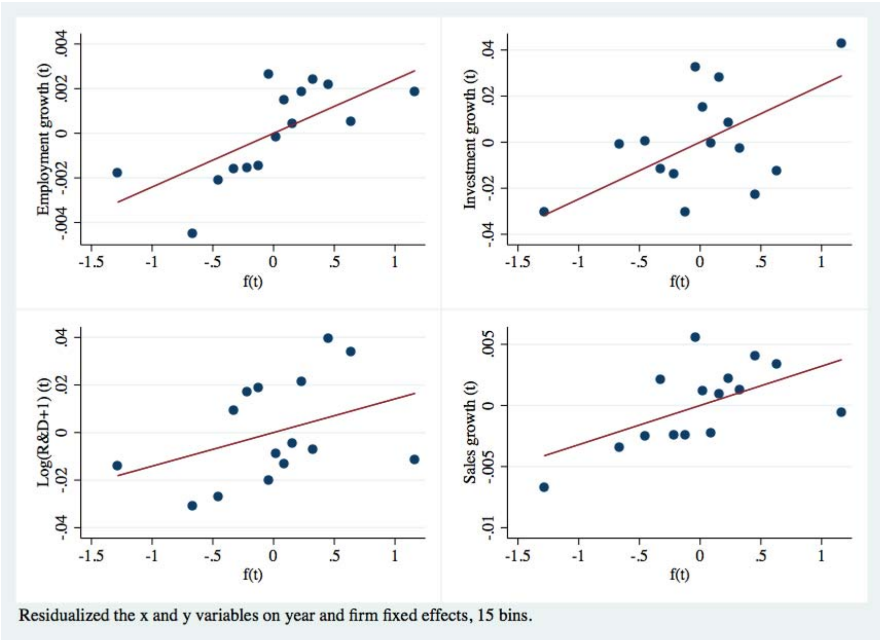
Figure 4: Distribution of cyclicality index



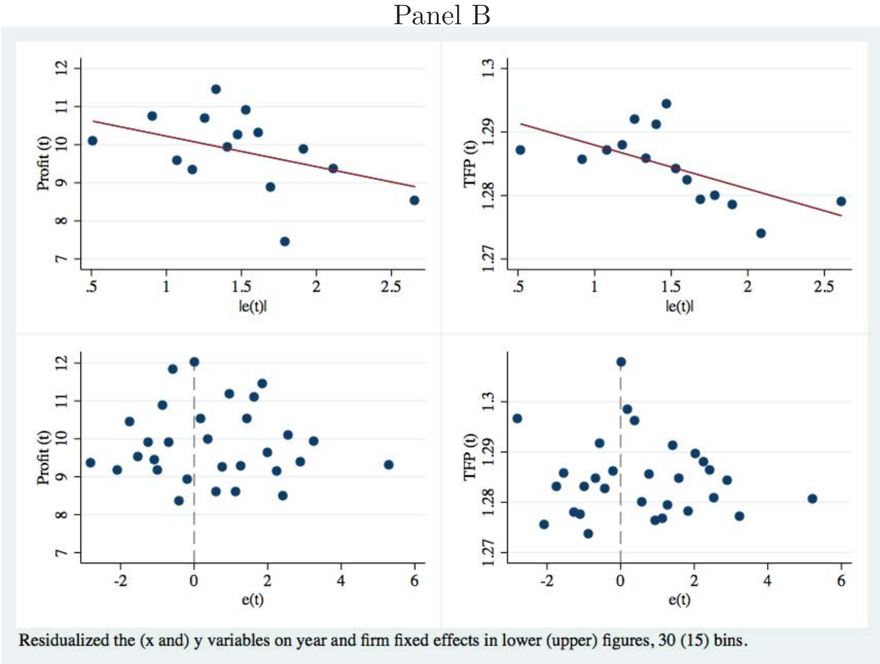
Notes: The distribution of estimated coefficient β_i based on equation (1). The distribution is drawn after winsorizing the variable by replacing observations with more than $\mu \pm 3\sigma$, where μ and σ denote for the mean and the standard deviation of the estimates of β_i .

Figure 5: Binscatter plots

Panel A



Panel B



Notes: Panel A shows the relationship between forecast and firms' input choices by binned scatterplots. The x-axis shows residual values of $f_{it-1}(t)$ after regressing on year fixed effects and firm fixed effects. The residual value is grouped into equal-sized 15 bins, and for each bin, the y-axis plots the average of the residual value of Y_{it} (either employment growth, investment growth, or sales growth) after regressing it on year fixed effects and firm fixed effects. Panel B shows the relationship between forecast errors and firm's profit and TFP by binned scatterplots. In the upper figures, the x-axis shows residual values of $|e_{it-1}(t)|$ after regressing on year fixed effects and firm fixed effects. In the lower figures, the x-axis shows the raw value of $e_{it-1}(t)$ without residualizing this variable. In both upper and lower figures, the y-axis shows the average of the residual value of V_{it} (either profit increase from t to $t+1$ or TFP growth) for each equal-sized bins of x-axis. The number of bins is 15 for the upper figures and 30 for the lower figures.

