

# Do Managerial Forecasting Biases Matter? \*

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## Abstract

This paper quantifies the economic implications of forecast errors made by firm managers. Using firm-level data on managerial expectations of future sales, we document that managerial forecast errors are *significantly* correlated with past forecast errors. The observed positive correlation is consistent with managerial under-reaction to new information. To investigate the micro- and macro-economic effects of this forecasting bias, we develop a dynamic equilibrium model with heterogeneous firms and distorted expectations. We estimate the model using firm-level production *and* forecast data. The model matches exactly the significant under-reaction observed in managerial forecast data. However, our quantitative analysis reveals a limited influence of distorted expectations on both firm-level and aggregate efficiency.

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# 1. Introduction

The behavioral corporate finance literature has convincingly demonstrated the existence of systematic biases in managerial decision-making. In a large sample of entrepreneurs, optimism correlates with excessive short-term leverage (Landier and Thesmar, 2009). CEO overconfidence tends to correlate with expansive acquisitions (Malmendier and Tate, 2008) and excess investment (Malmendier and Tate, 2005), particularly in R&D (?). A nascent, related, literature emphasizes the importance of systematic errors in managerial forecasting. Ben-David et al. (2013) provide evidence that CEOs have mis-calibrated expectations of returns, and that such overconfidence correlates with investment and leverage in the cross-section of firms. Gennaioli et al. (2015) show that managerial expectations tend to be extrapolative, and that expectations drive investment across firms. While these papers establish a *statistically significant* relationship between systematic forecast errors and managerial decisions, our paper asks whether such forecasting biases matter quantitatively. Do they create significant distortions in firm-level decisions? Do they contribute significantly to aggregate inefficiency?

We start by documenting systematic forecasting biases by managers of publicly-traded US corporations using simple regression-based evidence. This first step is similar in spirit to recent contributions in the macroeconomics and finance literature that investigate the dynamics of beliefs using expectation data (see e.g. Coibion and Gorodnichenko (2015), Bordalo et al. (2017a), Malmendier and Nagel (2016), Bouchaud et al. (2018), among others). We use guidance on one-year ahead sales by publicly-traded companies as a measure of managerial expectations (Chen (2018)). We show that forecasting errors are highly persistent: the auto-regression coefficient is .17 and significant at the 1% confidence level. This reduced-form result supports the hypothesis that firm managers under-react to recent news about their firm's output. We establish the robustness of this finding in two ways. First, we obtain similar estimates when using analyst expectation data instead of guidance (Bouchaud et al. (2018)). Second, we show that

managerial guidance are strongly predictive of firms' investment behavior, above and beyond standard determinants of corporate investment.

We develop an economic framework to quantify the effect of forecasting biases. We start from a standard neoclassical model of investment with heterogeneous firms. Productivity follows an AR(1) process. Every period, managers observe the realization of productivity and a private signal informative about next-period productivity. Firms face a one period time-to-build for capital investment, so that managerial forecast about future TFP determines current capital expenditures. Managers may have non-rational expectations about next period TFP. We generalize the formulation of expectations in [Bordalo et al. \(2017b\)](#) to allow for both over- and under-reaction to news about the firm's next period TFP. We also allow managers to exhibit different biases in the way they process public and private information. Beyond the one-period time-to-build and the distorted expectations, the baseline model has no additional friction. We obtain simple closed-form solutions for managerial forecast errors and how they relate to capital expenditures.

We then take this baseline model to the data. On the production side, the model's key parameters are the persistence and productivity of TFP shocks. Using Compustat data, we construct TFP residuals following [David et al. \(2016\)](#) and fit an AR(1) process on these residuals. We use our guidance data to identify the distortions in beliefs and the variance of managerial private information. We target the persistence in forecast errors, the dispersion in forecast errors, and the covariance between TFP innovations and forecast errors. We estimate significant distortions in forecasting relative to rational expectations. Managers under-react to public news and over-react to their private information. However, the partial equilibrium effect of these distortions is limited: in our baseline estimation, firms average profit would be only .18% larger in a counterfactual where managers hold rational expectations. While the persistence in managerial forecast errors constitutes a rejection of rational expectations, the low dispersion of forecast

errors in the data implies limited distortions on firms investment decision.

We consider a number of extensions to this baseline model. We first allow guidance to be a noisy proxy for managerial expectations. We identify the variance of this noise by matching the covariance of real investment decisions with the reported forecast. We also introduce variable adjustment costs to the model. We include time-to-build in labor, so that firm capital *and* labor decisions depend on productivity forecasts. We allow for industry heterogeneity in production and forecasting biases. Across all these specifications, distorted beliefs have only a limited effect on firm efficiency, as in our baseline model.

We also consider how distorted beliefs affect macroeconomic outcomes. We show that aggregate efficiency is proportional to the dispersion in log-sales forecast errors, a result reminiscent of [Hsieh and Klenow \(2009\)](#) and [David et al. \(2016\)](#). Intuitively, dispersion in forecast errors implies capital misallocation: firms with positive (resp. negative) TFP shocks relative to expectations end up with too little (resp. too much) capital ex post. Quantitatively, aggregate TFP losses from distorted beliefs are proportional to the difference between the dispersion in log-sales forecast errors in the data and the dispersion in log-sales forecast errors under rational expectations. We use our estimated structural model of forecasting biases to compute the dispersion in log-sales forecast errors under rational expectations. We estimate aggregate TFP losses from distorted beliefs lower than .05%. This result is not surprising given the partial equilibrium finding that firm profits do not vary much with

Our paper builds on a recent literature that uses forecast data to test rationality. [Coibion and Gorodnichenko \(2015\)](#) document that past revisions positively predict forecast errors in macroeconomic forecasts. They argue that this predictability arises from informational frictions. [Bouchaud et al. \(2018\)](#) document under-reaction among security analysts. Also looking at analysts, [Bordalo et al. \(2017b\)](#) show that forecast errors on long-term EPS growth forecasts are positively correlated with past growth, suggest-

ing over-reaction. [Bordalo et al. \(2018\)](#) document over-reaction in macro and financial variables among professional forecasters. [Bloom et al. \(2017\)](#) show that 15% of plant managers cannot form and express subjective probability distributions. Using data on household expectations of inflation, [Malmendier and Nagel \(2016\)](#) find evidence consistent with “experience effects”: heavy discounting of pre-birth data combined with recency bias. We contribute to this literature by documenting significant under-reaction to new information in guidance data. More importantly, our paper provides a tractable framework to quantify the economic effects of this forecasting bias. We incorporate non-rational forecasts into an otherwise standard neo-classical model of investment with heterogeneous firms.

Through its aggregation approach, our paper is also related to a small number of papers that investigate the impact of managerial information on long-term output in steady state models. On the theory side, [Akerlov and Yellen \(1985\)](#) show that, in most equilibrium settings, near-rational behavior can have first-order aggregate consequences, even when it has second-order individual effects. [Hassan and Mertens \(2017\)](#) builds on [Akerlov and Yellen \(1985\)](#) and show that near-rational errors lead to first-order distortions in household savings decisions. On the empirical side, [David et al. \(2016\)](#) develop a steady-state production model similar to ours, but use it to quantify aggregate efficiency improvements that results from a well-developed stock market. Our paper is concerned with inefficiencies arising from non-rational expectations.

The rest of the paper is organized as follow. Section 2 presents reduced-form evidence of persistence in managerial forecast errors. Section 3 builds a production framework with heterogeneous firms and distorted expectations. Section ?? provides a structural estimation of the model and quantify a number of partial equilibrium counterfactuals. Section ?? provides aggregation results. Section 5 concludes.

## 2. Evidence on Managerial Biases

### 2.1. Data and Summary Statistics

We use data on firms' expectations from the IBES Guidance dataset, a feed that offers quantitative (numeric) company expectations from press releases and transcripts of corporate events. We focus on forecasts of fiscal year total sales, which is one of the most common forecast. The forecast horizon ranges 1 quarter out (current quarter corresponds to the fiscal year end quarter) to about 30 quarters out; forecast horizon longer than 12 quarters is rare. For consistency, we restrict the sample to forecasts made in the first fiscal quarter about total sales of that fiscal year. Comprehensive data coverage starts from 2003 onward. Since we are interested in the persistence of forecast errors, we also restrict the sample to firms that issue at least 5 guidance over the sample period.

