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FIRM PERFORMANCE AND MACRO FORECAST ACCURACY

Mari Tanaka
Nicholas Bloom
Joel M. David
Maiko Koga

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ABSTRACT

Ever since Keynes' famous quote about animal spirits, there has been an interest in linking firms' expectations and actions. However, empirical evidence has been limited due to a lack of firm-level panel data on expectations and outcomes. In this paper, we build such a dataset by combining a unique survey of Japanese firms' GDP forecasts with company accounting data for 25 years for over 1,000 large Japanese firms. We find four main results. First, firms' GDP forecasts are positively associated with their employment, investment, and output growth in the subsequent year. Second, both optimistic and pessimistic forecast errors lower profitability. Third, while over-optimistic forecasts lower measured productivity, over-pessimistic forecasts do not tend to have an effect on productivity. Overall, these results are stronger for firms whose performance is more sensitive to the state of macroeconomy. We show that a simple model of firm input choice under uncertainty and costly adjustment can rationalize these results. Finally, larger and more cyclically sensitive firms make more accurate forecasts, presumably reflecting a higher return to accuracy for these firms. 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, our results highlight the importance of firms' forecasting ability for micro and macro performance.

Mari Tanaka
Hitotsubashi University
Graduate School of Economics
2-1 Naka, Kunitachi, Tokyo, Japan
mari.tanaka@r.hit-u.ac.jp

Nicholas Bloom
Stanford University
Department of Economics
579 Serra Mall
Stanford, CA 94305-6072
and NBER
nbloom@stanford.edu

Joel M. David
Department of Economics
University of Southern California
3620 South Vermont Ave. Kaprielian Hall, 300
Los Angeles, CA 90089
joeldavi@usc.edu

Maiko Koga
Bank of Japan
Research and Statistics Department
Tokyo, Japan
maiko.koga@boj.or.jp

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 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 ultimately matter for economic outcomes, under what circumstances, and to what extent does their level and accuracy vary across firms?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 run by the Economic and Social Research Institute (ESRI) within the Cabinet Office over the period 1989–2015 and achieved a response rate of about 40% from all publicly listed firms in Japan, generating a panel sample of around 1,000 firms. The survey asks firms for a quantitative estimate 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 four 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. Prior year forecast accuracy has significant predictive power for profits, even after controlling for time fixed effects, longer-run forecast accuracy, and firm fixed effects. This is true both for over-optimistic firms (positive forecast errors) as well as over-pessimistic ones (negative forecast errors). Third, measured productivity (TFPR) is negatively affected by excessively optimistic forecasts, but excessively pessimistic forecasts do not seem to affect productivity. For all of these results, the effects are strongest in firms whose performance is more sensitive to the state of the business cycle. 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,

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

and the interaction of pricing effects with costs of adjustment can generate asymmetric effects of optimism/pessimism (e.g., positive/negative forecast errors) on measured productivity.

Finally, we find significant variation in forecast accuracy across firms. Larger and more cyclically sensitive firms have the most accurate forecasts, presumably because their returns from accuracy are largest. Interestingly, we also see that more productive, older, and bank-owned firms tend to be more accurate, suggesting that experience, management ability, and governance may also play an important role in forecast accuracy. The results are similar when we measure firms' forecast accuracy alternatively by the distance to professionals' forecasts.

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; Mankiw and Reis 2002). More recently, David, Hopenhayn, and Venkateswaran (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; Schmitt-Grohé and Uribe 2012; Ilut and Schneider 2014).

Second, this paper builds on a growing empirical literature investigating expectations formation. Mankiw, Reis, and Wolfers (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 (Carroll 2003; Coibion and Gorodnichenko 2012, 2015). Coibion, Gorodnichenko, and Kumar (2015) document substantial heterogeneity in firms' macroeconomic forecasts in a firm survey in New Zealand and find that firms with higher incentives to predict (e.g. facing higher competition) are more accurate than others. Bachmann and Elstner (2015) and Massenot and Pettinicchi (2018) use a German manufacturing survey that asked about predictions about 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. Bloom et al. (2018) use US Census data and look at whether more productive and better managed firms have improved forecast accuracy. 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. Most datasets collect forecast information about the manager’s own firm performance, 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 the forecasts on a common object – GDP growth – the second source of variation is not present.

Third, some recent works provide evidence related to ours about the relationship between firms’ expectations and outcomes. Gennaioli, Ma, and Shleifer (2015) examine rationality of CFOs’ expectations, and as a part of their exercises, they show that investment plans and realizations are well explained by expectations of earning growth. In a related effort, Massenot and Pettinicchi (2018) use a German survey data containing firms’ qualitative assessment of their business conditions and show that over-optimistic firms subsequently report lower profits and that over-pessimistic firms report higher profits. Overall, our study is unique in that we use a long panel data of firms’ quantitative GDP forecasts matched with their accounting data, which enables us to quantitatively examine the effects of firms’ forecasts on 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.

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 explains the data, section 4 discusses our main results 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_{it}) and labor (N_{it}) 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 substitution 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 elasticity of substitution across goods. Firm revenues are then given by

$$P_{it} Y_{it} = A_{it} K_{it}^{\hat{\alpha}_1} N_{it}^{\hat{\alpha}_2} ,$$

where

$$\hat{\alpha}_1 = \alpha \frac{\sigma - 1}{\sigma}, \quad \hat{\alpha}_2 = (1 - \alpha) \frac{\sigma - 1}{\sigma}, \quad \hat{\alpha}_1 + \hat{\alpha}_2 = \frac{\sigma - 1}{\sigma} .$$

Input markets work as follows. The firm accumulates capital internally. 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 δ . The firm discounts time at rate β .

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 the realization of the fundamental. Specifically, the firm solves

$$\max_{K_{it}, N_{it}} E_{it} [\Pi_{it}] = E_{it} [A_{it}] K_{it}^{\hat{\alpha}_1} N_{it}^{\hat{\alpha}_2} - R K_{it} - W_t N_{it} . \quad (1)$$

where $R = 1 - \beta(1 - \delta)$ is the user cost of capital.² Fundamentals and expectations are distributed

²Notice that the setup is equivalent to one with a rental market for capital where the rental rate is equal to R .

jointly log-normal. 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

$$K_{it} = C_{1t} E_{it} [A_{it}]^\sigma \quad (2)$$

$$N_{it} = C_{2t} E_{it} [A_{it}]^\sigma ,$$

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

$$P_{it} Y_{it} = C_{3t} A_{it} E_{it} [A_{it}]^{\sigma-1} \quad (3)$$

$$\Pi_{it} = C_{3t} \left(A_{it} E_{it} [A_{it}]^{\sigma-1} - \frac{\sigma-1}{\sigma} E_{it} [A_{it}]^\sigma \right) , \quad (4)$$

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 $E_{it} [A_{it}] = A_{it}$ and are declining in the difference between actual 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

$$TFPR_{it} = C_{4t} \left(\frac{E_{it} [A_{it}]}{A_{it}} \right)^{-1} , \quad (5)$$

where C_{4t} 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 its true fundamental, 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. These costs directly 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 monotonic in the forecast error for pessimistic firms – while optimistic firms always have lower TFPR, because of the disruption cost, the relationship is ambiguous for pessimistic firms.³

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

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

where K_{it} denotes the final amount of capital used in production and ξ expresses the degree of the disruption costs. Similar specifications are commonly used to describe settings where firms find it harder to work efficiently with excessive or inadequate inputs.⁴

³In 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. $N_{it} = \eta_t K_{it}$, where η_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 generally similar patterns to the ones here.

⁴One reason may be fixed costs of operations and diminishing returns to scale - see, for example, Bartelsman, Haltiwanger, and Scarpetta (2013).

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

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

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

$$K_{it} = C_{5t} A_{it}^{\phi_1} E_{it} [A_{it}]^{\sigma \phi_2} ,$$

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 ϕ_1 and ϕ_2 . If the disruption cost, ξ , approaches infinity, ϕ_1 approaches zero and ϕ_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 ξ approaches zero, the firm can respond fully to the true fundamental, e.g., ϕ_2 goes to zero.

We can then derive the following expression for TFPR:

$$TFPR_{it} = C_{6t} \left((1 + \xi) Z_{it}^{-\frac{\sigma}{\sigma-1}(1-\phi_1)-\phi_1} - \frac{\xi}{2} Z_{it}^{-\frac{\sigma}{\sigma-1}(1-\phi_1)-2\phi_1} - \frac{\xi}{2} Z_{it}^{-\frac{\sigma}{\sigma-1}(1-\phi_1)} \right)^{\frac{\sigma-1}{\sigma}} , \quad (6)$$

where $Z_{it} \propto \frac{E_{it}[A_{it}]}{A_{it}}$ captures the firm's forecast error. Similar to equation (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 $Z_{it} < \hat{Z}$. Thus, the effect of expectational errors on TFPR is ambiguous for pessimistic firms.

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. 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. Thus, for these firms, the relationship between TFPR and forecast error is ambiguous. 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 but the effect is ambiguous for 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 during the period from 1989 to 2015, as individual firm identifies 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 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 business outlook for GDP and industry demand, and their business plans regarding investment, employment, and pricing. The items we use are forecasts of real GDP growth rate of Japan in the following fiscal year that starts from April. The forecasts are made for three horizons: growth rate of upcoming fiscal year; average growth rate over next three years; and average growth rate over next five years. For example, the questions asked in December 2004 were phrased the following way⁵:

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

⁵Appendix Figure A.2 shows the corresponding part of the questionnaire

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).

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 $f_{i,t}(t + 1)$ hereafter). The right hand side of Figure 1 shows the distribution of the absolute value of forecast errors in each year, namely $|e_{i,t-1}(t)| \equiv |f_{i,t-1}(t) - g(t)|$, where $g(t)$ is the realized GDP growth rate of the year t .⁶

A potential concern on this survey measure is whether the answers truly reflect the firms’ forecasts of future macro economic 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. 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,⁷ suggesting that the sample of firms in this study, which consists of relatively larger firms in Japan, would have incentive 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 the current year GDP growth (for the results, see Appendix Table A.4). Fourth, on average, the GDP forecasts provided by firms align well with that of professional forecasts overtime (see Appendix Figure A.4). These observations suggest that most of the respondents are answering some meaningful numbers that are on average following professionals’ forecasts. Even so, there may be some outliers that answer unrealistic forecasts and affect our analysis. Therefore, in order to reduce the effects of outliers, we exclude the observations with growth forecasts of more than $\pm 3\sigma$ with $\pm 3\sigma$, where σ is the standard deviation, and also firms that answered the survey less than three times within the sample period. These procedures drop about 8.8% of the original observations. In the following section, we further test and confirm the firms’ input choices are

⁶In this study, we assume that the survey respondents interpreted “the real economic growth rate” as the real GDP growth rate.

⁷In the Appendix, Figure A.3 shows this by a binned scatter plot.

indeed significantly correlated with their macro forecasts even after controlling for firm fixed effects and year fixed effects.

As additional checks of the survey data, in Figure 2, we plot time-series of the mean of $f_{i,t}(t+1)$ 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.⁸ In Figure 3, we show the yearly average of “absolute value of forecast errors in each year”, namely $|e_{i,t-1}(t)| \equiv |f_{i,t-1}(t) - g(t)|$. 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.⁹ All time series are standardized by the year-level observations. The three lines share the peaks around mid 1990s, 2000, and 2007, suggesting the periods with larger forecast errors correspond to those with larger macro uncertainty.

In addition to the forecasts on 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 the bins with 5% intervals, for example, “5% to 10%”.¹⁰ We approximate continuous variables of investment and employment growth forecasts by the middle values of these intervals.¹¹

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. In our baseline specification, 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 A.2 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 investment, employment, and sales growth.

It is possible that the response rates to the ASCB are correlated with certain firm characteristics.

⁸Also see the binned scatter plots in Appendix Figure A.6.

⁹<http://www.policyuncertainty.com>

¹⁰Figure A.5 in the Appendix shows this part of the questionnaire.

¹¹For the top codes, we use + or – 5% of the base value. For example, for investment growth forecast of “25% or more”, we approximate the continuous version of forecast by 30%.

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 A.3 for the results). The magnitude of the response differences are 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-estimate our main equations by weighting samples by inverse of response rates as robustness checks and find qualitatively the same results.

On calculating firm-level TFP, we follow Syversson (2011) and assume Cobb-Douglas production function in which TFP is derived as follows: $TFP_{it} = \ln Y_{it} - S_{jt}^L \ln L_{it} - S_{jt}^K \ln K_{it} - S_{jt}^M \ln M_{it}$, where S_{jt}^k 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 measured by sales revenue, labor, capital, and other intermediate inputs of firm i in year t , respectively.¹² Cost shares are defined as the industry level to reduce the impact of firm-level measurement error, as is standard in the literature. 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 in the industry. 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 Appendix in detail.