Table 1. GDP forecasts, employment, investment, and sales growth

	(1) $DLn(Emp_{it})$	(2) $DLn(Emp_{it})$	(3) $DLn(Inv_{it})$	(4) $DLn(Inv_{it})$	(5) $DLn(Sales_{it})$	(6) $DLn(Sales_{it})$
$f_{it-1}(t)$	0.0025**	0.0024**	0.0258**	0.0247*	0.0036**	0.0032*
	(0.0001)	(0.001)	(0.0130)	(0.0147)	(0.0015)	(0.0017)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	No	Yes	No	Yes	No
Firm FE	No	Yes	No	Yes	No	Yes
Observations	15,617	15,617	15,618	15,618	15,618	15,618
Number of firms		2,080		2,081		2,081
Mean dep var	-0.0179	-0.0179	-0.0477	-0.0477	-0.00367	-0.00367

Notes: Standard errors are clustered at firm levels. Sample is restricted to firms that answered the survey in the two preceding consecutive years. $f_{it-1}(t)$ is firm i's forecast of GDP growth in year t answered in year $t-1$. $DLn(Emp_{it}) = Ln(Employment_{it}) - Ln(Employment_{it-1})$, $DLn(Inv_{it}) = Ln(Investment_{it}+1) - Ln(Investment_{it-1}+1)$, and $DLn(Sales_{it}) = Ln(Sales_{it}) - Ln(Sales_{it-1})$.

Table 2. GDP forecasts, employment, investment, and sales growth by cyclicality

	(1) $DLn(Emp_{it})$	(2) $DLn(Emp_{it})$	(3) $DLn(Inv_{it})$	(4) $DLn(Inv_{it})$	(5) $DLn(Sales_{it})$	(6) $DLn(Sales_{it})$
Sample Cyclicality	High	Low	High	Low	High	Low
$f_{it-1}(t)$	0.00377**	0.00114	0.0417*	0.00260	0.00537*	-0.00168
	(0.00159)	(0.00151)	(0.0226)	(0.0230)	(0.00304)	(0.00246)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,926	5,891	5,926	5,892	5,926	5,892
N firms	694	756	694	757	694	757

Notes: Standard errors are clustered at firm levels. Sample is restricted to firms that answered the survey in the two preceding consecutive years. The sample is divided to high and low cyclicality firms based on cyclicality index constructed based on stock price responses to quarterly GDP announcements. Firms in high cyclicality sample have cyclicality index above median. $f_{it-1}(t)$ is firm i's forecast of GDP growth in fiscal year t answered in year $t-1$. $DLn(Emp_{it}) = Ln(Employment_{it}) - Ln(Employment_{it-1})$, $DLn(Inv_{it}) = Ln(Investment_{it}+1) - Ln(Investment_{it-1}+1)$, and $DLn(Sales_{it}) = Ln(Sales_{it}) - Ln(Sales_{it-1})$.

Table 3. GDP forecast errors and firm performance

	(1) $Profit_{it}$	(2) TFP_{it}	(3) $Profit_{it}$	(4) TFP_{it}	(5) $Profit_{it}$	(6) TFP_{it}
$\lvert e_{it-1}(t)\rvert$	-0.802***	-0.00691**			-1.291**	-0.0119**
	(0.204)	(0.00276)			(0.533)	(0.00479)
$e_{it-1}(t)(+)$			-0.973***	-0.0105***		
			(0.293)	(0.00366)		
$e_{it-1}(t)(-)$			-0.586**	-0.00231		
			(0.270)	(0.00390)		
$\frac{1}{5}\sum_{k=t-5}^{t-1}\lvert e_{ik-1}(k)\rvert$					2.632	-0.0205
					(2.918)	(0.0248)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,618	12,663	15,618	12,663	5,114	4,237
Number of firms	2,081	1,733	2,081	1,733	935	784
Mean dep var	9.825	1.285	9.825	1.285	9.825	1.285

Notes: Standard errors are clustered at firm levels. Sample is restricted to firms that answered the survey in the two preceding consecutive years. $|e_{it-1}(t)|$ 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. $e_{it-1}(t)(+) \equiv |e_{it-1}(t)| * 1\{e_{it-1}(t) > 0]\}$ and $e_{it-1}(t)(-) \equiv |e_{it-1}(t)| * 1\{e_{it-1}(t) < 0]\}$, where $e_{it-1}(t)$ 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. $\frac{1}{5}\sum_{k=t-5}^{t-1}|e_{ik-1}(k)|$ is the average absolute forecast errors in the last 5 years of firm i. Unit of profit is million JPY.