We focus on US non-financial firms (SIC outside of 6000 to 6999). The final sample – which we will refer to as the guidance sample – contains 5,222 firm-year observations, corresponding to about 470 firms per year. All variables are winsorized at the median +/- 5 times the interquartile range.<sup>1</sup>

Table 1 Panel A provides summary statistics for firms in the guidance sample. Panel B reports statistics for firms in the contemporaneous full COMPUSTAT sample. The average firm in the guidance sample is larger and more profitable than the average firm in the COMPUSTAT sample.

Panel A also contains summary statistics on the forecast errors from guidance, together with forecast errors computed from the consensus of analysts' forecasts. We compute log-sales forecast errors as the logarithm of actual sales minus the logarithm of forecast sales provided in the guidance. Average log-sales forecast errors in the guidance are 2% and have a 9% standard deviation (Panel A, Table 1). In contrast, analysts' log-

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<sup>1</sup>If we only winsorize at the 1% level, some observations still have log-sales forecast errors greater than 50% in absolute value. These observations mostly correspond to firms experiencing a significant corporate event, such as a merger. These large forecast errors should therefore not be attributed to managerial forecasting bias.

sales forecast errors are lower than .1% on average and have an 11% standard deviation. Note that, since average forecast errors may be driven by strategic considerations, our subsequent analysis ignore this moment of the data.

## 2.2. Forecast Informativeness

We examine the informativeness of firm forecasts measured through guidance data. The guidance data is consistent with firm forecasts collected by the Duke University CFO survey; it is predictive of actual sales; it has strong explanatory power on investment decisions.

### *Cross-Check with Duke CFO Survey Data*

We cross-check sales forecasts measured using guidance data and forecasts collected in the Duke CFO Survey led by John Graham and Campbell Harvey. The survey is anonymous and takes place on a quarterly basis; respondents come from around 400 major firms in the US.<sup>2</sup> Each quarter, respondents report expectations of the future 12 month growth of sales and other key corporate variables. The aggregate statistics are published on the CFO Survey's website.

Figure 1 presents the time series of aggregate (sales-weighted) expected sales growth using IBES guidance data and Duke CFO Survey data. Note that the forecast horizon for the CFO Survey is rolling 12 months, while the guidance data is every fiscal year. Thus every quarter we use guidance data with forecast horizon ranging from 2 to 6 quarters as an approximate.

Figure 1 shows managerial forecasts are consistent across these two sources. The guidance data is not systematically biased upward or downward. The guidance aggregate also appears to be slightly more volatile than the CFO Survey aggregate.

### *Predicting Actuals*

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<sup>2</sup>Other segments of the CFO Survey also have firms from other countries. Here we focus on US firms for both CFO Survey data and guidance data.

Are sales guidance a reliable forecast of realized sales? Table 2 predicts actual sales in fiscal year  $t$  using sales forecasts for year  $t$  made in the first quarter and additional control variables. We estimate the following regression:

$$\frac{sales_{it}}{assets_{i,t-1}} = \alpha_i + \delta_t + \frac{F_{i,t-1}sales_{it}}{assets_{i,t-1}} + X'_{it}\gamma + \epsilon_{it},$$

where  $F_{i,t-1}sales_{it}$  corresponds to the guidance for firm  $i$  and fiscal year  $t$  made in the first quarter of that year. The set of control variables  $X$  includes: contemporaneous (consensus) analyst sales forecasts, lagged sales, beginning-of-year  $Q$ , beginning-of-year log assets, year fixed effects, industry fixed effects (Fama-French 12 industries), industry-year fixed effects, and firm fixed effects. Standard errors are clustered by firm and time. Column 1 of Table 2 only includes the guidance forecast. The coefficient on the guidance is 1.016 and the regression's  $R^2$  is 97%. The various specifications estimated in Table 2 confirm the robustness of this finding.

#### *Expectations and Investment*

Do sales guidance explain contemporaneous investment activities? Table 3 regresses capital expenditures in fiscal year  $t$  on sales forecasts for year  $t$  made in the first quarter and additional control variables. We estimate the following regression:

$$\frac{capx_{it}}{assets_{i,t-1}} = \alpha_i + \delta_t + \frac{F_{i,t-1}sales_{it}}{assets_{i,t-1}} + X'_{it}\gamma + \epsilon_{it},$$

where  $F_{i,t-1}sales_{it}$  corresponds to the guidance for firm  $i$  and fiscal year  $t$  made in the first quarter of that year. The set of control variables  $X$  includes: contemporaneous (consensus) analyst sales forecasts, lagged capex over asset, beginning-of-year  $Q$ , beginning-of-year log assets, cash flows (income before extraordinary items plus depreciation and amortization, normalized by lagged assets), lagged cash flows year, fixed effects, industry fixed effects (Fama-French 12 industries), industry-year fixed effects, and firm fixed effects.



Table 3 shows that sales guidance are significantly correlated with contemporaneous investment decisions. This result is consistent with (Gennaioli et al., 2015), who document that managers earnings expectations have strong explanatory power for investment activities. This relationship is robust to controlling for standard determinants of capital expenditures used in the literature, such as Q or cash flows. Obviously, a threat to interpretation is reverse causality: when firms are investing a lot, managers expect sales to increase. Note that capital expenditures capture long-term capital investments, which are unlikely to pay off immediately. Quantitatively, if we switch the left-hand side and right-hand side variables (i.e. use capital expenditures to explain sales forecast), the coefficient becomes greater than 2.5, implying that \$1 of capital expenditure immediately turns into \$2.5 of sales. This is unreasonably large.

### 2.3. Persistence of Forecast Errors

With rational expectations, managerial forecast errors should be i.i.d. We document instead that forecasts errors implied by guidance are persistent. This finding is consistent with under-reaction to new information. We estimate the following model:

$$Error_{it} = \alpha + \delta_t + \beta Error_{i,t-1} + \epsilon_{it}, \quad (1)$$

where  $Error_{it}$  is log-sales forecast error (logarithm of actual sales minus logarithm of forecast sales provided in guidance made at the beginning of the fiscal year) and  $\delta_t$  correspond to year fixed-effects. Figure 2 provides a binned scatter plot of this relationship between past log-sales forecast errors and current log-sales forecast errors. It uses our sample of firms with at least 5 guidance. To construct this figure, we split the sample in vingitiles of lagged log-sales forecast error (x-axis) and represent, on the y-axis, the average current log-sales forecast error: the relationship between lagged and current log-sales forecast error is increasing and close to linear.

Table 4, Panel A, reports the regression results. Column (1) estimates Equation 1 on the baseline sample using OLS. Standard errors are clustered at the firm and year level. The estimated  $\beta$  is .18 and is statistically significant at the 1% confidence level. Column (2) repeats this analysis, using analysts consensus forecasts to compute log-sales forecast errors. The sample is larger, since the sample includes all firms with at least 5 analysts consensus forecasts. The estimated  $\beta$  is .17. Column (3) and (4) augment the model of column (1) and (2) by including firm fixed-effects. Such fixed-effects can arise, for example, for strategic reasons or goal-setting purposes. This augmented model cannot be estimated consistently using OLS given the short time period in our sample (Nickell (1981)). As a result, we further restrict the sample to firms with at least 9 forecasts in the sample and estimate the model using dynamic panel GMM (Arellano and Bover (1995)). Using both guidance and analysts consensus forecasts, these augmented models lead to an estimate of .12, which is significant at the 1% confidence level in both cases. The quantitative interpretation of these estimates does, however, require a structural model, which we describe in Section 3.

## 2.4. Link between Error and Revisions

We also document the link between forecast errors and forecast revisions, drawing on the specification in (Coibion and Gorodnichenko, 2015). When a forecaster receive positive news, she revise her forecast upward. When she under-reacts to the information, however, the revision fail to fully account for the news content. The new forecast therefore leads to a positive forecast error, creating a positive correlation between forecast revisions and errors.

One limitation of the guidance data is the forecast horizon is rarely longer than six quarters and the forecasts are also not necessarily regular. Thus it is difficult to run regressions that utilize forecast error of year  $t$  sales made at the beginning of  $t$ , together with forecast revision of year  $t$  sales from the beginning of  $t - 1$  to the beginning of

year  $t$ . To utilize more data, we mix forecast horizons and revision duration: we use all available forecasts, together with the revision since the previous forecast of the same outcome (we require the forecast horizon to be at least 2 quarters). Again we perform this test using both firm guidance data and contemporaneous analyst forecast data.

We estimate the following model:

$$\log \text{sales}_{it} - \log F_{t-h} \text{sales}_{it} = cst + \gamma (\log F_{t-h} \log \text{sales}_{it} - \log F_{t-k} \text{sales}_{it}) + \epsilon_{iht}$$

where we lump together different horizons of revisions  $h$  (as long as  $h$  is no less than 2 quarters), and  $k$  is the time when the previous forecast of  $\text{sales}_{it}$  is made.