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

$$\ln \left(\frac{p_{it}^a}{p_{it}^b} \right) = \beta_i \ln GDP_t + \sum_{k=1}^3 \phi_k \ln GDP_{t-k} + \phi_q FC_{t-1} + F_i + F_y + F_q + u_{it}. \quad (7)$$

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. $\ln GDP_t$ is log of quarterly

¹²Investment 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.

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 log 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 made for the coming calendar year (so their forecast horizon varies by quarter). Firm fixed effects F_i , fiscal year fixed effects F_y , and quarter fixed effects F_q (for $q = 1, 2, 3$) are also controlled. Hence, β_i is firm i specific response to the announced GDP, which is a measure of firm cyclicality for our study.¹³ 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), 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%.

4 Forecasts and firm performance

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

4.1 Firm input choices and sales

First, we estimate the following empirical equation:

$$Y_{it} = \rho f_{i,t-1}(t) + \gamma_i + \lambda_t + \eta_{it} \quad (8)$$

where Y_{it} is either growth of employment, investment, or sales of firm i in fiscal year t from fiscal year $t - 1$ measured by the difference in logarithm.¹⁴ $f_{i,t-1}(t)$ is the forecast of GDP growth rate in fiscal year t answered by firm i in year $t - 1$. The growth rates are all measured in decimal points. We include firm fixed effects (γ_i) to control for unobserved time-invariant characteristics

¹³For 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.

¹⁴Only 2% of the sample had 0 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. $\ln(\text{investment}_t + 1) - \ln(\text{investment}_{t-1} + 1)$) and found that qualitative results were unchanged.

of the firms. We also control for realizations of macro economic shocks by controlling for year fixed effects (λ_t).¹⁵ Since some firms responded the survey sporadically within 25 years, making the identification of within-effects harder, we further limit our samples 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).

A primary purpose of estimating equation (8) 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 actually used for the company’s decision making. If the firm’s survey response reflects a certain belief shared among the firm’s organizers and actually used for its decision making, then we would expect to see positive associations between a firm’s forecasts and its input choice decisions such as investment and employment.

The specification of one-year lag between forecast and firm 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 the most concentrated around the period from April to June of year $t-1$ due to customs of Japanese freshmen labor market. Similarly, it is natural to assume that firms need to make arrangements (e.g. financing) at least in a year before for raising investment in year t .

Panel A of Figure 5 graphically shows the relationship of equation (8) by binned scatterplots. The horizontal axis shows residual values of $f_{i,t-1}(t)$ after regressing on year fixed effects and firm fixed effects. The residual values is grouped into equal-sized 15 bins, and for each bin, the vertical axis shows the mean of residual values of Y_{it} after regressing 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 (8) by OLS. Columns (1) and (2) estimate the equations for employment and investment growth including year fixed effect and firm fixed effects. The estimated coefficients of forecast is positive and statistically significant. The estimates suggest

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

that having 1 percent higher GDP growth rate forecast is associated with around 0.2 percentage points higher employment growth rate and 2.5 percentage points higher investment growth rate on average.¹⁶ 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 seems to be economically large, presumably reflecting the importance of GDP growth for employment and investment in large Japanese firms.

Column (3) estimates the equation (8) for sales growth measured by changes in the log of sales. The estimated coefficients suggest that having 1 percentage point higher GDP growth rate forecast predicts an increase of sales growth rate by 0.3 percentage points. Overall, the results imply that firm's reported forecasts of GDP growth are significantly correlated with its input choice as predicted by the baseline model (Prediction1). As a robustness check, we also estimate Table 1 controlling for the lagged forecast of GDP growth as this specification is more consistent with our model, and confirm the results are qualitatively the same (for the results, see Table A.5 in the Appendix).

A natural conjecture is that macro forecasts affect firms' realized inputs through affecting their initial plans of employment and investment. Using the data on the firms' forecasts of own investment and employment, we find consistent evidence for this. Specifically, in columns (4) and (5), we regress the firm's forecast of investment or 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 1 percent level, implying that 1 percentage point change in GDP growth rate forecast corresponds to 0.258 and 0.669 percentage points changes in employment and investment growth forecasts. We then examine the relationship between forecasts and realizations of employment and investment growths. In columns (6) and (7), the dependent variables are realized growth of employment and investment over the corresponding three years measured by the changes in log of employment and investment 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.

¹⁶If we look at R&D, we get similar significant results. For example, in a specification like column (4) with firm fixed-effects the coefficient (and standard error) on the $\text{Ln}(1+\text{R\&D})$ is 0.014 (0.060).

4.2 Profit and productivity

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

$$V_{it} = \theta|e_{i,t-1}(t)| + \gamma_i + \lambda_t + \omega_{it} \quad (9)$$

where V_{it} is either profit or TFP of firm i in year t . $|e_{i,t-1}(t)|$ is the absolute value of firm i 's GDP growth forecast error defined by $e_{i,t-1}(t) = f_{i,t-1}(t) - g_t$, in which g_t is the realized GDP growth rate in fiscal year t . We control for time-invariant firm characteristics and realizations of macro-level shocks by including firm fixed effect (γ_i) and year fixed effect (λ_t). As before, we limit our samples to observations with non-missing forecasts in the last two consecutive years.

Panel B of Figure 5 graphically illustrates the results by binned scatterplots. In the upper two figures, the horizontal axis shows residual values of $|e_{i,t-1}(t)|$ after regressing on year 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} in each bin, after regressing on year fixed effects and firm fixed effects. The results show negative associations of forecast errors with profit and productivity. In the lower two figures, we change only the horizontal axis to the raw value of $e_{i,t-1}(t)$ without taking absolute value nor residualizing this. The figures show higher values of profit and TFP around the locations where the raw value of error is close to zero. In particular, as for profit (left figure), the relationship appears to be symmetric around zero. As for TFP, the positive forecast errors seem to be associated with lower TFP, while the relationship in the negative side of forecast errors is less clear.

Table 2 shows the estimates for regressions of the equation (9). Column (1) reports the results for profit. The estimated coefficient is negative and statistically significant at 1 percent significance level. The estimate implies sizable effect of forecast error on profit: having 1 percent higher or lower GDP growth rate forecast error tends to lower the level of profit by around 8 percent. 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 forecast error is associated with 0.54 percent lower TFP. We also examined robustness against possible sampling selection effects by estimating the equation (9) by weighting observations by inverse of response rates and found similar results as in the main specification (Table A.6 in the Appendix show the

results).¹⁷ Also, we observe qualitatively the same results when we regress the growth rate of TFP (i.e. the first difference in the logarithm of TFP) instead of the level of TFP on absolute forecast errors (the estimated coefficient is -0.0037 and the standard error is 0.0012).

Next, we estimate the same equation (9) by allowing the coefficients of under-forecast error ($|e_{i,t-1}(t)| \cdot 1\{e_{i,t-1}(t) < 0\}$) and over-forecast error ($|e_{i,t-1}(t)| \cdot 1\{e_{i,t-1}(t) > 0\}$) 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 in the subsequent year. For TFP, the coefficient estimate of optimistic errors is negative and significant, while the coefficient of pessimistic error is estimated to be negative and insignificant.

Our results on profit are consistent with Prediction 3 derived based on a standard dynamic model of firms. That is, firms' profit would be maximized when firms make investment with perfect information about its future productivity. Profit declines because firms over- or under- invest by mis-forecasting growth rate.

The results on TFP are consistent with Prediction 5 obtained based on a model where firms adjust input choices subject to disruption costs. In the model, this result arises in combination of two effects. First, as depicted in the baseline model of section 2.1, if firms are over-optimistic and expand, and thus lower prices, this will cut TFPR¹⁸ as in Prediction 4. The other mechanism is "true TFP" effects, as described in the model of section 2.2, whereby having too few or too many inputs reduces TFP through disruption costs. This would lead to lower TFP for both positive and negative forecast errors.

Another explanation is that over-optimistic firms excessively invest and hire, which reduces capacity utilization (such as working hours and capital utilization), and so does measured TFP because we do not observe capacity utilization at firm level. In reverse, over-pessimistic forecasts lead to higher utilization and higher measured TFP. Therefore, this capacity utilization effect goes to the same direction as the price effect. To examine this channel, we employ an alternative TFP measure where labor input is measured by the total wage bill, which includes overtime pay, and

¹⁷Additionally, we examined a different specification using a squared loss function (i.e. $(e_{i,t-1}(t))^2$) instead of using the absolute loss function. The results are shown in the Table A.6 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 (possibly due to the offsetting two possible mechanisms for the influence of forecasts on TFP discussed in the theory section).

¹⁸We use industry level price deflators to calculate TFP, but not firm level prices. Thus, the measured TFP is interpreted as TFPR.

thus would reflect total hours worked.¹⁹ The result for this TFP measure is shown in column (5). The estimated coefficient of optimistic forecast errors is muted compared to that of column (4) as expected, but it is still significant at 10 percent level. On the other hand, the coefficient of pessimistic forecast errors is slightly lowered but remains insignificant.

An alternative explanation of the results in the above 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 firm's forecast errors for five years preceding the year $t - 1$ (i.e. $t - 2, \dots, t - 6$). 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, historical average of past forecast errors are 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 this hypothesis, columns (6) and (7) of Table 2 show the results of adding historical average of forecast errors. Overall, only the coefficients of 1 year lagged forecast errors are negative and significant. Finally, in columns (8) and (9), we also estimate the specification where the forecast errors are those of the next year ($|e_{i,t}(t + 1)|$) rather than the current year ($|e_{i,t-1}(t)|$) and find insignificant results, ruling out basic reverse causality mechanisms.²⁰

4.3 Results by firm cyclical status and export status

Standard models of firms as in section 2 would also imply that firms whose performance are more sensitive to the macro economy would be more responsive to their GDP growth rates forecasts. We explore this possibility by dividing the sample into high and low cyclical firms using the firm cyclical measure (as described in the data section). In addition, since firms selling in foreign markets may be less influenced by Japanese GDP growth, we further divide the sample

¹⁹A caution of this exercise is that the total wage bill also includes bonus payment, so this can be influenced by firm performance.

²⁰We also examined similar specifications using forecast errors of 2-5 years ahead ($|e_{i,t+1}(t + 2)|$, $|e_{i,t+2}(t + 3)|$, $|e_{i,t+3}(t + 4)|$, and, $|e_{i,t+4}(t + 5)|$) and find insignificant results.

into exporting and non-exporting firms.²¹ Table 3 shows the results. Columns (1), (4), (7), (10), and (13) show the estimates for non-exporting firms with above median cyclical index, the next columns show the results for non-exporting firms with below median cyclical index, and the rest of the columns show the results for exporting firms. Overall, we find strong evidence that non-exporting and more cyclical firms see a tighter correlation between GDP forecasts and firm outcomes than the other firms.²²

5 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. We examine determinants of firms' forecasts quality that is measured in two alternative ways.

One measure of forecast quality is its difference from realization. As its natural counterpart in data, we use $|e_{i,t}(t+1)|$, 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 4 shows the results of regressing absolute forecast errors $|e_{i,t}(t+1)|$ on various contemporaneous firm characteristics in year t .²³ 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) and Bloom et al. (2018) who find similar evidence for firms' forecasts and forecast uncertainty about own production performance in German and US firm data.²⁴ Secondly, we examine whether more productive firms make the more accurate

²¹There is a question in ASCB asked only to exporting firms. We identify exporting companies based on whether the firm answered this question.

²²We also test alternative specifications and find qualitatively similar results. One of these is to use only the cyclical measure to divide the sample by taking the stance that the cyclical measure already takes into account for the firm's foreign operation that are less correlated with Japanese GDP growth. Another specification is to include an interaction terms of cyclical and forecasts. Table A.7 in the appendix shows these results, which are qualitatively similar to the results in Table 3.

²³As 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.

²⁴One important difference from their results is that in our case we are evaluating firms' forecasts on a common

forecasts. Columns (2) and (3) show the results 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 is an important determinant of forecast accuracy.

Third, we test whether firm age matters for forecast errors. Columns (4) and (5) indicate that older firms tend to make smaller absolute errors, even after controlling for the firm size. This result suggest longer business experience may help firms make accurate forecasts.²⁵ 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 in columns (6) and (7) 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 inflation (due to facing higher competitions) make more accurate forecasts than the others.