Table 4. Forecast accuracy with respect to GDP growth realization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{i,t}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$
Ln(Employment)	-0.0190***		-0.0286***		-0.0237***		-0.0248***		-0.0366***	-0.0506***
	(0.00317)		(0.00475)		(0.00373)		(0.00370)		(0.00565)	(0.00839)
TFP (past 3 years)		-0.0490***	-0.0399**							-0.0270
		(0.0186)	(0.0183)							(0.0362)
Firm age				-0.00102***	-0.000657**					-0.000974
				(0.000270)	(0.000271)					(0.000595)
Cyclicality						-0.219**	-0.172*			-0.117
						(0.0958)	(0.0930)			(0.208)
Banks share								-0.639***	-0.455***	-0.337***
								(0.0878)	(0.0914)	(0.127)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,923	10,852	10,827	19,788	19,771	19,542	19,525	9,383	9,367	3,981

Notes: Standard errors are clustered at firm levels. TFP (past 3 years) is the average TFP of the firm in the preceding three years. Bank share is defined by the stock share owned by banks and other financial institutions among the firm's top 30 stock holders. $|e_{it}(t+1)|$ is a measure of forecast error defined by the absolute value of difference between firm i's forecast of GDP growth in fiscal year $t+1$ answered in year t and the realized GDP growth in fiscal year $t+1$.

Table 5. Forecast accuracy with respect to professional forecasts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$
Ln(Employment)	-0.0568***		-0.0650***		-0.0528***		-0.0554***		-0.0494***	-0.0657***
	(0.00320)		(0.00451)		(0.00378)		(0.00373)		(0.00556)	(0.00878)
TFP (past 3 years)		-0.0483**	-0.0273							-0.0164
		(0.0201)	(0.0190)							(0.0361)
Firm age				-0.00186***	-0.00105***					-0.00122**
				(0.000279)	(0.000266)					(0.000582)
Cyclicality						-0.171*	-0.0689			0.281
						(0.102)	(0.0944)			(0.211)
Banks share								-0.764***	-0.515***	-0.342***
								(0.0862)	(0.0885)	(0.132)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,923	10,852	10,827	19,788	19,771	19,542	19,525	9,383	9,367	3,981

Notes: Standard errors are clustered at firm levels. TFP (past 3 years) is the average TFP of the firm in the preceding three years. Bank share is defined by the stock share owned by banks and other financial institutions among the firm's top 30 stock holders. $|ep_{it}(t+1)|$ 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.

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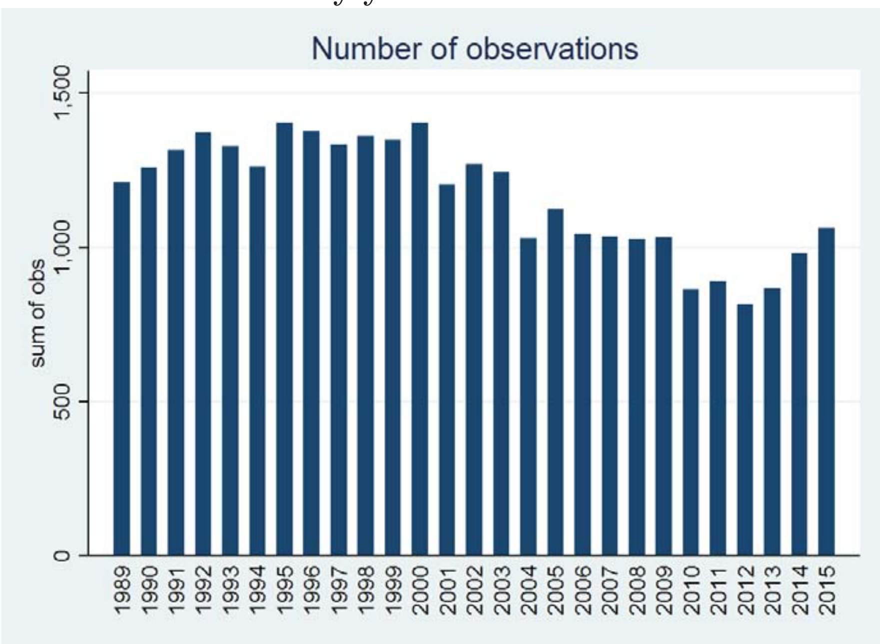
Appendix

Notes on TFP calculation

Output is measured by the firm's sales from DBJ data divided by the industry-level output deflator from JIP database. Labor input is measured by the number of workers from DBJ data multiplied by the industry-level average hours worked from JIP database. As for capital input measure, we use the book value of tangible asset excluding land from DBJ data deflated by corresponding item-level deflator from Corporate Goods Price Index of the Bank of Japan. Intermediary input cost is measured by the sum of total production cost and cost of sales and general management subtracting wages and depreciation. We use industry-level intermediate goods deflator from JIP database to deflate the intermediary input cost. As for the cost share parameters, we use industry-level labor cost share, capital input share, and intermediate input shares from JIP database.