Table 4, Panel B reports the results. We estimate a significant  $\gamma$  of around 0.34 in both guidance and analyst forecast data. In sum, guidance data are informative about future sales (Table 2) and corporate investment (Table 3). However, the persistence in forecast errors, as well the positive correlation between forecast revisions and errors observed both in the guidance and the analyst forecast data are consistent with managers underreacting to new information. Such bias may arise because of inattention, or because of informational or institutional rigidities. In the rest of the paper, we investigate the quantitative consequences of such biases for production and efficiency.

### 3. A Model of Investment with Distorted Beliefs

#### 3.1. Baseline Model

We start from a standard neoclassical model of investment with two frictions: (1) 1 period time to build (2) distorted beliefs.

### 3.1.1. Set-up

Time is discrete. At date  $t$ , firm  $i$  combines capital  $k_{it}$  and labor  $l_{it}$  to generate sales with a Cobb-Douglas technology:

$$p_{it}y_{it} = Ae^{v_{it}} \left( k_{it}^\alpha l_{it}^{1-\alpha} \right)^\theta,$$

where  $v_{it}$  is revenue-based log-productivity,  $\alpha$  is the capital share and  $\theta$  captures decreasing returns to scale in revenues, which may arise from technology or market power. Input markets are competitive.  $w$  is the wage on the labor market and  $R$  is the rental rate of capital.<sup>3</sup> At date  $t$ , firms hire  $l_{it}$  employees after observing  $v_{it}$ . However, we assume a one-period time-to-build in capital: firms invest in the capital stock  $k_{it}$  before  $v_{it}$  is realized. As a result, managers need to form expectations about next-period productivity before investing. We assume an AR(1) process for  $v_{it}$ :

$$v_{it} = \rho v_{it-1} + \psi_{it} + \omega_{it} \quad \text{with:} \quad (\omega_{it}, \psi_{it}) \sim \mathcal{N} \left[ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\omega^2 & 0 \\ 0 & \sigma_\psi^2 \end{pmatrix} \right],$$

where  $\omega_{it}$  is realized at date  $t$ , after  $k_{it}$  has been purchased; in contrast,  $\psi_{it}$  is observed by the manager at date  $t - 1$ , but not by the econometrician. Our model thus allows for managerial private information about future productivity.

Managers may exhibit distorted expectations about future productivity. Precisely, we assume that date  $t-1$  managerial forecasts about  $v_{it}$  are normally distributed:

$$(v_{it} | \mathcal{I}_{t-1}) \underset{\mathbb{F}}{\sim} \log \mathcal{N} \left( \rho v_{it-1} + \psi_{it} + \gamma \rho \omega_{it-1} + \lambda \psi_{it}, \sigma_\omega^2 \right), \quad (2)$$

where  $\mathcal{I}_{t-1}$  is the manager's information set at date  $t - 1$ . This formulation entails two deviations from rational expectations: (1) when  $\gamma > 0$  (resp.  $< 0$ ), managers are over-reacting (resp. under-reacting) to the date  $t-1$  innovation in productivity  $\omega_{it-1}$  (2) when

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<sup>3</sup>We omit the time subscript for  $w$  and  $R$ , as we only consider steady-state economies.

$\lambda > 0$  (resp.  $< 0$ ), managers are over-reacting (resp. under-reacting) to their date t-1 private information about date-t productivity  $\psi_{it}$ . When  $\gamma = \lambda > 0$ , these expectations are similar to [Bordalo et al. \(2017a\)](#): agent overweights “exceptional” past realizations when forming beliefs (i.e. date t-1 realizations that deviate from date t-2 forecasts). Our formulation allows for under-weight of such realizations:  $\gamma$  and  $\lambda$  can be negative. It also allows for different treatment of private and public information:  $\gamma$  and  $\lambda$  are not necessarily equal.<sup>4</sup>

Finally, we allow reported managerial forecasts about future sales,  $\widehat{\mathbb{F}}_{i,t-1}[p_{it}y_{it}]$ , to differ from true managerial forecasts  $\mathbb{F}_{i,t-1}[p_{it}y_{it}]$ . Specifically:

$$\ln \left( \widehat{\mathbb{F}}_{i,t-1}[p_{it}y_{it}] \right) = \ln \left( \mathbb{F}_{i,t-1}[p_{it}y_{it}] \right) + \zeta_{it}, \quad \text{where: } \zeta_{it} \sim \mathcal{N} \left( 0, \sigma_{\zeta}^2 \right) \quad (3)$$

### 3.1.2. Firm behavior

We characterize firms behavior in the following proposition:

**Proposition 1.** Let  $\Phi = \frac{\alpha\theta}{1-(1-\alpha)\theta}$ . Firm  $i$ 's optimal capital stock at date  $t$  is:

$$k_{it} = \tilde{\Omega}_1 \left( \mathbb{F}_{i,t-1} \left[ e^{\frac{\Phi}{\alpha\theta} v_{it}} \right] \right)^{\frac{1}{1-\Phi}} = \tilde{\Omega}_1 e^{\frac{1}{1-\Phi} \left( \frac{\Phi}{\alpha\theta} (\rho v_{it-1} + \gamma \rho \omega_{it-1} + (1+\lambda)\psi_{it}) + \frac{1}{2} \left( \frac{\Phi}{\alpha\theta} \right)^2 \sigma_{\omega}^2 \right)},$$

where  $\tilde{\Omega}_1$  is constant across firms. Firm  $i$ 's sales at date  $t$  are simply given by:

$$p_{it}y_{it} = \tilde{\Omega}_2 e^{\frac{\Phi}{\alpha\theta} v_{it}} k_{it}^{\Phi}$$

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<sup>4</sup>Using the notations in [Bordalo et al. \(2017b\)](#), equation 3 can be derived from a model in which agents rely on two separate “diagnostics” with different weights  $\gamma$  and  $\lambda$  :

$$h_{t-1}^{\gamma}(v_{it}) = h(v_{it}|v_{it-1}) \left[ \frac{h(v_{it}|v_{it-1}, \psi_{it})}{h(v_{it}|\widehat{v}_{it-1} = \rho v_{it-2} + \psi_{it-1}, \psi_{it})} \right]^{\gamma} \left[ \frac{h(v_{it}|v_{it-1}, \psi_{it})}{h(v_{it}|v_{it-1}, \widehat{\psi}_{it} = 0)} \right]^{\lambda} \frac{1}{Z}$$

The first diagnostic makes full use of new private information  $\widehat{\psi}_{it} = \psi_{it}$ , but fails to account for new public information at  $t-1$ :  $\widehat{v}_{it-1} = \rho v_{it-2} + \psi_{it-1}$ . The second diagnostic fails to account for new private information at  $t-1$   $\widehat{\psi}_{it} = 0$  but fully accounts for new public information  $\widehat{v}_{it-1} = v_{it-1}$ .

where  $\tilde{\Omega}_2$  is constant across firms. Log-sales forecast error at date  $t$  using reported forecasts at date  $t-1$  are:

$$\widehat{FE}_{it} = \ln(p_{it}y_{it}) - \ln\left(\widehat{\mathbb{F}}_{i,t-1}[p_{it}y_{it}]\right) = -\frac{\Phi}{\alpha\theta}(\gamma\rho\omega_{it-1} + \lambda\psi_{it}) + \frac{\Phi}{\alpha\theta}\omega_{it} - \frac{1}{2}\left(\frac{\Phi}{\alpha\theta}\right)^2\sigma_\omega^2 - \zeta_{it}$$

*Proof.* See Appendix C.1. □

Firm  $i$ 's investment decision at date  $t-1$  depends on firm  $i$ 's forecast of date- $t$  productivity. This forecast is distorted: with  $\gamma \neq 0$  and  $\lambda \neq 0$ , managers put non-rational weights on date  $t-1$  innovations in productivity ( $\omega_{it-1}$  and  $\psi_{it}$ ). These distorted forecasts lead to predictable forecast errors that depend systematically on these past innovations.