Finally, we examine differences in forecast accuracy by firms’ ownership types. We use the names of the top 25 largest stock owners of each firm to construct the measures of stock share owned by banks and financial institutions (“bank share”). As shown in columns (8) and (9), the coefficients of bank share are negative and statistically significant. This result remains qualitatively the same 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 planing of their client firms in the post-war period (Hoshi and Kashap 2001). Therefore, given that banks are likely to have professional forecasters²⁶, it is not surprising that banks’ share predicts firms’ forecast accuracies.

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.²⁷ Hence, it should strip

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 striking since we find that larger firms are more accurate even for the common outcome.

²⁵Another interpretation of this result is that firms that have ability make the more accurate forecasts tend to survive longer.

²⁶Most of the professional forecasters in the Consensus Forecast are banks and financial institutions.

²⁷There 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.

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 A.4). To see the differences, we regressed forecasts and forecast errors on a dummy variable indicating professional forecasters using dataset pooling both professional and firm forecasts.²⁸ We find that professional forecasts are on average marginally more optimistic and make smaller absolute error than firm forecasts, although the difference is statistically insignificant. However, we find that squared forecast errors (i.e. $(e_{i,t}(t+1))^2$) are significantly smaller for professional forecasts. The results indicate that professional forecasts tend to make fewer extreme forecast errors than firms.²⁹

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 the ones before 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, cyclicalilty, and bank ownership 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).³⁰ As another robustness check, 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.8 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 to their input choices and performance and what are the factors that explain the heterogeneity of forecast accuracy across firms.

²⁸There were in total 635 professional forecasts in the observed period.

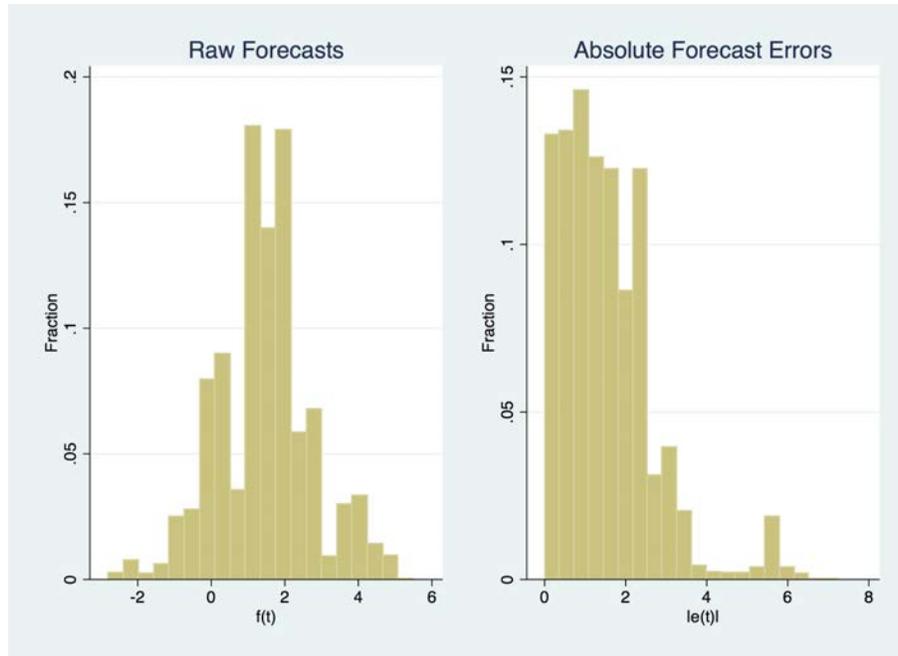
²⁹Distributions of the forecast errors by professionals and firms show that firms' forecast errors have longer tails (see Appendix Figure A.7 Panel B).

³⁰Family 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.

However, micro-level evidence on these questions has been rarely provided due to lack of firm-level panel data tracking both firms' forecasts and performance.

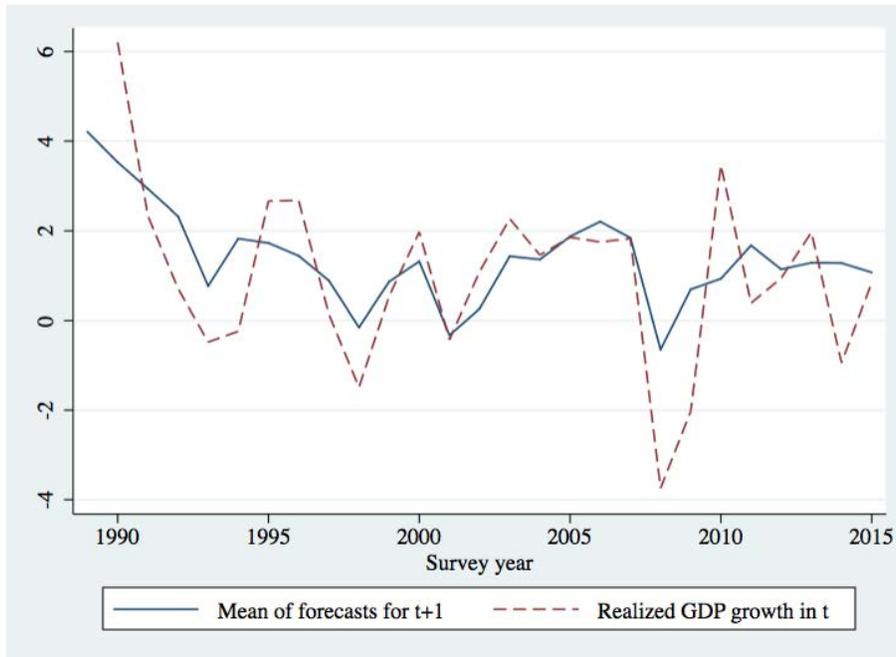
This paper matches panel data on firms' forecasts of GDP growth from the Japanese Annual Survey of Corporate Behavior (ASCB) to company accounting data to provide new evidence on these questions. We find four main results. First, firms' GDP forecasts are positively associated with firms' input choices such as investment, employment, and output. Second, forecast accuracy is strongly related with profitability. A higher forecast error (of either sign) significantly predicts lower profits. Third, we find that measured productivity is negatively associated with excessively optimistic forecasts, while no effect was found for excessively pessimistic forecasts. For all of these results, we find the strongest effects for firms whose performance is more sensitive to the state of the business cycle. We show that a simple model of firm input choice under uncertainty and costly adjustment can rationalize these results. Finally, we find that larger and more cyclically sensitive firms have the most accurate forecasts, presumably because their returns from accuracy are largest. We also see that more productive, older, and bank owned firms tend to be more accurate, suggesting that experience, management ability, and governance may also play an important role in forecast accuracy.

Figure 1: Forecasts and forecast errors



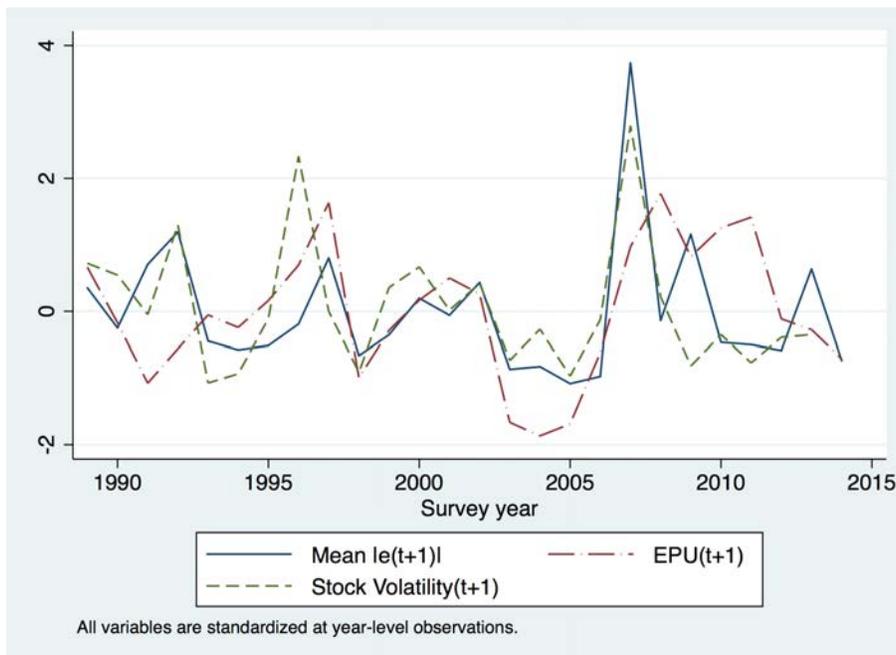
Notes: Left figure shows the histogram of $f_{i,t-1}(t)$, the forecast of fiscal year t GDP growth rate answered by firm i in fiscal year $t - 1$ in the ASCB, for the entire sample periods. The right figure shows the histogram of $|e_{i,t-1}(t)|$, the absolute forecast errors which are the absolute values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

Figure 2: First moments of forecasts



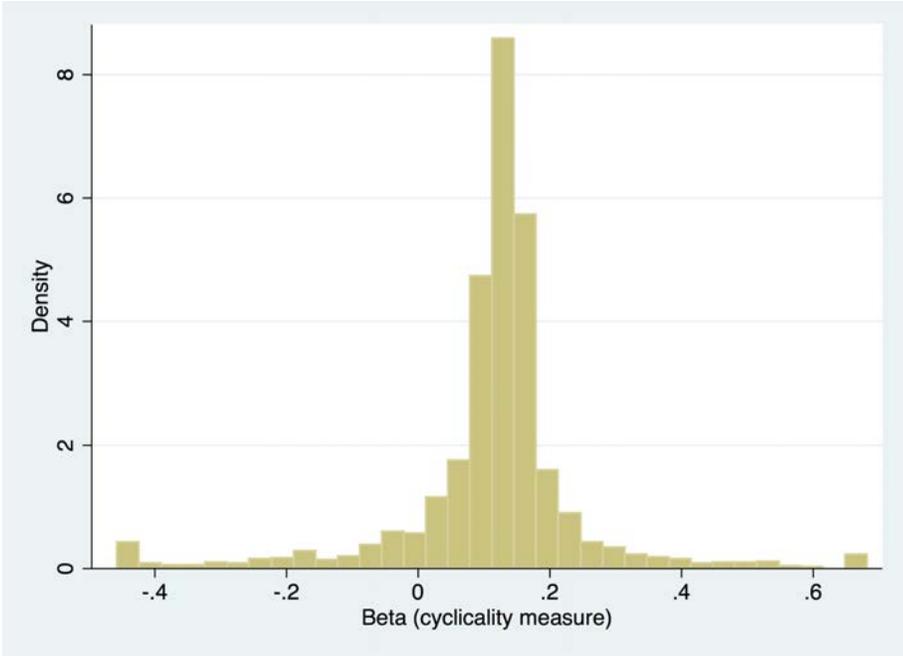
Notes: The horizontal axis indicates fiscal year t . The solid line shows the average of $f_{i,t}(t+1)$, forecast of fiscal year $t+1$ GDP growth rate answered by firm i in fiscal year t in the ACSB. The dashed line shows the realized GDP growth rate in fiscal year t .