Figure A1: Number of observations by year



Note: The number of firms that responded to the ASCB by year.

Figure A2: Survey question on GDP growth forecasts

I. Business environment and basic management policy

(Business outlook and demand forecast)

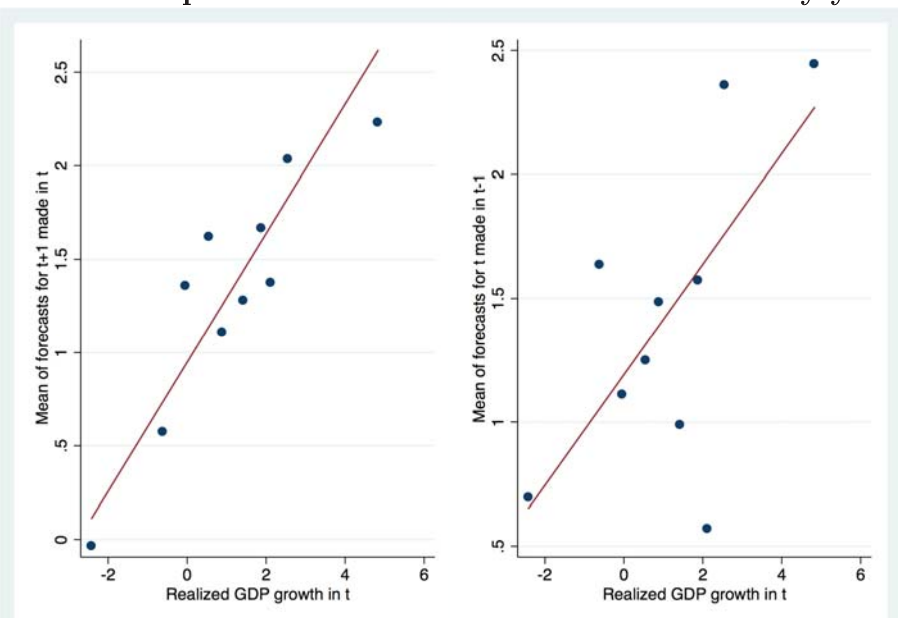
Q1: Give your rough forecast about nominal and real growth rates of the Japanese economy and the demand in your industry for FY2005, the next three years (annual average rate for FY2005-07) and the next five years (annual average rate for FY2005-09), respectively. Enter in the blank below <u>forecast figures to the first decimal point</u>.

Period / Growth rate	FY2005	Next three years (FY2005-07 annual average)	Next five years (FY2005-09 annual average)
Nom. growth rate of JPN. economy	. %	. %	. %
Real growth rate of JPN. economy	. %	. %	. %
Nom. growth rate of demand in your industry	. %	. %	. %
Real growth rate of demand in your industry	. %	. %	. %

Note: If you are engaged in wide-ranging activities, please reply regarding the industry of your principal business line.

Note: The part of ASCB questionnaire that asked firms about GDP growth rate forecasts.

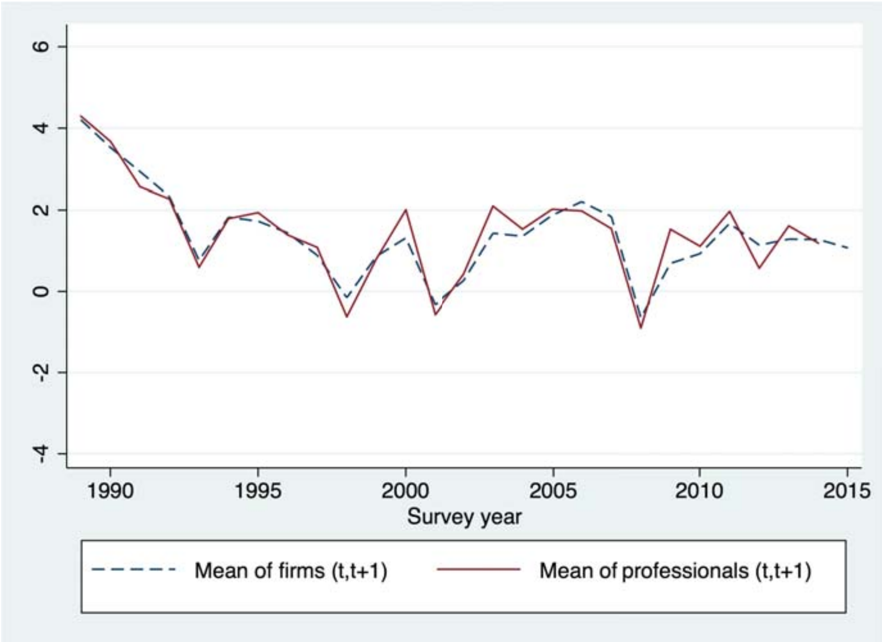
Figure A3: Binned scatter plots of mean forecasts and realization by year