### 3.1.3. Model Estimation

We calibrate two parameters related to production:  $\alpha = .33$  and  $\theta = .8$  ((Broda and Weinstein, 2006)). We estimate 6 parameters ( $\rho, \sigma_\omega, \sigma_\psi, \gamma, \lambda, \sigma_\zeta$ ). We follow David et al. (2016) and construct revenue-based productivity for firm  $i$  at date  $t$  as:  $\hat{v}_{it} = \frac{\alpha\theta}{\Phi}(\ln(p_{it}y_{it}) - \Phi\ln(k_{it}))$ . We use the net value of property, plant and equipment in year  $t - 1$  as our measure of  $k_{it}$ <sup>5</sup> and  $p_{it}y_{it}$  is firm  $i$ 's total sales for fiscal year  $t$ . We use dynamic panel GMM to estimate the following process for  $\hat{v}_{it}$  (Arellano and Bover (1995)):

$$\hat{v}_{it} = \delta_i + \delta_t + \chi\hat{v}_{it} + \tau_{it}$$

The estimated persistence,  $\hat{\chi}$ , is an estimator for  $\rho$ . We estimate the remaining structural parameters through a moment estimator that targets five sample moments from both production and forecast data. Since the model does not allow for aggregate shocks, all the moments used in the estimation control for year fixed-effects. The five moments we target are:

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<sup>5</sup>In the model,  $k_{it}$  is determined at date  $t - 1$  but can only be used for production in period  $t$ . PPE observed in year  $t - 1$  include to the capital expenditures made in year  $t$  and thus corresponds to our definition of  $k_{it}$  in the model.

1. the variance of the estimated productivity residuals  $\hat{\sigma}_\tau^2$ . In the model,  $\sigma_\tau^2 = \sigma_\omega^2 + \sigma_\psi^2$
2. the variance of residuals from a regression of log-sales forecast errors on year fixed-effects ( $\widehat{\text{Var}}[\widehat{FE}_{it}]$ ). In the model,  $\text{Var}[\widehat{FE}_{it}] = \sigma_\zeta^2 + \left(\frac{\Phi}{\alpha\theta}\right)^2 \left((1 + \gamma^2\rho^2)\sigma_\omega^2 + \lambda^2\sigma_\psi^2\right)$
3. the estimated coefficient  $\hat{\kappa}_1$  from a regression of log-sales forecast error on lagged log-sales forecast error, controlling for year fixed-effects. This regression corresponds to Column 1, Table 4. As discussed in Section 2.3, a positive  $\hat{\kappa}_1$  implies that managers are under-reacting to TFP innovations ( $\gamma < 0$ ). In the model, 
$$\kappa_1 = -\frac{\left(\frac{\Phi}{\alpha\theta}\right)^2 \gamma \rho \sigma_\omega^2}{\sigma_\zeta^2 + \left(\frac{\Phi}{\alpha\theta}\right)^2 \left((1 + \gamma^2\rho^2)\sigma_\omega^2 + \lambda^2\sigma_\psi^2\right)}$$
4. the estimated coefficient  $\hat{\kappa}_2$  of a regression of date t productivity residual,  $\hat{\tau}_{it}$  on date-t reported log-sales forecast error, controlling for year and firm fixed-effects. Intuitively, under-reaction to private information (i.e.  $\lambda < 0$ ) creates a positive correlation between what the econometrician observes as a positive innovation to TFP and managerial forecast error. In the model, 
$$\kappa_2 = \frac{\left(\frac{\Phi}{\alpha\theta}\right) (\sigma_\omega^2 - \lambda\sigma_\psi^2)}{\sigma_\zeta^2 + \left(\frac{\Phi}{\alpha\theta}\right)^2 \left((1 + \gamma^2\rho^2)\sigma_\omega^2 + \lambda^2\sigma_\psi^2\right)}$$
5. the estimated coefficient  $\hat{\kappa}_3$  of a regression of the log sales-to-capital ratio,  $\ln(p_{it}y_{it}) - \ln(k_{it})$ , on date-t reported log-sales forecast error, controlling for year and firm fixed-effects. We know that in the model,  $\ln(k_{it}) = C_0 + \ln(\mathbb{F}_{it-1}[p_{it}y_{it}])$ , where  $\mathbb{F}_{it-1}[k_{it}]$  is the manager's true forecast at  $t - 1$  of date t sales and  $C_0$  is constant across firms. If managers were truthfully reporting their sales forecast, the log sales-to-capital ratio would simply be equal to the log-sales forecast error plus a constant, so that  $\kappa_3$  would be 1. However, managers may distort their reported forecast. This introduces measurement error. Precisely, 
$$\kappa_3 = 1 - \frac{\sigma_\zeta^2}{\sigma_\zeta^2 + \left(\frac{\Phi}{\alpha\theta}\right)^2 \left((1 + \gamma^2\rho^2)\sigma_\omega^2 + \lambda^2\sigma_\psi^2\right)}.$$

The way our model is identified is straightforward. We directly identify  $\rho$  from the estimation of the AR(1) process for TFP. The estimated variance of log-TFP innovations directly provides us with  $\sigma_\eta^2 + \sigma_\omega^2$ .  $\kappa_3$  directly measures the attenuation bias that arises from managerial guidance being a noisy measure of true forecasts and identifies  $\sigma_\zeta$ ,

conditional on the observed dispersion of forecast errors observed in the data.  $\kappa_1$  – the persistence in log-sales forecast errors – is increasing in both  $\gamma$ , the managerial bias on public information, and  $\sigma_\omega^2$ .  $\kappa_2$  is an increasing function of  $\sigma_\omega$  – rational forecast errors correlate positively with TFP innovations – and a decreasing function of  $\lambda\sigma_\eta^2$  – if managers over-react to private information, then forecast errors are negatively correlated with the overall log-TFP innovations. Finally, the dispersion of forecast errors increases with fundamental volatility ( $\sigma_\omega^2$  and  $\sigma_\eta^2$ ), with behavioral biases ( $\gamma$  and  $\lambda$ ) and with  $\sigma_\zeta^2$ , the variance of the noise introduced by managers in guidance.

Table 5, Panel A reports the 6 moments used in the estimation. Standard errors are obtained by bootstrapping on the estimation sample using a block bootstrap at the firm-level. The persistence of log-TFP is estimated to be .72, while the variance of log-TFP innovations is .008. The variance of log-sales forecast errors after projecting on year fixed-effects is .008. As shown on Table 4, column 1, the persistence of log-sales forecast error is .175. The other two regression coefficients,  $\hat{\kappa}_2$  and  $\hat{\kappa}_3$ , are both positive and significant at the 1% level.

Table 5, Panel B shows the estimated structural parameters of our model. We estimate  $\gamma$  – the parameter governing the distortion in expectations related to public information – at -.25: managers put negative weights on recent innovations to the public component of TFP innovations,  $\omega_{it}$ . In other words, manager under-react significantly to new public information about TFP. We estimate a  $\lambda$  – the parameter governing the distortion in expectations related to private information – at .082. While this coefficient is statistically significant, it is quantitatively small: there is some limited over-reaction to private information.

### 3.1.4. Partial equilibrium counterfactual

We consider how the profits of a firm would change if its manager had rational forecasts. We perform this counterfactual in partial equilibrium: prices ( $w, R$ ) as well as revenue



productivity  $A$  are held constant. We first compute  $\mathbb{E}[\pi_{it}^F]$ , the average profits of a firm in our model at the estimated parameters. We then compute  $\mathbb{E}[\pi_{it}^E]$ , the average profits of a firm operating under similar structural parameters except for  $\gamma = \lambda = 0$ , i.e. rational expectations.  $\Delta$  is the percentage increase in average firm-level profits obtained due to rational expectations and is defined as:<sup>6</sup>

$$\Delta = \frac{\mathbb{E}[\pi_{it}^E] - \mathbb{E}[\pi_{it}^F]}{\mathbb{E}[\pi_{it}^F]} = \frac{0.079\%}{(0.017\%)}$$

In Table 4, we rejected rational forecasts by showing evidence of significant persistence in managerial forecast errors. In Table 5, we structurally estimated significant parameters characterizing the distortions in managerial expectations. Quantitatively, however, we see that these distortions in managerial expectations lead to limited distortions on profits: average profits are only .08% higher for a firm with a rational manager.