Figure 3: Second moments of forecasts



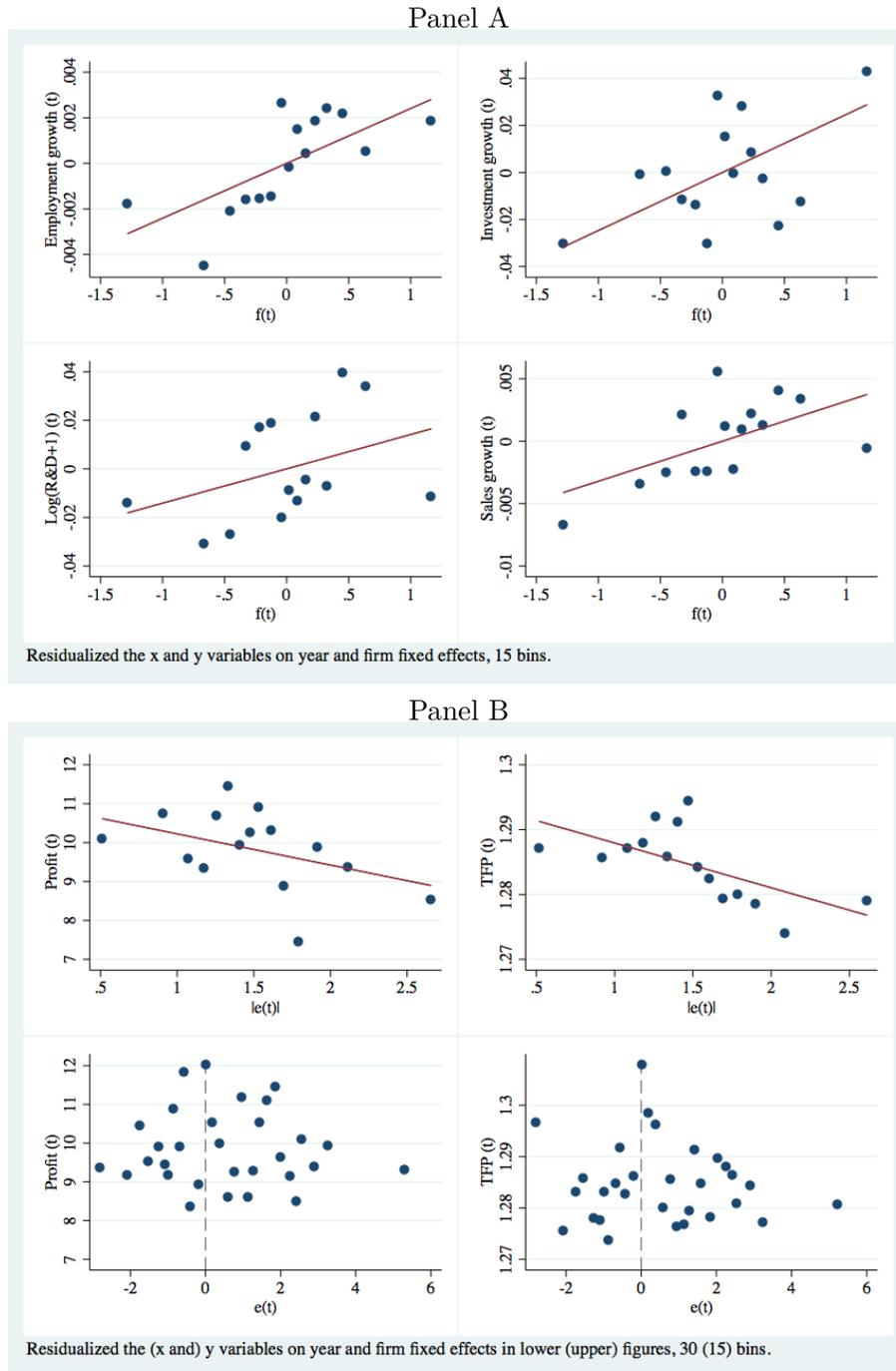
Notes: The horizontal axis indicates fiscal year t . The solid line shows the average of $|e_{i,t}(t+1)|$, absolute forecast error of fiscal year $t+1$ GDP growth rate made by firm i in fiscal year t in the ACSB. The dashed line shows the Japanese stock volatility based on TOPIX in fiscal year t . The 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 cyclical index



Notes: The distribution of the coefficient estimates for β_i in 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



Notes: Panel A shows the relationship between forecasts and firms' input choices by binned scatterplots. The x-axis shows residual values of $f_{i,t-1}(t)$ 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 $Y_{i,t}$ (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 $|e_{i,t-1}(t)|$ after regressing on year fixed effects and firm fixed effects. In the lower figures, the x-axis shows the raw value of $e_{i,t-1}(t)$ without residualizing this variable. In both upper and lower figures, the y-axis shows the average of the residual value of $V_{i,t}$ (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. 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 1. Forecasts of GDP, employment, and investment growth and realizations of employment, investment, and sales growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	D ln(Emp)	D ln(Inv)	D ln(Sales)	$f_{t-1}^E(t+2)$	$f_{t-1}^I(t+2)$	$g.Emp_{t-1,t+2}$	$g.Inv_{t-1,t+2}$
$f_{t-1}(t)$	0.241** (0.0955)	2.443* (1.432)	0.321* (0.165)	0.258*** (0.0741)	0.668*** (0.145)		
$f_{t-1}^E(t+2)$						0.162*** (0.0202)	
$f_{t-1}^I(t+2)$							0.461*** (0.0402)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,617	15,618	15,618	12,728	14,864	11,755	9,511
Number of firms	2,080	2,081	2,081	2,006	2,067	1,693	1,771
Mean dep var	-0.0179	-0.0477	-0.00367	-0.469	3.024	-2.686	-3.953

Notes: Standard errors are clustered at firm levels. $f_{t-1}(t)$ is the firm's forecast of GDP growth in year t answered in year $t-1$. $D \ln(\text{Emp}) = \ln(\text{employment}_t) - \ln(\text{employment}_{t-1})$, $D \ln(\text{Inv}) = \ln(\text{investment}_t) - \ln(\text{investment}_{t-1})$, and $D \ln(\text{Sales}) = \ln(\text{sales}_t) - \ln(\text{sales}_{t-1})$. $f_{t-1}^E(t+2)$ and $f_{t-1}^I(t+2)$ are the firm's forecasts of its employment and investment growth, respectively, over the next three years answered in year $t-1$. $g.Emp_{t-1,t+2}$ and $g.Inv_{t-1,t+2}$ are the firm's realized employment and investment growth, respectively, from year $t-1$ to $t+2$ measured by the changes in log employment and investment +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).

Table 2. GDP forecast errors and firm performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Profit	TFP	Profit	TFP	TFP (WB)	Profit	TFP	Profit	TFP
$ e_{i,t-1}(t) $	-80.2*** (20.4)	-0.691** (0.276)				-129.1** (53.3)	-1.19** (0.479)		
$e_{i,t-1}(t)(+)$			-97.3*** (29.3)	-1.05*** (0.366)	-0.668* (0.362)				
$e_{i,t-1}(t)(-)$			-58.6** (27)	-0.231 (0.390)	-0.303 (0.372)				
$\frac{1}{5} \sum_{k=t-5}^{t-1} e_{i,k-1}(k) $						263.2 (291.8)	-2.05 (2.48)		
$ e_{i,t}(t+1) $								-32.23 (36.53)	-0.0502 (0.273)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,618	12,663	15,618	12,663	12,639	5,114	4,237	14,175	11,157
Number of firms	2,081	1,733	2,081	1,733	1,733	935	784	1,744	1,445
Mean dep var	9.825	1.285	9.825	1.285	0.072	9.825	1.285	9.825	1.285

Notes: Standard errors are clustered at firm levels. $|e_{i,t-1}(t)|$ 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 . $e_{i,t-1}(t)(+) \equiv |e_{i,t-1}(t)| * 1\{e_{i,t-1}(t) > 0\}$ and $e_{i,t-1}(t)(-) \equiv |e_{i,t-1}(t)| * 1\{e_{i,t-1}(t) < 0\}$, where $e_{i,t-1}(t)$ 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 million JPY. TFP (WB) is an alternative measure of TFP using the same method described in section 3 but replacing the labor input by the total wage bill of the firm. $\frac{1}{5} \sum_{k=t-5}^{t-1} |e_{i,k-1}(k)|$ is the average absolute forecast errors in the last 5 years of firm i . 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 3. GDP forecasts and firm performance by export status and cyclicalty

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	D ln(Emp)	D ln(Emp)	D ln(Emp)	D ln(Inv)	D ln(Inv)	D ln(Inv)	D ln(Sales)	D ln(Sales)	D ln(Sales)
Export status	Non-exporter	Non-exporter	Exporter	Non-exporter	Non-exporter	Exporter	Non-exporter	Non-exporter	Exporter
Firm cyclicalty	High	Low	All	High	Low	All	High	Low	All
$f_{i,t-1}(t)$	0.439* (0.249)	0.285 (0.213)	0.0120 (0.131)	7.28** (3.46)	-2.03 (3.19)	1.82 (2.13)	0.889** (0.390)	0.288 (0.328)	-0.225 (0.275)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,130	3,344	6,671	2,891	3,201	6,628	3,130	3,345	6,671
N firms	504	588	1,063	482	579	1,054	504	589	1,063
	(10)	(11)	(12)	(13)	(14)	(15)			
	Profit	Profit	Profit	TFP	TFP	TFP			
Export status	Non-exporter	Non-exporter	Exporter	Non-exporter	Non-exporter	Exporter			
Firm cyclicalty	High	Low	All	High	Low	All			
$ e_{i,t-1}(t) $	-160.4** (63.9)	-55.0* (32.6)	-51.1** (25.2)	-1.94*** (0.605)	-0.159 (0.648)	-0.451 (0.412)			
Year FE	Yes	Yes	Yes	Yes	Yes	Yes			
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes			
Observations	3,130	3,345	6,671	2,288	2,437	5,808			
N firms	504	589	1,063	391	451	948			

Notes: Standard errors are clustered at firm levels. The sample is divided into exporting and non-exporting firms and into high and low cyclicalty firms. Cyclicalty is measured by the index constructed based on stock price responses to quarterly GDP announcements as described in section 3. Firms in high cyclicalty sample have cyclicalty index above the median. $f_{i,t-1}(t)$ is firm i 's forecast of GDP growth in fiscal year t answered in year $t - 1$. $|e_{i,t-1}(t)|$ 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 . $D \ln(\text{Emp}) = \ln(\text{employment}_t) - \ln(\text{employment}_{t-1})$, $D \ln(\text{Inv}) = \ln(\text{investment}_t) - \ln(\text{investment}_{t-1})$, and $D \ln(\text{Sales}) = \ln(\text{sales}_t) - \ln(\text{sales}_{t-1})$. Profit and TFP are the measures of fiscal year t . Unit of profit is million JPY. 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 4. Forecast accuracy with respect to GDP growth realization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$ e_{i,t}(t+1) $	$ e_{i,t}(t+1) $	$ e_{i,t}(t+1) $	$ e_{i,t}(t+1) $	$ e_{i,t}(t+1) $	$ e_{i,t}(t+1) $	$ e_{i,t}(t+1) $	$ e_{i,t}(t+1) $	$ e_{i,t}(t+1) $	$ e_{i,t}(t+1) $
ln(Employment)	-0.0190*** (0.00325)		-0.0288*** (0.00483)		-0.0239*** (0.00384)		-0.0250*** (0.00380)		-0.0375*** (0.00589)	-0.0509*** (0.00856)
TFP (past 3 years)		-0.0490*** (0.0186)	-0.0398** (0.0183)							-0.0272 (0.0362)
Firm age				-0.00102*** (0.00027)	-0.000668** (0.000272)					-0.000976 (0.000597)
Cyclicalilty						-0.219** (0.0958)	-0.170* (0.0938)			-0.115 (0.208)
Banks share								-0.639*** (0.0878)	-0.454*** (0.0918)	-0.336*** (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. Cyclicalilty is measured by the index constructed based on stock price responses to quarterly GDP announcements as described in section 3. Bank share is defined by the stock share owned banks and other financial institutions among the firm's top 30 stock holders. $|e_{i,t}(t+1)|$ 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 $t+1$. The unit of $|e_{i,t}(t+1)|$ is percent (i.e. decimal points multiplied by 100).

Table 5. Forecast accuracy with respect to professional forecasts

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$ ep_{i,t}(t+1) $	$ ep_{i,t}(t+1) $	$ ep_{i,t}(t+1) $	$ ep_{i,t}(t+1) $	$ ep_{i,t}(t+1) $	$ ep_{i,t}(t+1) $	$ ep_{i,t}(t+1) $	$ ep_{i,t}(t+1) $	$ ep_{i,t}(t+1) $	$ ep_{i,t}(t+1) $
ln(Employment)	-0.0583*** (0.00328)		-0.0657*** (0.00457)		-0.0539*** (0.00391)		-0.0567*** (0.00386)		-0.0509*** (0.00580)	-0.0665*** (0.00894)
TFP (past 3 years)		-0.0483** (0.0201)	-0.0271 (0.0190)							-0.0165 (0.0362)
Firm age				-0.00186*** (0.000279)	-0.00106*** (0.000267)					-0.00122** (0.000584)
Cyclicality						-0.171* (0.102)	-0.0642 (0.0948)			0.285 (0.211)
Banks share								-0.764*** (0.0862)	-0.512*** (0.0889)	-0.340** (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 banks and other financial institutions among the firm's top 30 stock holders. $|ep_t(t+1)|$ 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 . The unit of $|ep_{i,t}(t+1)|$ is percent (i.e. decimal points multiplied by 100).