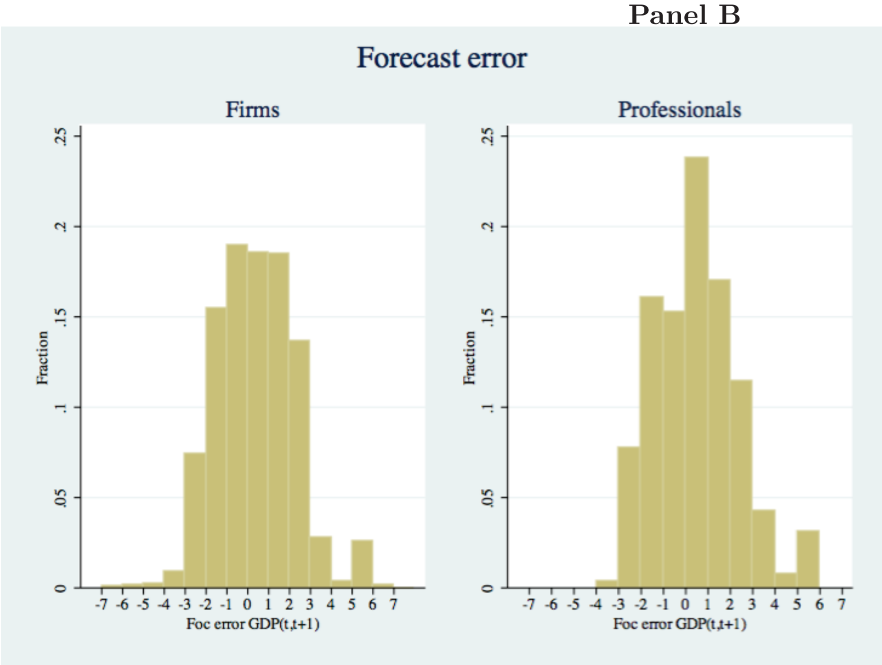
Note: Binned scatter plots with 10 bins.

Figure A4: Comparison of firm forecasts and professional forecasts

Panel A



Panel B



Notes: Panel A shows the average firm forecasts from ASCB and average professional forecasts from the Consensus Forecasts for the next year's $(t+1)$ GDP growth rates. Panel B shows the distribution of firm forecast errors and professional forecast errors.

Table A1. Departments of the survey respondents

	Departments (in English)	Departments (in Japanese)
54%	Corporate planning and strategy	”Kikaku”, ”Keikaku”, ”Senryaku”
12%	Management, CEO office	”Keiei”, ”Kanri”, ”Syacho”, ”Torishimariyaku”
12%	Finance	”Zaimu”, ”Keiri”, ”Zaikei”, ”Kansa”, ”Kaikei”
12%	General affairs	”Soumu”, ”Gyoumu”
7%	IR, Public relations	”IR”, ”Koho”
3%	Others	

Notes: ASCB collected the name of department that answered the questionnaire in the respondent firms. We classified department names in Japanese to six categories corresponding to the above terms. The first column shows the fraction of firms in which the responding department correspond to each category.

Table A2. Basic sample statistics

Variable	Mean	SD	Min	Max	N
Forecast of GDP growth in $t+1$	1.483	1.305	-2.8	5.5	25864
Forecast of GDP growth in $t+1$ - realization	0.409	1.88	-6.263	7.244	25864
|Forecast of GDP growth in $t+1$- realization|	1.536	1.16	0.008	7.244	25864
|Forecast of GDP growth in $t+1$ - professional forecast*|	0.549	0.546	0	5.571	25864
Employment	2567	6517	1	257627	25864
Ln(Employment)	6.901	1.315	0	12.459	25864
Employment growth	-0.015	0.077	-0.362	0.254	20061
Investment value (1 mill JPY)	6,963	27,223	0	1,010,000	25864
Ln(Investment value +1)	13.896	2.049	2.554	20.733	25250
Investment growth	-0.033	1.05	-3.235	3.3	19483
Sales (1 mill JPY)	253,623	966,789	141	21E06	25864
Sales growth	0.001	0.118	-0.461	0.371	20063
Firm age	58.232	18.958	0	129	19714
Share of stock owned by banks	0.131	0.09	0	0.568	9315

Notes: *Professional forecast is measured by the yearly average of professional forecasts in the Consensus forecast.