## 3.2. Extensions

### 3.2.1. Adjustment costs

We now assume that firms face a fixed cost of adjusting their capital stock, as well as quadratic adjustment costs. With our formulation of distorted expectations, we can easily write the Bellman representation of the firm optimization problem:

$$V(k_{it}, v_{it}, \omega_{it}, \psi_{it+1}) = \left| \begin{array}{l} \max_{(k_{it+1}, l_{it})} \left\{ \pi(z_{it}, k_{it}, k_{it+1}, l_{it}) + \frac{1}{1+r} \mathbb{E}^{\gamma, \lambda} [V(k_{it+1}, v_{it+1}, \omega_{it+1}, \psi_{it+2}) | z_{it}, \omega_{it}, \psi_{it+1}] \right\} \\ \pi(z_{it}, k_{it}, k_{it+1}, l_{it}) = Ae^{v_{it}} k_{it}^{\alpha} l_{it}^{(1-\alpha)\theta} - wl_{it} - (k_{it+1} - (1-\delta)k_{it}) \\ - c_k \frac{(k_{it+1} - (1-\delta)k_{it})^2}{k_{it}} - f_k p_{it} y_{it} \mathbb{1}_{k_{it+1} \neq (1-\delta)k_{it}} \end{array} \right.$$

---

<sup>6</sup>Note that  $\Delta$  is independent of  $w$ ,  $R$  and  $A$  since, in our Cobb-Douglas environments, realized profits are log-linear in the wage  $w$ , the user cost of capital  $R$  and the average productivity  $A$

where  $(v_{it+1}, \omega_{it+1}, \psi_{it+2}) | (v_{it}, \omega_{it}, \psi_{it+1}) \stackrel{\text{IF}^{\gamma, \lambda}}{\sim} \mathcal{N} \left[ \begin{pmatrix} \rho(v_{it} + \gamma\omega_{it}) + (1 + \lambda)\psi_{it+1} \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\omega^2 & 0 & 0 \\ 0 & \sigma_\omega^2 & 0 \\ 0 & 0 & \sigma_\psi^2 \end{pmatrix} \right]$

### 3.2.2. Time-to-build in labor

In our baseline model, capital is the only quasi-fixed factor. We consider the case where labor also needs to be hired one period ahead of production. Both capital and labor depends on productivity forecasts

Appendix C.2 provides the derivation for the firm's optimal investment and hiring decision under this assumption.

### 3.2.3. CES production function

In our baseline model, production combines labor and capital with a Cobb-Douglas technology. We consider the case of a CES production function instead:

$$p_{it}y_{it} = Ae^{v_{it}} \left( \alpha k_{it}^{\frac{\xi}{1-\xi}} + (1 - \alpha)l_{it}^{\frac{\xi}{1-\xi}} \right)^{\frac{1-\xi}{\xi}},$$

where  $\xi$  is the elasticity of substitution between capital and labor. Appendix 3.2.3 provides the derivation for the firm's optimal investment and hiring decision with this alternative production function.

## 4. Aggregation

We consider the general equilibrium implications of distorted managerial forecasts. We nest the firm-level investment model of Section 3 into a general equilibrium framework.

## 4.1. Aggregation in the baseline model

We consider a simple market structure following [Dixit and Stiglitz \(1977\)](#). There is a continuum of intermediate input producers: at date  $t$ , firm  $i$  produces a quantity  $y_{it}$  of an intermediary input at a price  $p_{it}$ . These inputs are used in the production of a final good. The final good market is perfectly competitive, and aggregates intermediate inputs with a CES technology:

$$Y_t = \left( \int_i y_{it}^\theta di \right)^{\frac{1}{\theta}}, \quad (4)$$

The price of the final good is normalized to 1. Profit maximization in the final good market implies that the demand for product  $i$  is given by:  $p_{it} = \left( \frac{Y}{y_{it}} \right)^{1-\theta}$  and  $-\frac{1}{1-\theta}$  is the price elasticity of demand. There is a single labor market from which all firms hire.  $w_t$  is the wage, which firms take as given. Households have GHH preferences over leisure and consumption:  $u(c_t, l_t) = \left( c_t - \frac{w_0}{L_0^{\frac{1}{\epsilon}}} l_t^{1+\frac{1}{\epsilon}} \right)$ . As a result, labor supply is  $L_0 \left( \frac{w}{w_0} \right)^\epsilon$  and  $\epsilon$  is the constant labor supply elasticity.

We start by showing how the firm-level model of investment of [Section 3](#) can be nested into this framework. Assume firm  $i$  production combines labor and capital with a Cobb-Douglas technology:  $y_{it} = B e^{z_{it}} k_{it}^\alpha l_{it}^{1-\alpha}$ . The capital good is the final good. Log-productivity  $z_{it}$  is stochastic and follows an AR(1) process:

$$z_{it} = \rho z_{it-1} + \epsilon_{it} + \eta_{it} \quad \text{with:} \quad (\epsilon_{it}, \eta_{it}) \sim \mathcal{N} \left[ \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\epsilon^2 & 0 \\ 0 & \sigma_\eta^2 \end{pmatrix} \right],$$

where  $\eta_{it}$  is privately observed by the manager in period  $t - 1$ . In particular, we assume no aggregate uncertainty so that aggregate output is constant  $Y_t = Y$  and the equilibrium wage on the labor market is also constant  $w_t = w$ . Firms operate under monopolistic competition. Profit maximization implies that firms revenue exhibit decreasing returns

to scale:

$$p_{it}y_{it} = \underbrace{Y^{1-\theta}B^\theta}_{=A} \underbrace{e^{\theta z_{it}}}_{=e^{v_{it}}} \left( k_{it}^\alpha l_{it}^{1-\alpha} \right)^\theta$$

Therefore, this model is equivalent to the baseline firm-level model discussed in Section 3:  $A = Y^{1-\theta}B^\theta$ ,  $v_{it} = \theta z_{it}$ ,  $\omega_{it} = \theta \epsilon_{it}$  and  $\psi_{it} = \theta \eta_{it}$ . As in our baseline firm-level model, we assume a one period time-to-build in capital and a user cost of capital  $R$ . Because of the time-to-build in capital, firms need to form expectation about next period productivity. Let  $\mathbb{F}_{t-1} [p_{it}y_{it}]$  be the managerial forecast of date  $t$  total sales made at date  $t - 1$ . The log-sales forecast error is  $FE_{it} = \ln(p_{it}y_{it}) - \ln(\mathbb{F}_{t-1} [p_{it}y_{it}])$ . The following proposition provides two results on aggregate efficiency loss resulting from non-rational expectations:

**Proposition 2.** *Assume either:*

- *managerial log-sales forecasts are log-normally distributed*
- *variations in log-sales forecast error  $FE_{it}$  and log-sales forecast  $\ln(\mathbb{F}_{t-1} [p_{it}y_{it}])$  are small around their respective mean*

*Then aggregate TFP is simply given by:*

$$\ln(TFP) = -\frac{\alpha}{2} \left( 1 + \frac{\alpha\theta}{1-\theta} \right) \text{Var} [FE_{it}] \quad (5)$$

*Proof.* See Appendix C.4. □

Proposition 2 is based on the observation that forecast errors made when investing are formally equivalent to a wedge between the real cost of capital  $r + \delta$  and the marginal productivity of capital  $\alpha\theta \frac{p_{it}y_{it}}{k_{it}}$ . When the realization of productivity is lower than the forecast, the firms has too much capital compared to the frictionless benchmark where there is no time to build and the firm would observe its productivity. Hence, the marginal productivity of capital is lower than  $r + \delta$  in this case. As in [Hsieh and Klenow](#)

(2009), when this wedge is assumed to follow a log-normal distribution, log-aggregate TFP is proportional to the dispersion in the log-wedge. In our case this assumption boils down to managerial forecast following a log-normal distribution. Alternatively, one can assume small variations of wedges and TFP realizations around their mean (or equivalently here, small variations in log-sales forecast errors and log-sales forecasts) and obtain a similar formula through a second-order Taylor expansion around the population average. Importantly, note that the TFP formula in Proposition 5 holds for all forecasting rules  $\mathbb{F}_{t-1}$  as long as it either follows a log-normal distribution or generates only small variations around the average forecast in the population.

**Corollary 1.** *For any forecasting rule satisfying the assumptions of Proposition 5, the TFP losses due to imperfect foresight are:*

$$\Delta \ln(TFP)^0 = \ln(TFP^{\text{perfect foresight}}) - \ln(TFP) = \frac{\alpha}{2} \left( 1 + \frac{\alpha\theta}{1-\theta} \right) \text{Var}[FE_{it}]$$

*In particular, the TFP losses due to non-rational forecasts are bounded by:*

$$\Delta \ln(TFP) = \ln(TFP^{\text{rational forecasts}}) - \ln(TFP) < \Delta \ln(TFP)^0 = \frac{\alpha}{2} \left( 1 + \frac{\alpha\theta}{1-\theta} \right) \text{Var}[\widehat{FE}_{it}]$$

*Proof.* The variance of forecast errors when managers have perfect foresight is 0, which proves the first part of the Corollary.