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7 Appendix

Model derivations

Predictions under imperfect information. The first order conditions from (1) give

$$\begin{aligned}\hat{\alpha}_1 E_{it} [A_{it}] K_{it}^{\hat{\alpha}_1 - 1} N_{it}^{\hat{\alpha}_2} &= R \\ \hat{\alpha}_2 E_{it} [A_{it}] K_{it}^{\hat{\alpha}_1} N_{it}^{\hat{\alpha}_2 - 1} &= W_t ,\end{aligned}$$

which imply

$$N_{it} = \frac{\hat{\alpha}_2}{\hat{\alpha}_1} \frac{R}{W_t} K_{it} .$$

Substituting into the first order condition for K_{it} , we can solve for

$$\begin{aligned}K_{it} &= C_{1t} E_{it} [A_{it}]^\sigma \\ N_{it} &= C_{2t} E_{it} [A_{it}]^\sigma ,\end{aligned}$$

where

$$\begin{aligned}C_{1t} &= \left(\frac{\hat{\alpha}_1}{R} \right)^{\frac{1 - \hat{\alpha}_2}{1 - \hat{\alpha}_1 - \hat{\alpha}_2}} \left(\frac{\hat{\alpha}_2}{W_t} \right)^{\frac{\hat{\alpha}_2}{1 - \hat{\alpha}_1 - \hat{\alpha}_2}} \\ C_{2t} &= \left(\frac{\hat{\alpha}_1}{R} \right)^{\frac{\hat{\alpha}_1}{1 - \hat{\alpha}_1 - \hat{\alpha}_2}} \left(\frac{\hat{\alpha}_2}{W_t} \right)^{\frac{1 - \hat{\alpha}_1}{1 - \hat{\alpha}_1 - \hat{\alpha}_2}} .\end{aligned}$$

Then, revenues are equal to

$$P_{it} Y_{it} = A_{it} K_{it}^{\hat{\alpha}_1} N_{it}^{\hat{\alpha}_2} = C_{1t}^{\hat{\alpha}_1} C_{2t}^{\hat{\alpha}_2} A_{it} E_{it} [A_{it}]^{\frac{\hat{\alpha}_1 + \hat{\alpha}_2}{1 - \hat{\alpha}_1 - \hat{\alpha}_2}} = C_{3t} A_{it} E_{it} [A_{it}]^{\sigma - 1} ,$$

and profits are equal to

$$\Pi_{it} = C_{3t} \left(A_{it} E_{it} [A_{it}]^{\sigma - 1} - \frac{\sigma - 1}{\sigma} E_{it} [A_{it}]^\sigma \right)$$

and finally, TFPR:

$$\begin{aligned}\frac{P_{it} Y_{it}}{K_{it}^\alpha N_{it}^{1 - \alpha}} &= \frac{C_{3t}}{C_{1t}^\alpha C_{2t}^{1 - \alpha}} \frac{A_{it} E_{it} [A_{it}]^{\sigma - 1}}{E_{it} [A_{it}]^\sigma} \\ &= C_{4t} \frac{A_{it}}{E_{it} [A_{it}]} .\end{aligned}$$

Predictions 1, 2 and 4 are immediate. Turning to prediction 3, the first derivative of expression (4) can be shown to be positive if $E_{it} [A_{it}] < A_{it}$ and otherwise is negative. Then, since the profit function is globally concave in the expectation of A_{it} , it is maximized at $E_{it} [A_{it}] = A_{it}$. This proves prediction 3.

Predictions with additional adjustment and disruption costs. We work with a more general version of the framework than in the text that explicitly includes both capital and labor. We then specialize to the case described in the text to prove prediction 5. This case is always nested where $\alpha = 1$. For purposes of tractability, we assume that the disruption costs due to labor adjustments are denominated in labor units with the same

cost parameter, ξ . With these assumptions, the output of the firm is given by:

$$Y_{it} = K_{it}^\alpha N_{it}^{1-\alpha} - \Phi(K_{it}, K_{it}^0) - W_t \Phi(N_{it}, N_{it}^0) .$$

In this setup, the firm makes a one-time payment to hire incremental labor so the cost of labor, W_t should be interpreted as the present discounted value of wages. A related setup is in David and Venkateswaran (2017).

Second stage. In the second stage of time t , the firm observes the realization of the fundamental and chooses inputs for production, K_{it} and N_{it} , taking as given its initial choices, K_{it}^0 and N_{it}^0 in the first stage of period t . The firm's second stage problem takes the form:

$$\begin{aligned} \max_{K_{it}, N_{it}} \quad & A_{it} \left(K_{it}^\alpha N_{it}^{1-\alpha} - \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 K_{it}^0 - W_t \frac{\xi}{2} \left(\frac{N_{it}}{N_{it}^0} - 1 \right)^2 N_{it}^0 \right)^{\frac{\sigma-1}{\sigma}} \\ & + \beta(1-\delta) K_{it} - (K_{it} - K_{it}^0) + W_t \beta(1-\delta) N_{it} - W(N_{it} - N_{it}^0) . \end{aligned} \quad (10)$$

In this setup, the firm makes a one-time payment to hire incremental labor so the cost of labor W_t should be interpreted as the present discounted value of wages. See DV for a related setup.

The first order conditions give:

$$\begin{aligned} \frac{\sigma-1}{\sigma} A_{it} Y_{it}^{-\frac{1}{\sigma}} \left(\alpha K_{it}^{\alpha-1} N_{it}^{1-\alpha} - \xi \left(\frac{K_{it}}{K_{it}^0} - 1 \right) \right) - R &= 0 \\ \frac{\sigma-1}{\sigma} A_{it} Y_{it}^{-\frac{1}{\sigma}} \left((1-\alpha) K_{it}^\alpha N_{it}^{-\alpha} - W_t \xi \left(\frac{N_{it}}{N_{it}^0} - 1 \right) \right) - R W_t &= 0 , \end{aligned}$$

where, as in the text, $R = 1 - \beta(1 - \delta)$.

To simplify the problem, we prove that there exists an η_t such that $N_{it} = \eta_t K_{it}$ and $N_{it}^0 = \eta_t K_{it}^0$, i.e., the labor choice is proportional to the capital choice. The factor of proportionality is common across firms within a period, but is potentially time-varying.

Under this conjecture, we can rewrite the firm's problem in (10) as

$$\begin{aligned} \max_{K_{it}} \quad & A_{it} \left(\eta_t^{1-\alpha} K_{it} - \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 K_{it}^0 - W_t \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 \eta_t K_{it}^0 \right)^{\frac{\sigma-1}{\sigma}} \\ & + \beta(1-\delta) K_{it} - (K_{it} - K_{it}^0) + W_t \beta(1-\delta) \eta_t K_{it} - W_t \eta_t (K_{it} - K_{it}^0) . \end{aligned}$$

The first order condition gives:

$$\frac{\sigma-1}{\sigma} A_{it} Y_{it}^{-\frac{1}{\sigma}} \left(\frac{\eta_t^{1-\alpha}}{1 + \eta_t W_t} - \xi \left(\frac{K_{it}}{K_{it}^0} - 1 \right) \right) - R = 0 . \quad (11)$$

Now, substitute the conjecture that $N_{it} = \eta_t K_{it}$ and $N_{it}^0 = \eta_t K_{it}^0$ into the labor first order condition from the original problem and rearrange to get:

$$\frac{\sigma-1}{\sigma} A_{it} Y_{it}^{-\frac{1}{\sigma}} \left(\frac{(1-\alpha) \eta_t^{1-\alpha}}{\eta_t W_t} - \xi \left(\frac{K_{it}}{K_{it}^0} - 1 \right) \right) - R = 0 . \quad (12)$$

If η_t satisfies:

$$\frac{1}{1 + \eta_t W_t} = \frac{1-\alpha}{\eta_t W_t} \Rightarrow \eta_t = \frac{1-\alpha}{\alpha} \frac{1}{W_t} , \quad (13)$$

then (11) is identical to (12), so that the solution under our conjecture satisfies the optimality condition for

labor from the original problem. It is straightforward to verify that the capital choice under our conjecture also satisfies the optimality condition for capital from the original problem.

To obtain an analytic expression for the choice of K_{it} , we log-linearize the first order condition (11) around the non-stochastic steady state, where $K_{it} = K_{it}^0 = \bar{K}$ solves

$$\frac{\sigma - 1}{\sigma} \bar{A} \bar{\eta}^{(1-\alpha)\frac{\sigma-1}{\sigma}} \bar{K}^{-\frac{1}{\sigma}} = R$$

This gives the choice of capital (in logs) as

$$k_{it} = \phi_1 a_{it} + \phi_2 k_{it}^0 + \phi_3 \eta_t + \phi_1 \ln \left(\frac{\sigma - 1}{\sigma} \frac{1}{R} \right),$$

where

$$\phi_1 = \frac{\sigma}{1 + \sigma \hat{\xi}}, \quad \phi_2 = \frac{\sigma \hat{\xi}}{1 + \sigma \hat{\xi}}, \quad \phi_3 = \frac{(1 - \alpha)(\sigma - 1)}{1 + \sigma \hat{\xi}},$$

and

$$\hat{\xi} = \frac{1 + \eta_t W_t}{\bar{\eta}^{1-\alpha}} \xi = \frac{\xi}{\alpha \bar{\eta}^{1-\alpha}}$$

is a transformation of the disruption cost parameter that captures the severity of these costs. In levels, we have

$$K_{it} = \left(\frac{\sigma - 1}{\sigma} \frac{1}{R} \right)^{\phi_1} A_{it}^{\phi_1} (K_{it}^0)^{\phi_2} \eta_t^{\phi_3}, \quad (14)$$

where, from (13), η_t captures the effect of fluctuations in wages.

First stage. In the first stage, the firm makes its initial choices of inputs, K_{it}^0 and N_{it}^0 , under imperfect information regarding the fundamental, A_{it} and taking into account its choices in the second stage. The firm's problem takes the form:

$$\begin{aligned} \max_{K_{it}^0, N_{it}^0} \quad & E_{it} \left[A_{it} \left(K_{it}^\alpha N_{it}^{1-\alpha} - \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 K_{it}^0 - W_t \frac{\xi}{2} \left(\frac{N_{it}}{N_{it}^0} - 1 \right)^2 N_{it}^0 \right)^{\frac{\sigma-1}{\sigma}} \right. \\ & \left. + \beta (1 - \delta) K_{it} - (K_{it} - K_{it}^0) + W_t \beta (1 - \delta) N_{it} - W_t (N_{it} - N_{it}^0) \right] - K_{it}^0 - W_t N_{it}^0 \\ \text{s.t.} \quad & K_{it} = \left(\frac{\sigma - 1}{\sigma} \frac{1}{R} \right)^{\phi_1} A_{it}^{\phi_1} (K_{it}^0)^{\phi_2} \eta_t^{\phi_3} \\ & N_{it} = \eta_t K_{it}. \end{aligned} \quad (15)$$

The first order condition for capital, K_{it}^0 , gives

$$\begin{aligned} 0 &= E_{it} \left[\frac{\partial \left(A_{it} \left(K_{it}^\alpha N_{it}^{1-\alpha} - \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 K_{it}^0 - W_t \frac{\xi}{2} \left(\frac{N_{it}}{N_{it}^0} - 1 \right)^2 N_{it}^0 \right)^{\frac{\sigma-1}{\sigma}} - (1 - \beta(1 - \delta)) K_{it}}{\partial K_{it}^0} \right) \frac{\partial K_{it}}{\partial K_{it}^0} \right] \\ &+ E_{it} \left[\frac{\sigma - 1}{\sigma} A_{it} Y_{it}^{-\frac{1}{\sigma}} \left(\xi \left(\frac{K_{it}}{K_{it}^0} - 1 \right) \frac{K_{it}}{K_{it}^0} - \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 \right) \right] \\ &= E_{it} \left[A_{it} Y_{it}^{-\frac{1}{\sigma}} \left(\xi \left(\frac{K_{it}}{K_{it}^0} - 1 \right) \frac{K_{it}}{K_{it}^0} - \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 \right) \right]. \end{aligned}$$

Similar steps give the first order condition for labor, N_{it}^0 :

$$0 = E_{it} \left[A_{it} Y_{it}^{-\frac{1}{\sigma}} W_t \left(\xi \left(\frac{N_{it}}{N_{it}^0} - 1 \right) \frac{N_{it}}{N_{it}^0} - \frac{\xi}{2} \left(\frac{N_{it}}{N_{it}^0} - 1 \right)^2 \right) \right]. \quad (16)$$

To prove our conjecture that $N_{it}^0 = \eta_t K_{it}^0$, substitute the conjecture into the original problem (15):

$$\begin{aligned} \max_{K_{it}} \quad & E_{it} \left[A_{it} \left(\eta_t^{1-\alpha} K_{it} - \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 K_{it}^0 - W_t \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 \eta_t K_{it}^0 \right)^{\frac{\sigma-1}{\sigma}} \right. \\ & + \beta (1 - \delta) K_{it} - (K_{it} - K_{it}^0) + W_t \beta (1 - \delta) \eta_t K_{it} - W_t \eta (K_{it} - K_{it}^0) \left. \right] - K_{it}^0 - \eta_t W_t K_{it}^0 \\ \text{s.t.} \quad & K_{it} = \left(\frac{\sigma - 1}{\sigma} \frac{1}{R} \right)^{\phi_1} A_{it}^{\phi_1} (K_{it}^0)^{\phi_2} \eta_t^{\phi_3}. \end{aligned}$$