Table A3. Response probit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES						Respond						
Sample	All	All	All	All	All	All	Restricted sample of firms that are observed at least for 5 years					
TFP	0.207***					0.163***	0.317***					0.247***
	(0.0346)					(0.0415)	(0.0273)					(0.0343)
Ln(Labor productivity)		0.0685***						0.184***				
		(0.0189)						(0.0152)				
Ln(Employment)			0.0241***			0.0484***			0.184***			0.230***
			(0.00865)			(0.0166)			(0.00726)			(0.0139)
Ln(Capital)				-0.0106		-0.0479***				0.0750***		-0.110***
				(0.00780)		(0.0154)				(0.00638)		(0.0128)
Firm age					0.00458***	0.00563***					0.0203***	0.0206***
					(0.000635)	(0.000890)					(0.000576)	(0.000769)
Observations	23,412	23,940	27,725	27,412	20,818	16,483	18,954	19,443	22,877	22,591	18,427	14,329
Mean of dep. var	0.910	0.909	0.901	0.902	0.854	0.906	0.568	0.567	0.571	0.571	0.559	0.568

Notes: Probit model. Respond=1 if the firm responds to the survey in the year. Year fixed effects and sector fixed effects are included in all regressions.

Table A4. Annual mean of firms' forecasts and forecast errors

VARIABLES	(1) $\overline{\lvert f_t(t+1)\rvert}$	(2) $\overline{\lvert f_{t-1}(t)\rvert}$	(3) $\overline{\lvert e_t(t+1)\rvert}$	(4) $\overline{\lvert e_{t-1}(t)\rvert}$	(5) $\overline{\lvert e_t(t+1)\rvert}$	(6) $\overline{\lvert e_{t-1}(t)\rvert}$
Realized growth in t	0.345***	0.223				
	(0.0598)	(0.141)				
Mean EPU in t			0.0217**	0.0132		
			(0.00999)	(0.0142)		
Stock volatility in t					0.0194	0.0766**
					(0.0127)	(0.0349)
Constant	0.948***	1.192***	-0.669	0.181	1.104***	-0.185
	(0.137)	(0.234)	(0.910)	(1.325)	(0.378)	(0.710)
Observations	26	26	26	26	26	26
R-squared	0.524	0.160	0.164	0.065	0.029	0.419

Notes: Regression based on the time-series data on annual mean of firms' forecasts and forecast errors. Robust standard errors are estimated and shown in the parenthesis. $\overline{\lvert f_t(t+1)\rvert}$is the average firms' forecast of GDP growth in fiscal year $t+1$ answered in year t. $\overline{\lvert e_t(t+1)\rvert}$is the average firms' forecast errors defined by the absolute value of difference between firm's forecast of GDP growth in fiscal year $t+1$ answered in year t and the realized GDP growth in fiscal year $t+1$. Mean EPU in t is the mean of monthly Economic and Policy Uncertainty index for the fiscal year t.

Table A5. GDP forecasts interacted with cyclicality

	(1) $DLn(Emp_{it})$	(2) $DLn(Emp_{it})$	(3) $DLn(Inv_{it})$	(4) $DLn(Inv_{it})$	(5) $DLn(Sales_{it})$	(6) $DLn(Sales_{it})$
$f_{it-1}(t)$	-0.000777	0.00115	-0.0131	-0.0388	-0.00385	-0.00143
	(0.00237)	(0.00239)	(0.0312)	(0.0376)	(0.00348)	(0.00385)
$f_{it-1}(t)$ × Cyclicality	0.0230	0.00926	0.303	0.463*	0.0444*	0.0241
	(0.0162)	(0.0169)	(0.206)	(0.245)	(0.0244)	(0.0268)
Cyclicality	-0.0196		0.0609		-0.0367	
	(0.0286)		(0.266)		(0.0377)	
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Sector FEs	Yes	No	Yes	No	Yes	No
Firm FEs	No	Yes	No	Yes	No	Yes
Observations	11,817	11,817	11,818	11,818	11,818	11,818
Number of firms		1,450		1,451		1,451

Notes: Standard errors are clustered at firm levels. Sample is restricted to firms that answered the survey in the two preceding consecutive years. Cyclicality index is constructed based on stock price responses to quarterly GDP announcements. $f_{it-1}(t)$ is firm's forecast of GDP growth in fiscal year t answered in year $t-1$. $DLn(Emp_{it}) = Ln(Employment_{it}) - Ln(Employment_{it-1})$, $DLn(Inv_{it}) = Ln(Investment_{it}+1) - Ln(Investment_{it-1}+1)$, and $DLn(Sales_{it}) = Ln(Sales_{it}) - Ln(Sales_{it-1})$.