The variance of forecast errors when managers have rational expectation is  $\geq 0$ . Additionally, reported log-sales forecast error have larger variance than actual log-sales forecast errors:  $\text{Var}[FE_{it}] \leq \text{Var}[\widehat{FE}_{it}]$ . This proves the second part of the Corollary.  $\square$

Corollary 1 is important because it provides us with a simple bound for the TFP losses due to non-rational forecasts, which requires minimal assumptions on the forecasting rules used by managers. This bound is also easily implementable, since the variance of log-sales forecast errors is directly observed in the data.

**Corollary 2.** *Assume that managers form expectation using the distorted belief model of Section 3.1.1, Equation 3. Forecasts follow a log-normal distribution, and the TFP losses due to non-rational forecasts are given by:*

$$\Delta \ln(TFP) = \frac{1}{2} \left( \frac{\Phi}{1-\Phi} \right) \left( \frac{\Phi}{\alpha} \right) \left( \gamma^2 \rho^2 \sigma_\epsilon^2 + \lambda^2 \sigma_\eta^2 \right) \quad (6)$$

*Proof.* When managers form expectation using Equation 3, their log-sales forecasts is given by:  $\ln(\mathbb{E}_{t-1} [p_{it}y_{it}]) = C + \frac{\theta}{1-\theta} (\rho(z_{it-1} + \gamma\epsilon_{it-1}) + (1+\lambda)\eta_{it})$ , where  $C$  is constant across firms (see Appendix C.4 with  $\nu = \theta z$ ,  $\omega = \theta\epsilon$  and  $\psi = \theta\eta$ ). Therefore, since  $z$ ,  $\epsilon$  and  $\eta$  are log-normally distributed, the log-sales forecast are log-normally distributed, and Proposition 2 applies. The variance of log-sales forecast errors is simply:  $\text{Var}[FE_{it}] = \left(\frac{\Phi}{\alpha}\right)^2 \left( (1 + \gamma^2 \rho^2) \sigma_\epsilon^2 + \lambda^2 \sigma_\eta^2 \right)$  (see Appendix C.4). Therefore, TFP in the actual economy is:  $\ln(TFP) = -\frac{1}{2} \left( \frac{\Phi}{1-\Phi} \right) \left( \frac{\Phi}{\alpha} \right) \left( (1 + \gamma^2 \rho^2) \sigma_\epsilon^2 + \lambda^2 \sigma_\eta^2 \right)$ . When managers have rational forecasts,  $\gamma = \lambda = 0$  and  $\ln(TFP^{\text{rational forecasts}}) = -\frac{1}{2} \left( \frac{\Phi}{1-\Phi} \right) \left( \frac{\Phi}{\alpha} \right) \sigma_\epsilon^2$ . The difference between these two expression is the formula in the corollary.  $\square$

We can combine the results in this section with the structural estimates recovered in Section 3.1.3 to quantify the TFP losses from non-rational forecasts in our context.  $\alpha$  and  $\theta$  are calibrated at 1/3 and .8 respectively, so that  $\Phi = .57$ . We can start by bounding the TFP losses using Corollary 1, which, again, does not rely on a particular forecasting rules:

$$\Delta \ln(TFP) \leq \underbrace{\frac{\alpha}{2} \left( 1 + \frac{\alpha\theta}{1-\theta} \right)}_{=0.383} \underbrace{\text{Var}[\widehat{FE}_{it}]}_{=0.008 \text{ (Table 5, Panel A)}} = 0.298\%$$

We can already see that given the low dispersion of log-sales forecast errors observed in the data, non-rational forecast can only have a limited impact on aggregate TFP. 0.298 % correspond to the aggregate gains that would prevail if managers had perfect foresights about future TFP. To get to the counterfactuals where managers have rational expectations, we use instead Corollary 2, combined with the structural estimates obtained

in Panel B of Table 5:

$$\Delta \ln(TFP) = \frac{1}{2} \underbrace{\left( \frac{\Phi}{1-\Phi} \right) \left( \frac{\Phi}{\alpha} \right)}_{=1.138} \underbrace{\left( \gamma^2 \rho^2 \sigma_\epsilon^2 + \lambda^2 \sigma_\eta^2 \right)}_{=0.0002} = 0.019\%$$

Despite the evidence of significant bias in the sales forecast data, our analysis concludes that forecasting bias in this sample have a negligible effect on aggregate efficiency. Our conclusion remains unaffected when we consider alternative calibrations for  $\alpha$  and  $\theta$ . Figure 3, Panel A shows the aggregate TFP losses from distorted forecasts when  $\theta$  varies from .7 to .95, holding  $\alpha$  constant at 1/3. Panel B of Figure 3 shows the aggregate TFP losses from distorted forecasts when  $\alpha$  varies from .2 to .6, holding  $\theta$  constant at .8. Across both figures, aggregate TFP losses are at most XXX %.

## 4.2. Aggregation in augmented models

## 4.3. Incorporating aggregate shocks

# 5. Conclusion

This paper incorporates forecasts into an otherwise standard neoclassical model of investment. Our model allows for managerial private information, distortion in the reports of forecasts as well as distorted forecasts due to non-rational expectations. We first document significant bias in managerial forecasts in guidance data: managerial forecast errors are persistent in a statistically significant way. This predictability is consistent with underreaction to new information by managers. However, when nested into a model of production, the estimated forecasting bias leads to negligible efficiency losses, both in partial and general equilibrium.

We believe this result is important as it calls into question the literature on managerial biases in decision-making. Standard data on managerial forecasts combined with a

standard model cannot deliver an important role for planning mistakes. Our analysis shows that natural extensions to the standard model of investment cannot increase the effect of distorted forecasts in a significant way: more complementarity between labor and capital, time-to-build in labor, or adjustment costs do not change our quantitative findings.

We think two deviations from the standard model could potentially allow for a greater role of distorted forecasts. First, a longer time-to-build is a clear candidate: however, our managerial forecasts data does not cover long-term forecasts, so that we cannot estimate a model with a longer time-to-build. Financial frictions may also lead to amplifications of distorted forecasts. We leave this analysis for future research.



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## A. Figures

Figure 1: Sales Growth Forecasts: IBES Guidance and Duke CFO Survey



Note: This plot shows the (sales-weighted) average forecast of sales growth from IBES guidance data and from Duke CFO survey data. The IBES guidance data forecasts fiscal year sales; for each quarter, we keep forecasts that have horizons 2 to 6 quarters (i.e. between 2 to 6 quarters before the fiscal year end of the relevant fiscal year). The CFO survey forecasts are about rolling 12 months sales growth.