The first order condition gives:

$$\begin{aligned} 0 = E_{it} \left[\frac{\partial \left(A_{it} \left(\eta^{1-\alpha} K_{it} - (1 + \eta W_t) \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 K_{it}^0 \right)^{\frac{\sigma-1}{\sigma}} - (1 + \eta W_t) (1 - \beta (1 - \delta)) K_{it} \right)}{\partial K_{it}} \frac{\partial K_{it}}{\partial K_{it}^0} \right] \\ + E_{it} \left[\frac{\sigma - 1}{\sigma} A_{it} Y_{it}^{-\frac{1}{\sigma}} (1 + \eta W_t) \left(\xi \left(\frac{K_{it}}{K_{it}^0} - 1 \right) \frac{K_{it}}{K_{it}^0} - \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 \right) \right] \\ = E_{it} \left[A_{it} Y_{it}^{-\frac{1}{\sigma}} \left(\xi \left(\frac{K_{it}}{K_{it}^0} - 1 \right) \frac{K_{it}}{K_{it}^0} - \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 \right) \right]. \quad (17) \end{aligned}$$

Now substitute the conjecture into the labor first order condition from the original problem (16):

$$0 = E_{it} \left[A_{it} Y_{it}^{-\frac{1}{\sigma}} W_t \left(\xi \left(\frac{K_{it}}{K_{it}^0} - 1 \right) \frac{K_{it}}{K_{it}^0} - \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 \right) \right]. \quad (18)$$

Dividing through by W_t shows that (17) and (18) are the same.

We can rearrange the first order condition (17) as:

$$0 = E_{it} \left[A_{it} Y_{it}^{-\frac{1}{\sigma}} \left(\left(\frac{K_{it}}{K_{it}^0} \right)^2 - 1 \right) \right],$$

or

$$E_{it} \left[A_{it} Y_{it}^{-\frac{1}{\sigma}} \right] = E_{it} \left[A_{it} Y_{it}^{-\frac{1}{\sigma}} \left(\frac{K_{it}}{K_{it}^0} \right)^2 \right],$$

or

$$\begin{aligned}
& \exp\left(E_{it}\left[a_{it} - \frac{1}{\sigma}y_{it}\right] + \frac{1}{2}\text{var}_t\left(a_{it} - \frac{1}{\sigma}y_{it}\right)\right) \\
= & \exp\left(E_{it}\left[a_{it} - \frac{1}{\sigma}y_{it}\right] + 2E_{it}\left[k_{it} - k_{it}^0\right] + \frac{1}{2}\text{var}_t\left(a_{it} - \frac{1}{\sigma}y_{it}\right) + 2\text{var}_t\left(k_{it} - k_{it}^0\right)\right. \\
& \left. + 2\text{cov}_t\left(a_{it} - \frac{1}{\sigma}y_{it}, k_{it} - k_{it}^0\right)\right) \\
\Rightarrow 0 = & E_{it}\left[k_{it} - k_{it}^0\right] + \text{var}_t\left(k_{it} - k_{it}^0\right) + \text{cov}_t\left(a_{it} - \frac{1}{\sigma}y_{it}, k_{it} - k_{it}^0\right) \\
= & \phi_1 E_{it}\left[a_{it}\right] + (\phi_2 - 1)k_{it}^0 + \phi_3\eta_t + \left(\phi_1^2 + \phi_1 - \frac{1}{\sigma}\phi_1^2\right)\text{var}_t\left(a_{it}\right) + \phi_1 \ln\left(\frac{\sigma - 1}{\sigma} \frac{1}{R}\right) \\
\Rightarrow k_{it}^0 = & \frac{\phi_1}{1 - \phi_2} E_{it}\left[a_{it}\right] + \frac{\phi_3}{1 - \phi_2} \eta_t + \left(\frac{\phi_1^2 \frac{\sigma - 1}{\sigma}}{1 - \phi_2} + \frac{\phi_1}{1 - \phi_2}\right)\text{var}_t\left(a_{it}\right) + \frac{\phi_1}{1 - \phi_2} \ln\left(\frac{\sigma - 1}{\sigma} \frac{1}{R}\right) \\
= & \sigma E_{it}\left[a_{it}\right] + (1 - \alpha)(\sigma - 1)\eta_t + (\phi_1(\sigma - 1) + \sigma)\text{var}_t\left(a_{it}\right) + \sigma \ln\left(\frac{\sigma - 1}{\sigma} \frac{1}{R}\right) \\
\Rightarrow \frac{1}{\sigma}k_{it}^0 = & E_{it}\left[a_{it}\right] + \frac{1}{2}\text{var}_t\left(a_{it}\right) + (1 - \alpha)\frac{\sigma - 1}{\sigma}\eta_t + \left(\phi_1\frac{\sigma - 1}{\sigma} + \frac{1}{2}\right)\text{var}_t\left(a_{it}\right) + \ln\left(\frac{\sigma - 1}{\sigma} \frac{1}{R}\right),
\end{aligned}$$

where we have used the relationships $\frac{\phi_1}{1 - \phi_2} = \sigma$ and $\frac{\phi_3}{1 - \phi_2} = (1 - \alpha)(\sigma - 1)$ and the properties of the log-normal distribution. In levels,

$$K_{it}^0 = \Omega^\sigma \left(\frac{\sigma - 1}{\sigma} \frac{1}{R}\right)^\sigma (E_{it}[A_{it}])^\sigma \eta_t^{(1 - \alpha)(\sigma - 1)},$$

where

$$\Omega = e^{[\phi_1 \frac{\sigma - 1}{\sigma} + \frac{1}{2}]\text{var}_t(a_{it})}$$

captures a precautionary savings term. This term is strictly greater than one for $\xi \in (0, \infty)$ and for small values of the conditional variance, $\text{var}_t(a_{it})$, it is close to one. To ease notation, we define the ‘‘precautionary-savings adjusted expectation’’ as

$$\tilde{E}_{it}[A_{it}] = \Omega E_{it}[A_{it}],$$

so that

$$K_{it}^0 = \left(\frac{\sigma - 1}{\sigma} \frac{1}{R}\right)^\sigma \left(\tilde{E}_{it}[A_{it}]\right)^\sigma \eta_t^{(1 - \alpha)(\sigma - 1)}. \quad (19)$$

Combining (14) and (19), we can express the final choice of K_{it} as a function of A_{it} and $E_{it}[A_{it}]$:

$$K_{it} = \left(\frac{\sigma - 1}{\sigma} \frac{1}{R}\right)^\sigma A_{it}^{\phi_1} \left(\tilde{E}_{it}[A_{it}]\right)^{\sigma\phi_2} \eta_t^{(1 - \alpha)(\sigma - 1)}.$$

Calculating TFPR. To summarize, we have:

$$\begin{aligned}
K_{it}^0 &= \left(\frac{\sigma - 1}{\sigma} \frac{1}{R}\right)^\sigma \left(\tilde{E}_{it}[A_{it}]\right)^\sigma \eta_t^{(1 - \alpha)(\sigma - 1)} \\
K_{it} &= \left(\frac{\sigma - 1}{\sigma} \frac{1}{R}\right)^\sigma A_{it}^{\phi_1} \left(\tilde{E}_{it}[A_{it}]\right)^{\sigma\phi_2} \eta_t^{(1 - \alpha)(\sigma - 1)} \\
\frac{K_{it}}{K_{it}^0} &= A_{it}^{\phi_1} \tilde{E}_{it}[A_{it}]^{-\phi_1}.
\end{aligned}$$

TFPR is then:

$$\begin{aligned}
TFPR_{it} &= \frac{P_{it}Y_{it}}{K_{it}^\alpha N_{it}^{1-\alpha}} = \frac{A_{it}Y_{it}^{\frac{\sigma-1}{\sigma}}}{K_{it}^\alpha N_{it}^{1-\alpha}} \\
&= \frac{A_{it}}{K_{it}^\alpha N_{it}^{1-\alpha}} \left(K_{it}^\alpha N_{it}^{1-\alpha} - \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 K_{it}^0 - W_t \frac{\xi}{2} \left(\frac{N_{it}}{N_{it}^0} - 1 \right)^2 N_{it}^0 \right)^{\frac{\sigma-1}{\sigma}} \\
&= \frac{A_{it}}{\eta_t^{1-\alpha} K_{it}} \left(\eta_t^{1-\alpha} K_{it} - (1 + W_t \eta_t) \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 K_{it}^0 \right)^{\frac{\sigma-1}{\sigma}} \\
&= \frac{A_{it}}{\eta_t^{1-\alpha} K_{it}} \left(\eta_t^{1-\alpha} K_{it} - \frac{1}{\alpha} \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 K_{it}^0 \right)^{\frac{\sigma-1}{\sigma}} \\
&= \frac{1}{\alpha^{\frac{\sigma-1}{\sigma}} \eta_t^{1-\alpha} K_{it}} \left(\alpha \eta_t^{1-\alpha} K_{it} - \frac{\xi}{2} \left(\frac{K_{it}}{K_{it}^0} - 1 \right)^2 K_{it}^0 \right)^{\frac{\sigma-1}{\sigma}},
\end{aligned}$$

and substituting,

$$\begin{aligned}
TFPR_{it} &= \alpha^{\frac{1-\sigma}{\sigma}} \left(\frac{\sigma-1}{\sigma} \frac{1}{R} \right)^{-\sigma} A_{it} \eta_t^{\alpha-1} A_{it}^{-\phi_1} \tilde{E}_{it} [A_{it}]^{-\sigma \phi_2} \eta_t^{-(1-\alpha)(\sigma-1)} \\
&\times \left(\alpha \eta_t^{1-\alpha} A_{it}^{\phi_1} \tilde{E}_{it} [A_{it}]^{\sigma \phi_2} \eta_t^{(1-\alpha)(\sigma-1)} \left(\frac{\sigma-1}{\sigma} \frac{1}{R} \right)^\sigma \right. \\
&- \left. \frac{\xi}{2} \left(A_{it}^{\phi_1} \tilde{E}_{it} [A_{it}]^{-\phi_1} - 1 \right)^2 \left(\frac{\sigma-1}{\sigma} \frac{1}{R} \right)^\sigma \tilde{E}_{it} [A_{it}]^\sigma \eta_t^{(1-\alpha)(\sigma-1)} \right)^{\frac{\sigma-1}{\sigma}} \\
&= \alpha^{\frac{1-\sigma}{\sigma}} \left(\frac{\sigma-1}{\sigma} \frac{1}{R} \right)^{-1} \eta_t^{(1-\alpha)(\frac{1}{\sigma}-2)} \left(\alpha \eta_t^{1-\alpha} Z_{it}^{-\frac{\sigma}{\sigma-1}(1-\phi_1)-\phi_1} - \frac{\xi}{2} \left(Z_{it}^{-\phi_1} - 1 \right)^2 Z_{it}^{-\frac{\sigma}{\sigma-1}(1-\phi_1)} \right)^{\frac{\sigma-1}{\sigma}} \\
&= \alpha^{\frac{1-\sigma}{\sigma}} \left(\frac{\sigma-1}{\sigma} \frac{1}{R} \right)^{-1} \eta_t^{(1-\alpha)(\frac{1}{\sigma}-2)} \left(\alpha \eta_t^{1-\alpha} Z_{it}^{-\frac{\sigma}{\sigma-1}(1-\phi_1)-\phi_1} - \frac{\xi}{2} \left(Z_{it}^{-2\phi_1} - 2Z_{it}^{-\phi_1} + 1 \right) Z_{it}^{-\frac{\sigma}{\sigma-1}(1-\phi_1)} \right)^{\frac{\sigma-1}{\sigma}} \\
&= \alpha^{\frac{1-\sigma}{\sigma}} \left(\frac{\sigma-1}{\sigma} \frac{1}{R} \right)^{-1} \eta_t^{(1-\alpha)(\frac{1}{\sigma}-2)} \left(\left(\alpha \eta_t^{1-\alpha} + \xi \right) Z_{it}^{-\frac{\sigma}{\sigma-1}(1-\phi_1)-\phi_1} - \frac{\xi}{2} Z_{it}^{-\frac{\sigma}{\sigma-1}(1-\phi_1)-2\phi_1} - \frac{\xi}{2} Z_{it}^{-\frac{\sigma}{\sigma-1}(1-\phi_1)} \right)^{\frac{\sigma-1}{\sigma}} \\
&= C_{6t} \left(\left(\alpha \eta_t^{1-\alpha} + \xi \right) Z_{it}^{-\frac{\sigma}{\sigma-1}(1-\phi_1)-\phi_1} - \frac{\xi}{2} Z_{it}^{-\frac{\sigma}{\sigma-1}(1-\phi_1)-2\phi_1} - \frac{\xi}{2} Z_{it}^{-\frac{\sigma}{\sigma-1}(1-\phi_1)} \right)^{\frac{\sigma-1}{\sigma}}.
\end{aligned}$$