Table A6. Forecast errors and firm performance, adjusted by response weights

	(1) $DLn(Emp_{it})$	(2) $DLn(Inv_{it})$	(3) $DLn(Sales_{it})$	(4) $Profit_{it}$	(5) TFP_{it}	(6) $Profit_{it}$	(7) TFP_{it}
$f_{it-1}(t)$	0.0247*	0.00241**	0.00321*				
	(0.0147)	(0.000955)	(0.00165)				
$\lvert e_{it-1}(t)\rvert$				-0.698***	-0.00756***		
				(0.168)	(0.00279)		
$e_{it-1}(t)(+)$						-0.847***	-0.0123***
						(0.250)	(0.00382)
$e_{it-1}(t)(-)$						-0.517**	-0.00169
						(0.210)	(0.00401)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,618	15,617	15,618	15,479	12,663	15,479	12,663
Number of firms	2,081	2,080	2,081	2,063	1,733	2,063	1,733
Mean dep var	-0.0477	-0.0179	-0.00367	9.825	1.285	9.825	1.285

Notes: Standard errors are clustered at firm levels. Sample is restricted to firms that answered the survey in the two preceding consecutive years. $DLn(Emp_{it}) = Ln(Employment_{it}) - Ln(Employment_{it-1})$, $DLn(Inv_{it}) = Ln(Investment_{it} + 1) - Ln(Investment_{it-1} + 1)$, and $DLn(Sales_{it}) = Ln(Sales_{it}) - Ln(Sales_{it-1})$. $|e_{it-1}(t)|$ 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. Profit is the lagged value of profit in fiscal year t. Unit of profit is million JPY. The regressions weigh responses by inverse of estimated firm's response probability. We estimate the probability of survey response by estimating a probit model using information of DBJ data on log of sales, employment, and capital, firm age, a dummy of non-missing information on firm age, sector fixed effects, and year fixe effects. The firm's response probability is estimated as an average of the predicted response probability within each firm.

Table A7. Squared forecast errors and firm performance

	(1) $Profit_{it}$	(42) TFP_{it}
$e^2_{it-1}(t)$	-0.218***	-0.000484
	(0.0678)	(0.000737)
Year FEs	Yes	Yes
Firm FEs	No	Yes
Observations	15,618	12,658
Number of firms	2,081	1,732
Mean dep var	9.825	1.285

Notes: Standard errors are clustered at firm levels. Sample is restricted to firms that answered the survey in the two preceding consecutive years. $e^2_{it-1}(t)$ is a measure of forecast error defined by the square 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. Unit of profit is million JPY.

Table A8. Forecast errors and firm performance: dynamics and professional forecasts

	(1)	(2)
	$Profit_{it}$	TFP_{it}
Period	$t-1$	$t-1$
$\lvert e_{it-1}(t)\rvert$	-0.322	-0.000502
	(0.365)	(0.00273)
Year FEs	Yes	Yes
Firm FEs	Yes	Yes
Observations	14,406	11,709
Number of firms	1,975	1,644

Notes: Standard errors are clustered at firm levels. Sample is restricted to firms that answered the survey in the two preceding consecutive years. $|e_{it-1}(t)|$ 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. Profit and TFP are the lagged value of profit and TFP in fiscal year t. Unit of profit is million JPY.

Table A9. Forecast accuracy with respect to realized GDP growth (firm fixed effects)

	(1)	(2)	(3)	(4)	(5)
	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$
Ln(Employment)	0.00432		-0.00885		0.0114
	(0.0105)		(0.0219)		(0.0160)
TFP (past 3 yrs)		-0.00498	-0.00533		
		(0.0519)	(0.0518)		
Banks share				-0.303**	-0.302**
				(0.153)	(0.153)
Year FEs	Yes	Yes	Yes	Yes	Yes
Sector FEs	No	No	No	No	No
Firm FEs	Yes	Yes	Yes	Yes	Yes
Observations	25,923	10,852	10,827	9,383	9,367
Number of firms	2,349	1,543	1,541	1,522	1,521

Notes: Standard errors are clustered at firm levels. TFP (past 3 years) is the average TFP of the firm in the preceding three years. Bank share is defined by the stock share owned by banks and other financial institutions among the firm's top 30 stock holders.

Table A10. Forecast accuracy with respect to realized GDP growth (squared loss function)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$e_{it}^2(t+1)$	$e_{it}^2(t+1)$	$e_{it}^2(t+1)$	$e_{it}^2(t+1)$	$e_{it}^2(t+1)$	$e_{it}^2(t+1)$	$e_{it}^2(t+1)$	$e_{it}^2(t+1)$	$e_{it}^2(t+1)$	$e_{it}^2(t+1)$
Ln(Employment)	-0.0887***		-0.114***		-0.0948***		-0.101***		-0.137***	-0.186***
	(0.0145)		(0.0198)		(0.0176)		(0.0179)		(0.0280)	(0.0417)
TFP (past 3 yrs)		-0.185**	-0.149*							-0.173
		(0.0808)	(0.0799)							(0.169)
Firm age				-0.00423***	-0.00277**					-0.00309
				(0.00123)	(0.00122)					(0.00256)
Cyclicality						-0.657	-0.467			-0.382
						(0.452)	(0.448)			(0.884)
Banks share								-2.092***	-1.413***	-0.982
								(0.396)	(0.416)	(0.637)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	No	No	No	No	No	No	No	No	No	No
Observations	25,923	10,852	10,827	19,788	19,771	19,542	19,525	9,383	9,367	3,981