Figure 2: Forecast Error Persistence: Binned Scatter Plot

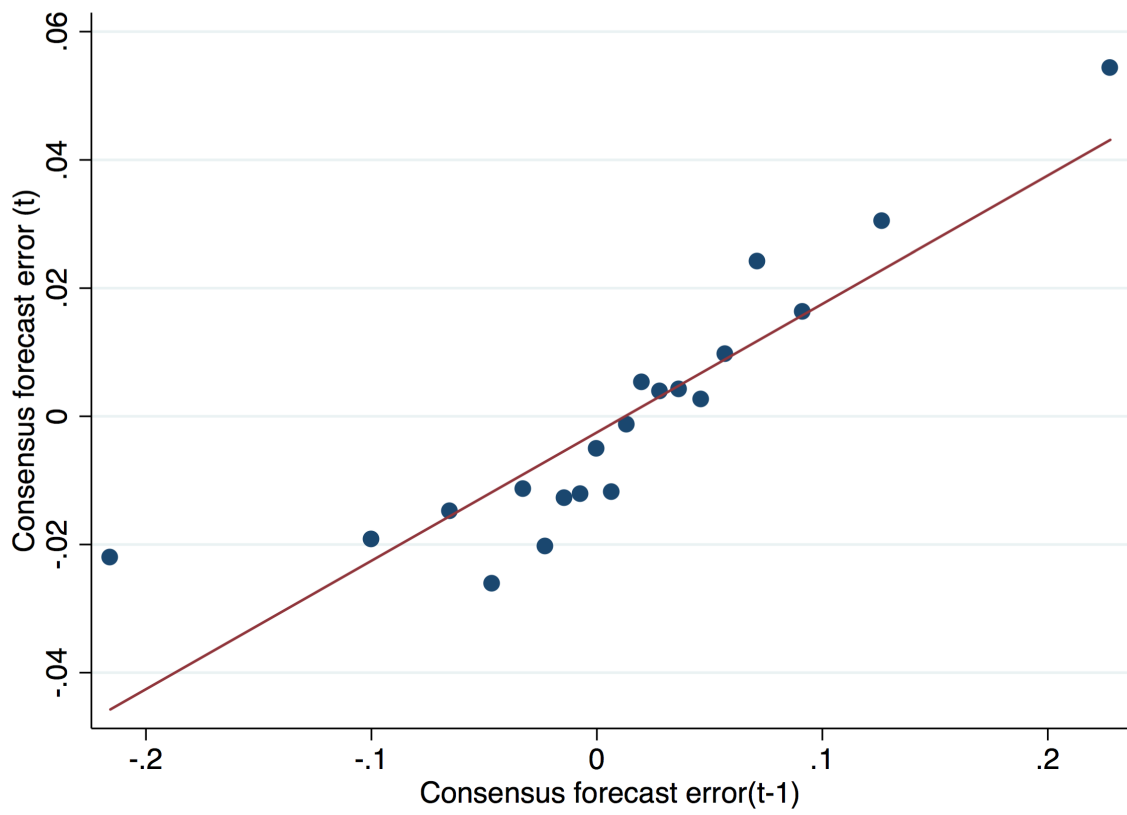


Figure 3: Sensitivity analysis:  $\theta$  and  $\alpha$

## B. Tables

Table 1: Summary Statistics

Variable	mean	p25	p50	p75	sd	N
<b>Panel A. Guidance Sample</b>						
Firm forecast error (log actual sales - log forecast)	0.00	-0.04	0.00	0.05	0.09	5,278
Analyst forecast error	0.00	-0.04	0.00	0.05	0.11	4,878
Log sales	7.09	5.92	7.03	8.23	1.69	5,278
Log assets	7.18	5.96	7.07	8.29	1.64	5,278
Sales/l.assets	1.18	0.70	1.02	1.43	0.72	5,270
Capex/l.assets	0.04	0.02	0.03	0.06	0.04	5,264
Cash flow/l.assets	0.19	0.05	0.13	0.28	0.19	5,278
Q	2.13	1.32	1.78	2.57	1.17	5,205
Book-to-market	0.44	0.22	0.36	0.59	0.39	5,261
<b>Panel B. Compustat Sample</b>						
Log sales	4.82	3.11	5.20	6.99	3.04	49,568
Log assets	4.82	3.05	5.05	7.02	3.09	54,076
Sales/l.assets	1.07	0.35	0.82	1.48	1.02	50,022
Capex/l.assets	0.05	0.01	0.03	0.06	0.06	48,939
Cash flow/l.assets	0.24	0.03	0.12	0.35	0.27	54,069
Q	1.88	1.12	1.47	2.20	1.20	33,370
Book-to-market	0.56	0.25	0.46	0.76	0.54	33,455

Note: Summary statistics of the guidance sample and the contemporaneous full Compustat sample. Sample period: 2004-2015. Both sample are restricted to firms outside the finance industry. The guidance sample is restricted to firms that have at least 5 guidance issued over the sample period. Firm forecast data are from IBES Guidance dataset, and analyst forecast uses contemporaneous consensus analyst forecast from the IBES analyst dataset. The forecasts are restricted to those made at the beginning of the first fiscal quarter, and the outcome is total sales of fiscal year. Firm forecast error is the logarithm of actual sales for the fiscal year minus the log of the guidance issued in the first quarter for the coming fiscal year. Analyst forecast error is the logarithm of actual sales minus the log of the analysts consensus forecast in the first quarter of the coming fiscal year. Q is the ratio of market value to total assets. Book-to-market is the ratio of the book value of equity to market value of equity. All variables are winsorized at the median +/- 5 times the interquartile range.

Table 2: Predicting Actual Sales

	Actual Sales							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm forecast	1.005*** (0.005)	1.076*** (0.034)	1.003*** (0.009)	1.052*** (0.029)	0.998*** (0.009)	1.003*** (0.009)	0.997*** (0.009)	0.948*** (0.021)
Analyst forecast		-0.072** (0.035)		-0.056 (0.035)				
l.Sales			-0.002 (0.011)	0.006 (0.013)	0.005 (0.010)	-0.003 (0.010)	0.005 (0.009)	-0.019 (0.017)
Q			0.006** (0.003)	0.006*** (0.002)	0.006** (0.002)	0.007** (0.003)	0.006** (0.002)	-0.001 (0.004)
Log(l.Assets)			-0.001 (0.011)	-0.009 (0.013)	-0.006 (0.011)	0.001 (0.010)	-0.006 (0.009)	-0.074*** (0.015)
Constant	0.002 (0.005)	0.004 (0.005)	0.005 (0.019)	0.020 (0.019)				
Fixed effects	No	No	No	No	Year	Industry	Ind-Year	Firm&Year
Observations	5,257	4,862	5,173	4,786	5,173	5,173	5,171	5,172
Adj R <sup>2</sup>	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.98

Note: Sample period is 2004-2015. The sample corresponds to non-financial Compustat firms with at least 5 sales guidance over the sample period. We use OLS to estimate  $sales_{it}/assets_{i,t-1} = \alpha + F_{i,t-1}sales_{it}/assets_{i,t-1} + X'_{it}\gamma + \epsilon_{it}$ , where  $sales_{it}$  is sales of firm  $i$  in fiscal year  $t$ ,  $F_{i,t-1}sales_{it}$  is beginning-of-year forecast (earliest forecast in first fiscal quarter) of fiscal year  $t$  sales (normalized by lagged assets). Controls include contemporaneous consensus analyst sales forecasts (normalized by lagged assets), sales in year  $t - 1$ , average  $Q$  (market value of assets/book value of assets) as of the beginning of year  $t$ , log total assets as of the beginning of year  $t$ . Industry is Fama-French 12 industries. Standard errors are clustered by both firm and time. \*\*\*, \*\* and \* means statistically significant at the 1%, 5% and 10% confidence level.



Table 3: Predicting Capital Expenditures

	Capital Expenditures							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm forecast	0.016*** (0.002)	0.017** (0.008)	0.004*** (0.001)	0.023*** (0.006)	0.004*** (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.020*** (0.004)
Analyst forecast		-0.001 (0.008)		-0.019*** (0.007)				
l.capx			0.742*** (0.025)	0.745*** (0.024)	0.746*** (0.025)	0.727*** (0.027)	0.733*** (0.027)	
Q			0.002*** (0.000)	0.002*** (0.001)	0.002*** (0.000)	0.003*** (0.001)	0.002*** (0.000)	0.006*** (0.001)
Cash flow			-0.041*** (0.008)	-0.041*** (0.008)	-0.037*** (0.007)	-0.040*** (0.008)	-0.037*** (0.007)	-0.043*** (0.006)
l.Cash flow			0.030*** (0.007)	0.031*** (0.008)	0.026*** (0.007)	0.032*** (0.007)	0.028*** (0.006)	0.014** (0.006)
Log(l.Assets)			-0.001** (0.000)	-0.001*** (0.000)	-0.001** (0.000)	-0.001* (0.000)	-0.001* (0.000)	-0.009*** (0.003)
Constant	0.025*** (0.003)	0.025*** (0.003)	0.007*** (0.003)	0.007*** (0.002)				
Fixed effects	No	No	No	No	Year	Industry	Ind-Year	Firm&Year
Observations	5,241	4,853	5,147	4,770	5,147	5,147	5,145	5,157
Adj R <sup>2</sup>	0.07	0.07	0.66	0.67	0.67	0.67	0.68	0.70

Note: Sample period is 2004-2015. The sample corresponds to non-financial Compustat firms with at least 5 sales guidance over the sample period. We use OLS to estimate  $capx_{it}/assets_{i,t-1} = \alpha + F_{i,t-1}sales_{it}/assets_{i,t-1} + X'_{it}\gamma + \epsilon_{it}$ , where  $capx_{it}$  is capital expenditures of firm  $i$  in fiscal year  $t$ ,  $F_{i,t-1}sales_{it}$  is beginning-of-year forecast (earliest forecast in first fiscal quarter) of fiscal year  $t$  sales (normalized by lagged assets). Controls include contemporaneous consensus analyst sales forecasts (normalized by lagged assets), capex-to-lagged assets in year  $t - 1$ , average  $Q$  (market value of assets/book value of assets) as of the beginning of year  $t$ , cash flows (income before extraordinary items plus depreciation and amortization, normalized by lagged assets) in fiscal year  $t$  and  $t - 1$ , log total assets as of the beginning of year  $t$ . Industry is Fama-French 12 industries. Standard errors are clustered by both firm and time. \*\*\*, \*\* and \* means statistically significant at the 1%, 5% and 10% confidence level.