Taking the derivative with respect to Z_{it} gives

$$\begin{aligned}
\frac{\partial TFPR_{it}}{\partial Z_{it}} &= C_{6t} (\dots)^{-\frac{1}{\sigma}} Z_{it}^{-(1-\phi_1)\frac{\sigma}{\sigma-1}-2\phi_1-1} \left(\left(-(1-\phi_1) \frac{\sigma}{\sigma-1} - \phi_1 \right) \left(\alpha \eta_t^{1-\alpha} + \xi \right) Z_{it}^{\phi_1} \right. \\
&+ \left. \left(\frac{\sigma}{\sigma-1} (1-\phi_1) + 2\phi_1 \right) \frac{\xi}{2} + \frac{\sigma}{\sigma-1} (1-\phi_1) \frac{\xi}{2} Z_{it}^{2\phi_1} \right)
\end{aligned}$$

Because the common term is positive, the sign of the derivative is determined by the sign of

$$\left(-(1-\phi_1) \frac{\sigma}{\sigma-1} - \phi_1 \right) \left(\alpha \eta_t^{1-\alpha} + \xi \right) Z_{it}^{\phi_1} + \left(\frac{\sigma}{\sigma-1} (1-\phi_1) + 2\phi_1 \right) \frac{\xi}{2} + \frac{\sigma}{\sigma-1} (1-\phi_1) \frac{\xi}{2} Z_{it}^{2\phi_1},$$

which, after simplifying, is equal to

$$\frac{\sigma}{2} (1-\phi_1) Z_{it}^{2\phi_1} - \frac{\sigma}{\eta_t^{1-\alpha}} \phi_1 \left(\eta_t^{1-\alpha} + \frac{\xi}{\alpha} \right) Z_{it}^{\phi_1} + \frac{\sigma}{2} (1-\phi_1) + \phi_1 (\sigma-1), \quad (20)$$

where we used

$$\frac{\sigma}{\sigma-1}(1-\phi_1) + \phi_1 = \frac{\sigma}{\sigma-1}\hat{\xi}\phi_1$$

and the definition of $\hat{\xi}$. Expression (20) is a quadratic equation in $Z_{it}^{\phi_1}$.

Prediction 5. To prove prediction 5, we now specialize to the case where $\alpha = 1$. We can rewrite expression (20) as

$$\frac{1}{2}\frac{\sigma}{\sigma-1}(1-\phi_1)Z_{it}^{2\phi_1} - \left(\frac{\sigma}{\sigma-1} + \phi_1\right)Z_{it}^{\phi_1} + \left(\frac{1}{2}\frac{\sigma}{\sigma-1}(1-\phi_1) + \phi_1\right),$$

and derive the roots as:

$$\begin{aligned} Z_1^{\phi_1} &= \frac{\sigma + \phi_1(\sigma - 1) - \sqrt{\sigma^2 + 2\phi_1^2(\sigma^2 - \sigma) + \phi_1^2(\sigma - 1)^2 - \sigma^2(1 - \phi_1)^2}}{\sigma(1 - \phi_1)} \\ Z_2^{\phi_1} &= \frac{\sigma + \phi_1(\sigma - 1) + \sqrt{\sigma^2 + 2\phi_1^2(\sigma^2 - \sigma) + \phi_1^2(\sigma - 1)^2 - \sigma^2(1 - \phi_1)^2}}{\sigma(1 - \phi_1)}, \end{aligned}$$

where the expression in the square root is non-negative.

The properties of the roots depend on ϕ_1 , which can be greater or less than one. Assume first that $\phi_1 > 1$. Then $Z_2^{\phi_1}$ is negative and we can ignore it. We can prove $Z_1^{\phi_1} < 1$:

$$\begin{aligned} Z_1^{\phi_1} &< 1 \\ \Rightarrow \sigma + \phi_1(\sigma - 1) - \sqrt{\sigma^2 + 2\phi_1^2(\sigma^2 - \sigma) + \phi_1^2(\sigma - 1)^2 - \sigma^2(1 - \phi_1)^2} &> \sigma(1 - \phi_1), \end{aligned}$$

and rearranging, squaring both sides and simplifying shows that this condition holds whenever $\phi_1 > 1$, which was our original assumption. Since $\phi_1 > 1$, this also implies $Z_1 < 1$.

Now assume $\phi_1 < 1$. Then Z_2 is positive, but it is very large, e.g., it is greater than

$$\left(\frac{1}{1-\phi_1} + \frac{\sigma-1}{\sigma}\frac{\phi_1}{1-\phi_1}\right)^{\frac{1}{\phi_1}}$$

This clearly goes to infinity as ϕ_1 goes to one from below. Ignoring the second term, Z_2 is greater than

$$\left(\frac{1}{1-\phi_1}\right)^{\frac{1}{\phi_1}} = \left(1 + \frac{1}{n}\right)^n$$

where $n = -\frac{1}{\phi_1}$. This term approaches $e \approx 2.72$ as ϕ_1 goes to zero, so the firm would have to be more than 172% overoptimistic, which we will assume is outside the relevant range. Thus, Z_2 is safely ignored. Following the same steps as above, we can show $Z_1 < 1$ whenever $\phi_1 < 1$.

Finally, evaluating the quadratic at $Z_{it} = 1$ shows it is strictly negative, (equal to $-\sigma\phi_1$). So we know the derivative is negative when $Z_{it} > 1$ and when $Z_{it} > Z_1$ and is positive for $Z_{it} < Z_1$. This proves prediction 5.

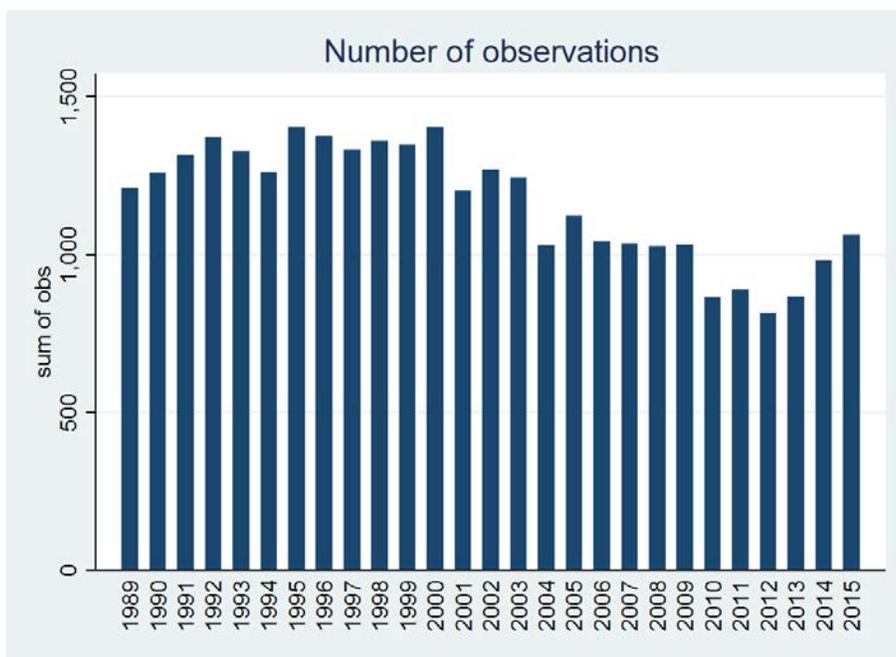
Similar logic should go through in the general case when $\alpha \neq 1$; deriving the quadratic equation, (20), did not depend on this assumption.

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 A.1: Number of observations by year



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

Figure A.2: 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 forecast figures to the first decimal point.

Growth rate \ Period	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.

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

Figure A.3: Binscatter plot of sales growth and GDP growth

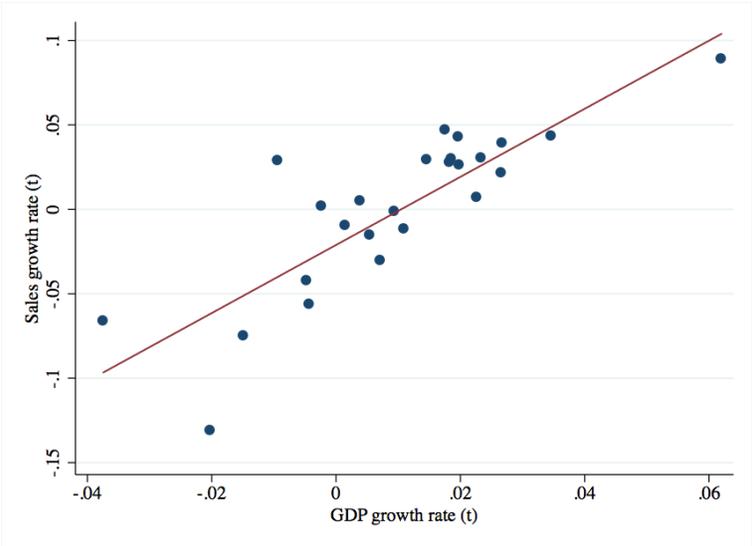
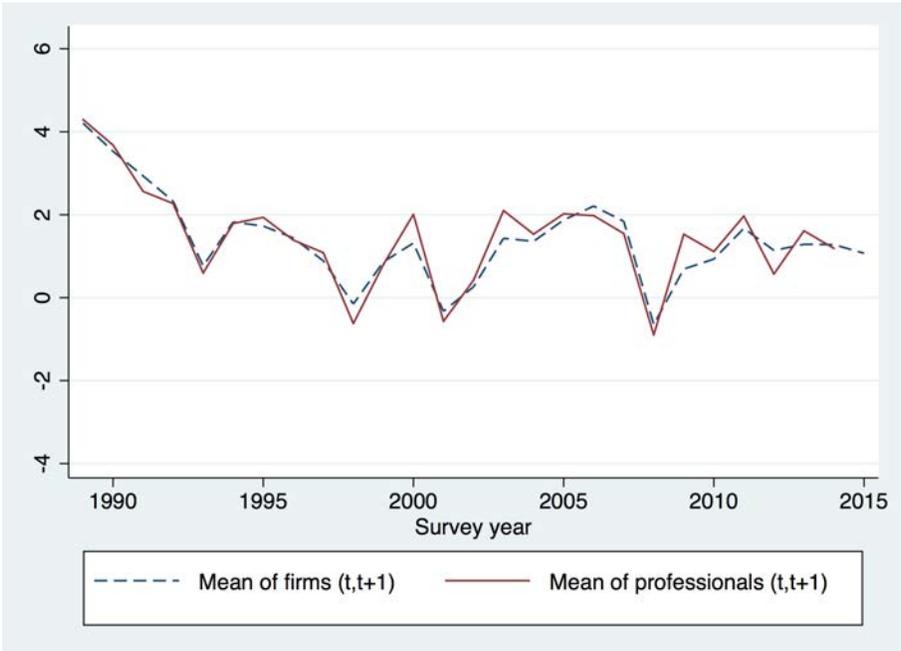


Figure A.4: Comparison of the yearly means of firm forecasts and professional forecasts



Notes: The figure shows the average firm forecasts from ASCB and the average professionals' forecasts from Consensus Forecasts for the following year's GDP growth rates.

Figure A.5: Survey question on employment and investment growth forecasts

(The growth rate of capital investment)

Q4 (1): How did/will you increase or decrease your total capital investment (work-based) on an annual average over the past three years (FY2002-04) and the next three years (FY2005-07)? Choose and circle only one number of the past and next three years.

Annual average rate of change (%)	Period	
	Past three years (FY2002-04)	Next three years (FY2005-07)
25% or more	1	1
20% to 25% (not inclusive)	2	2
15% to 20% (not inclusive)	3	3
10% to 15% (not inclusive)	4	4
5% to 10% (not inclusive)	5	5
0% (not incl.) to 5% (not incl.)	6	6
0%	7	7
-5% to 0% (not inclusive)	8	8
-10% (not inclusive) to -5%	9	9
-15% (not inclusive) to -10%	10	10
-20% (not inclusive) to -15%	11	11
-25% (not inclusive) to -20%	12	12
-25% and less	13	13

(Changes in the number of employees)

Q5: How far did/will the number of your employees be changed in the whole company, production, sales, etc. and administration, planning, etc. over the past three years (FY2002-04) and for the next three years (FY2005-07)? Choose and circle only one number for each section.