Notes: Standard errors are clustered at firm levels. TFP (past 3 years) is the average TFP of the firm in the preceding three years. Bank share is defined by the stock share owned by banks and other financial institutions among the firm's top 30 stock holders.

Table A11. Forecast accuracy with respect to realized GDP growth (response weighted)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$
Ln(Employment)	-0.0227***		-0.0319***		-0.0274***		-0.0286***		-0.0399***	-0.0544***
	(0.00337)		(0.00492)		(0.00400)		(0.00396)		(0.00619)	(0.00861)
TFP (past 3 yrs)		-0.0533***	-0.0435**							-0.0319
		(0.0194)	(0.0190)							(0.0370)
Firm age				-0.00113***	-0.000708**					-0.00100
				(0.000295)	(0.000294)					(0.000623)
Cyclicality						-0.240**	-0.188*			-0.130
						(0.102)	(0.0981)			(0.215)
Banks share								-0.682***	-0.470***	-0.339**
								(0.0919)	(0.0968)	(0.131)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	No	No	No	No	No	No	No	No	No	No
Observations	25,647	10,820	10,820	19,558	19,558	19,311	19,311	9,210	9,210	3,974

Notes: Standard errors are clustered at firm levels. TFP (past 3 years) is the average TFP of the firm in the preceding three years. Bank share is defined by the stock share owned by banks and other financial institutions among the firm's top 30 stock holders. Weighting response by inverse of probability of non-missing answers in the survey (using information of DBJ data on log of sales, employment, and capital, firm age, dummy of non-missing information on firm age, sector fixed effects, and year fixe effects).

Table A12. Forecast accuracy with respect to GDP growth realization (early estimates of GDP published in June of the following fiscal year)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$	$\lvert e_{i,t}(t+1)\rvert$	$\lvert e_{it}(t+1)\rvert$
Ln(Employment)	-0.0239***		-0.0290***		-0.0191***		-0.0210***		-0.0165***	-0.0296***
	(0.00326)		(0.00458)		(0.00370)		(0.00363)		(0.00547)	(0.00801)
TFP (past 3 years)		-0.0283	-0.0178							-0.0534
		(0.0201)	(0.0202)							(0.0396)
Firm age				-0.000789***	-0.000538**					5.98e-07
				(0.000249)	(0.000267)					(0.000592)
Cyclicality						0.0137	0.0673			0.236
						(0.0905)	(0.0965)			(0.195)
Banks share								-0.535***	-0.460***	-0.373**
								(0.0875)	(0.0956)	(0.145)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,923	10,852	10,827	20,480	19,771	20,227	19,525	10,075	9,367	3,981

Notes: Standard errors are clustered at firm levels. TFP (past 3 years) is the average TFP of the firm in the preceding three years. Bank share is defined by the stock share owned by banks and other financial institutions among the firm's top 30 stock holders. $|e_{it}(t+1)|$ is a measure of forecast error defined by the absolute value of difference between firm i's forecast of GDP growth in fiscal year $t+1$ answered in year t and the realized GDP growth in fiscal year $t+1$.

Table A13. Forecast accuracy with respect to professional forecasts in the preceding month (November)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$	$\lvert ep_{it}(t+1)\rvert$
Ln(Employment)	-0.0497***		-0.0517***		-0.0455***		-0.0481***		-0.0431***	-0.0520***
	(0.00318)		(0.00460)		(0.00373)		(0.00367)		(0.00550)	(0.00938)
TFP (past 3 years)		-0.0341*	-0.0172							0.00262
		(0.0198)	(0.0195)							(0.0377)
Firm age				-0.00166***	-0.000964***					-0.00175***
				(0.000266)	(0.000258)					(0.000578)
Cyclicality						-0.174*	-0.0855			0.172
						(0.0961)	(0.0908)			(0.199)
Banks share								-0.571***	-0.354***	-0.220
								(0.0845)	(0.0875)	(0.137)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,923	10,852	10,827	19,788	19,771	19,542	19,525	9,383	9,367	3,981

Notes: Standard errors are clustered at firm levels. TFP (past 3 years) is the average TFP of the firm in the preceding three years. Bank share is defined by the stock share owned by banks and other financial institutions among the firm's top 30 stock holders. $|ep_{it}(t+1)|$ 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 provided in the November of year t.