Annual average rate of change (%)	Period					
	Past three years (FY2002-04)			Next three years (FY2005-07)		
	Whole company	Production, Sales, etc.	Administration, Planning, etc.	Whole company	Production, Sales, etc.	Administration, Planning, etc.
15% or more	1	1	1	1	1	1
10% to 15% (not incl.)	2	2	2	2	2	2
5% to 10% (not incl.)	3	3	3	3	3	3
0% (not incl.) to 5% (not incl.)	4	4	4	4	4	4
0%	5	5	5	5	5	5
-5% to 0% (not incl.)	6	6	6	6	6	6
-10% (not incl.) to -5%	7	7	7	7	7	7
-15% (not incl.) to -10%	8	8	8	8	8	8
-15% and less	9	9	9	9	9	9

Figure A.6 Binned scatter plots of mean forecasts and realization by year

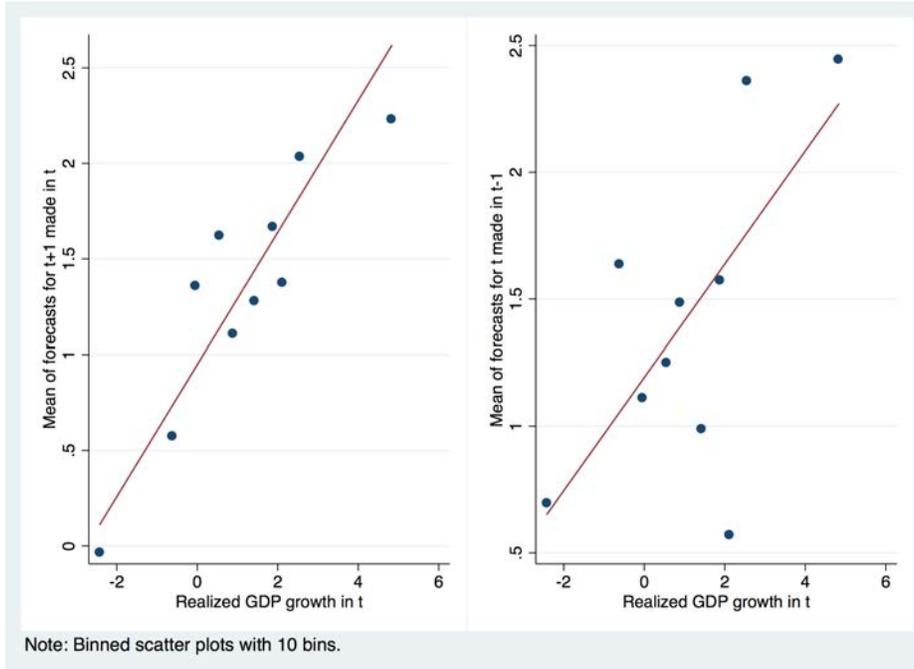
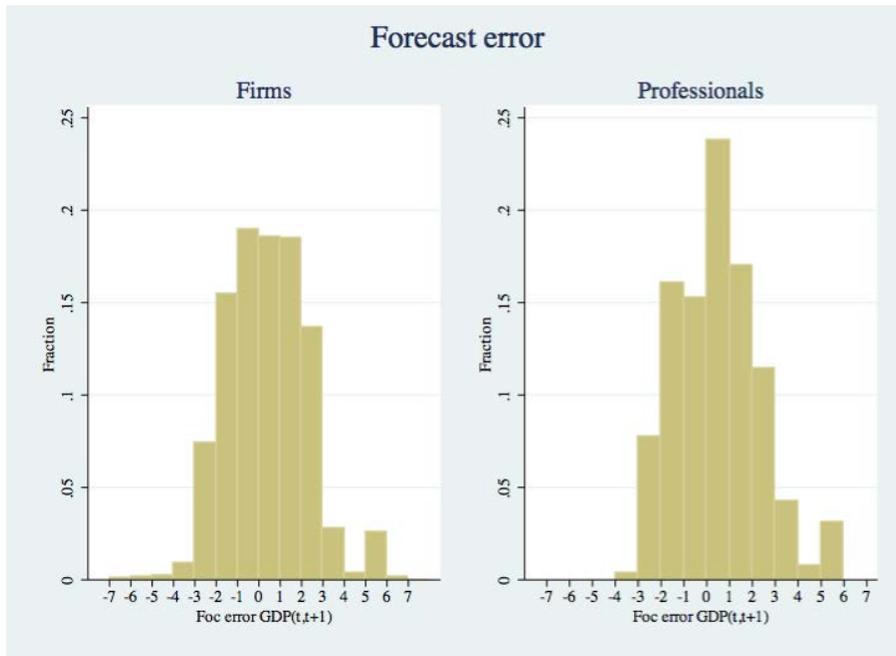


Figure A.7: Comparison of the distributions of firm forecasts and professional forecasts



Notes: The figure shows the distribution firm forecasts from ASCB and the distribution of professional forecasts from Consensus Forecasts for the following year's GDP growth rates.

Table A.1: 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 A.2: Basic sample statistics

Variable	Mean	SD	Min	Max	N
Forecast of GDP growth in t+1 (in percent)	1.483	1.305	-2.8	5.5	25864
Forecast of GDP growth in t+1 - realization (in percent)	0.409	1.88	-6.263	7.244	25864
Forecast of GDP growth in t+1 - realization (in percent)	1.536	1.16	0.008	7.244	25864
Forecast of GDP growth in t+1 - professional forecast* (in percent)	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 (1 mill JPY)	6,963	27,223	0	1,010,000	25864
Ln(Investment +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	966	0.139	21,404	25923
Sales growth	0.001	0.118	-0.461	0.371	20063
Profit (1 mill JPY)	8.6	37.7	-378	2125	25922
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 A.3: Response probit

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Sample	All	All	All	All	All	All	Restricted sample of firms that are observed at least for 5 years					
TFP	0.207*** (0.0346)					0.163*** (0.0415)	0.317*** (0.0273)					0.247*** (0.0343)
ln(labor prod)		0.0685*** (0.0189)						0.184*** (0.0152)				
Ln(Employment)			0.0241*** (0.00865)			0.0484*** (0.0166)			0.184*** (0.00726)			0.230*** (0.0139)
Ln(capital)				-0.0106 (0.00780)		-0.0479*** (0.0154)				0.0750*** (0.00638)		-0.110*** (0.0128)
Firm age					0.00458*** (0.000635)	0.00563*** (0.000890)					0.0203*** (0.000576)	0.0206*** (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 A.4: Autocorrelations of forecasts and errors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$f_t(t+1)$	$f_t(t+1)$	$f_t(t+1)$	$f_t(t+1)$	$e_t(t+1)$	$e_t(t+1)$	$e_t(t+1)$	$e_t(t+1)$
$f_{t-1}(t)$	0.250*** (0.00797)	0.166*** (0.00844)	0.155*** (0.0125)	0.00701 (0.0129)				
$e_{t-1}(t)$					0.827*** (0.0101)	0.803*** (0.0115)	0.135*** (0.0112)	0.00367 (0.0113)
$g(t)$	0.303*** (0.00542)	0.305*** (0.00568)			1.017*** (0.0121)	1.009*** (0.0132)		
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	11,842	11,842	11,842	11,842	11,842	11,842	15,061	15,061
Number of firms	1,758	1,758	2,054	2,054	1,758	1,758	2,054	2,054

Notes: Standard errors are clustered at firm levels. $e_{t-1}(t)$ is a measure of forecast error defined by the 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 . $g(t)$ is the realized GDP growth in year t .

Table A.5: GDP forecasts, employment, investment, and sales growth controlling for lagged forecasts

	(1)	(2)	(3)
	D ln(Emp)	D ln(Inv)	D ln(Sales)
$f_{t-1}(t)$	0.238** (0.0957)	2.44* (1.44)	0.319* (0.166)
$f_{t-2}(t-1)$	0.198** (0.0945)	0.0115 (1.52)	0.119 (0.145)
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	15,617	15,144	15,618
Number of firms	2,080	2,038	2,081
Mean dep var	-0.0179	-0.0443	-0.00367

Notes: Standard errors are clustered at firm levels. $f_{t-1}(t)$ is the firm's forecast of GDP growth in fiscal year t answered in year $t-1$, and $f_{t-2}(t-1)$ is the firm's forecast of GDP growth in fiscal year $t-1$ answered in year $t-2$. $D \ln(\text{Emp}) = \ln(\text{employment}_t) - \ln(\text{employment}_{t-1})$, $D \ln(\text{Inv}) = \ln(\text{investment}_t) - \ln(\text{investment}_{t-1})$, and $D \ln(\text{Sales}) = \ln(\text{sales}_t) - \ln(\text{sales}_{t-1})$.

Table A.6: Forecast errors and firm performance (response weights and squared forecast errors)

	(1)	(2)	(3)	(4)
	Profit	TFP	Profit	TFP
$ e_{t-1}(t) $	-69.8*** (16.8)	-0.756*** (0.279)		
$(e_{t-1}(t))^2$			-21.8*** (6.78)	-0.0484 (0.0737)
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	15,618	12,658	15,618	12,658
Number of firms	2,063	1,733	2,081	1,732

Notes: Standard errors are clustered at firm levels. In columns (1) and (2), 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. In columns (3) and (4), $(e_{t-1}(t))^2$ 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 . 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 A.7: GDP forecasts by cyclicity

Dividing sample	(1)	(2)	(3)	(4)	(5)	(6)
Firm cyclicity	D ln(Emp) High	D ln(Emp) Low	D ln(Inv) High	D ln(Inv) Low	D ln(Sales) High	D ln(Sales) Low
$f_{t-1}(t)$	0.377** (0.159)	0.114 (0.151)	4.17* (2.26)	0.260 (2.30)	0.00537* (0.00304)	-0.00168 (0.00246)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,926	5,892	5,926	5,891	5,926	5,892
Number of firms	694	757	694	756	694	757
Interaction			(1)	(2)	(3)	
			D ln(Emp)	D ln(Inv)	D ln(Sales)	
$f_{t-1}(t)$			0.115 (0.239)	-3.88 (3.76)	-0.143 (0.385)	
$f_{t-1}(t) \times$ Cyclicity			0.926 (1.69)	46.3* (24.5)	2.41 (2.68)	
Year FEs			Yes	Yes	Yes	
Firm FEs			Yes	Yes	Yes	
Observations			11,817	11,818	11,818	
Number of firms			1,450	1,451	1,451	

Notes: Standard errors are clustered at firm levels. Cyclicity index is constructed based on stock price responses to quarterly GDP announcements. $f_{t-1}(t)$ is firm's forecast of GDP growth in fiscal year t answered in year $t - 1$. $D \ln(\text{Emp}) = \ln(\text{employment}_t) - \ln(\text{employment}_{t-1})$, $D \log(\text{Inv}) = \ln(\text{investment}_t) - \ln(\text{investment}_{t-1})$, and $D \ln(\text{Sales}) = \ln(\text{sales}_t) - \ln(\text{sales}_{t-1})$. 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).

Table A.8: Forecast accuracy with respect to professional forecasts in the preceding month (November)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	$ ep_t(t+1) $	$ ep_t(t+1) $	$ ep_t(t+1) $	$ ep_t(t+1) $	$ ep_t(t+1) $	$ ep_t(t+1) $	$ ep_t(t+1) $	$ ep_t(t+1) $	$ ep_t(t+1) $	$ ep_t(t+1) $
ln(Employment)	-0.0497*** (0.00318)		-0.0517*** (0.00460)		-0.0455*** (0.00373)		-0.0481*** (0.00367)		-0.0431*** (0.00550)	-0.0520*** (0.00938)
TFP (past 3 years)		-0.0341* (0.0198)	-0.0172 (0.0195)							0.00262 (0.0377)
Firm age				-0.00166*** (0.000266)	-0.000964*** (0.000258)					-0.00175*** (0.000578)
Cyclicality						-0.174* (0.0961)	-0.0855 (0.0908)			0.172 (0.199)
Banks share								-0.571*** (0.0845)	-0.354*** (0.0875)	-0.220 (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 banks and other financial institutions among the firm's top 30 stock holders. $|ep_t(t+1)|$ 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 provided in the November of year t . The unit of $|ep_t(t+1)|$ is percent (i.e. decimal points multiplied by 100).