Table 4: Persistence of Forecast Errors

	(1)	(2)	(3)	(4)
	Firm	Analyst	Firm	Analyst
<b>Panel A. Forecast Error on Lagged Forecast Error</b>				
l.Forecast error	0.179*** (0.041)	0.172*** (0.037)	0.115*** (0.029)	0.119*** (0.017)
Year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Observations	4,251	18,552	1,892	12,248
Adj R <sup>2</sup>	0.08	0.11		
<b>Panel B. Forecast Error on Forecast Revision</b>				
Forecast revision	0.33*** (0.04)	0.35*** (0.035)		
Constant	0.007** (0.0028)	-0.005* (0.003)		
Year FE	Yes	Yes		
Obs	8,949	7,673		
R <sup>2</sup>	0.021	0.034		

Note: Panel A regresses log-sales forecast error (log actual sales minus log sales forecast made in first quarter of fiscal year  $t$ ) on log-sales forecast error of year  $t - 1$ . The firm forecasts come from IBES guidance dataset. The analyst forecasts use data from IBES analyst dataset. Columns (1) and (3) include year fixed-effects and are estimated using OLS on the sample of firms with at least 5 sales forecasts either from guidance (Column (1)) or analyst consensus (Column (3)). Columns (2) and (4) include both year and firm fixed-effects, and are estimated using dynamic panel GMM (Arellano and Bover (1995)) on the sample of firms with at least 9 sales forecasts either from guidance (Column (1)) or analyst consensus (Column (3)). Panel B regresses year  $t$  log-sales forecast error on the change in the log sales forecast since the last forecast for fiscal year  $t$  sales (forecast revision). Standard errors are clustered by both firm and time. \*\*\*, \*\* and \* means statistically significant at the 1%, 5% and 10% confidence level.

Table 5: Structural Estimation of Baseline Investment Model with Distorted Beliefs

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**Panel A: Moments**

$\hat{\chi}$	$\hat{\sigma}_\tau^2$	$\widehat{\text{Var}}[\widehat{FE}_{it}]$	$\hat{\kappa}_1$	$\hat{\kappa}_2$	$\hat{\kappa}_3$
0.727	0.008	0.008	0.175	0.406	0.787
( 0.031)	( 0.001)	( 0.000)	( 0.024)	( 0.022)	( 0.072)

**Panel B: Estimates**

$\hat{\gamma}$	$\hat{\lambda}$	$\hat{\rho}$	$\hat{\sigma}_\omega$	$\hat{\sigma}_\eta$	$\hat{\sigma}_\zeta$
-0.254	0.082	0.727	0.044	0.079	0.041
( 0.040)	( 0.015)	( 0.031)	( 0.002)	( 0.005)	( 0.007)

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Note: Panel A contains the targeted moments in our estimation. We estimate  $\hat{v}_{it} = \delta_i + \delta_t + \chi \hat{v}_{it} + \tau_{it}$  using dynamic panel GMM.  $\hat{\chi}$  and  $\hat{\sigma}_\tau^2$  are the estimated persistence and variance of residuals.  $\widehat{\text{Var}}[\widehat{FE}_{it}]$  is the variance of residuals from a regression of log-sales forecast errors on year fixed-effects.  $\hat{\kappa}_1$  is the estimated coefficient from a regression of log-sales forecast error on lagged log-sales forecast error, controlling for year fixed-effects.  $\hat{\kappa}_2$  is the estimated coefficient of a regression of date t productivity residual,  $\hat{\tau}_{it}$  on date-t reported log-sales forecast error, controlling for firm and year fixed-effects.  $\hat{\kappa}_3$  is the estimated coefficient of a regression of the log sales-to-capital ratio,  $\ln(p_{it}y_{it}) - \ln(k_{it})$ , on date-t reported log-sales forecast error, controlling for firm and year fixed-effects.  $\hat{\gamma}$  and  $\hat{\lambda}$  are the estimated coefficient characterizing distorted expectations.  $\hat{\rho}$  is the estimated persistence of TFP.  $\hat{\sigma}_\omega$  is the estimated volatility of TFP innovations.  $\hat{\sigma}_\eta$  is the volatility of private information.  $\hat{\sigma}_\zeta$  is the volatility of noise introduced by managers in reported forecasts. Standard error are obtained by bootstrapping on the estimation sample using a block bootstrap at the firm-level.  $\hat{\gamma}$  is the estimated

## C. Proofs

### C.1. Proof of Proposition 1

At date  $t$ , the firm hires employees after observing date  $t$  revenue-based productivity to maximize profits:

$$\Pi_{it} = \max_{l_{it}} \left\{ A e^{\nu_{it}} k_{it}^{\alpha\theta} l_{it}^{(1-\alpha)\theta} - w l_{it} \right\} = \Omega e^{\frac{\Phi}{\alpha\theta} \nu_{it}} k_{it}^{\Phi},$$

where  $\Phi = \frac{\alpha\theta}{1-(1-\alpha)\theta}$  and  $\Omega = (1 - (1 - \alpha)\theta) \left( \frac{(1-\alpha)\theta}{w} \right)^{\frac{1-\alpha}{\alpha}} A^{\frac{\Phi}{\alpha\theta}}$ . Let  $\mathbb{F}_{it-1}[e^{\frac{\Phi}{\alpha\theta} \nu_{it}}]$  be firm  $i$ 's forecast at date  $t - 1$ . At date  $t - 1$ , firm  $i$ 's capital stock is purchased to maximize expected profits:

$$\max_{k_{it}} \left\{ \Omega \mathbb{F}_{it-1} \left[ e^{\frac{\Phi}{\alpha\theta} \nu_{it}} \right] k_{it}^{\Phi} - R k_{it} \right\} \Rightarrow k_{it} = \left( \frac{\Phi}{R} \right)^{\frac{1}{1-\Phi}} \Omega^{\frac{1}{1-\Phi}} \left( \mathbb{F}_{it-1} \left[ e^{\frac{\Phi}{\alpha\theta} \nu_{it}} \right] \right)^{\frac{1}{1-\Phi}}$$

With our formulation of distorted expectations:

$$\ln \left( \mathbb{F}_{it-1} \left[ e^{\frac{\Phi}{\alpha\theta} \nu_{it}} \right] \right) = \frac{\Phi}{\alpha\theta} (\rho(\nu_{it-1} + \gamma\omega_{it-1}) + (1 + \lambda)\psi_{it}) + \frac{1}{2} \left( \frac{\Phi}{\alpha\theta} \right)^2 \sigma_{\omega}^2$$

Since  $k_{it}$  is purchased at date  $t - 1$ , the date  $t-1$  true forecast for date- $t$  sales is:

$$\mathbb{F}_{it-1} [p_{it} y_{it}] = \frac{\Omega}{1 - (1 - \alpha)\theta} \mathbb{F}_{it-1} \left[ e^{\frac{\Phi}{\alpha\theta} \nu_{it}} \right] k_{it}^{\Phi}$$

So that the log-sales forecast error at date  $t$  is:

$$\begin{aligned} FE_{it} &= \ln(p_{it} y_{it}) - \ln(\mathbb{F}_{it-1} [p_{it} y_{it}]) \\ &= \frac{\Phi}{\alpha\theta} \nu_{it} - \ln \left( \mathbb{F}_{it-1} \left[ e^{\frac{\Phi}{\alpha\theta} \nu_{it}} \right] \right) \\ &= -\frac{\Phi}{\alpha\theta} (\gamma\rho\omega_{it-1} + \lambda\psi_{it}) + \frac{\Phi}{\alpha\theta} \omega_{it} - \frac{1}{2} \left( \frac{\Phi}{\alpha\theta} \right)^2 \sigma_{\omega}^2 \end{aligned}$$

$\frac{\Phi}{\alpha\theta} \omega_{it} - \frac{1}{2} \left( \frac{\Phi}{\alpha\theta} \right)^2 \sigma_{\omega}^2$  corresponds to rational expectation errors.  $-\frac{\Phi}{\alpha\theta} (\gamma\rho\omega_{it-1} + \lambda\psi_{it})$  corresponds to expectation errors due to managers' distorted forecasts.

Accounting for mis-reporting of true forecasts, observed forecast errors are given by:

$$\begin{aligned} \widehat{FE}_{it} &= \ln(p_{it} y_{it}) - \ln \left( \widehat{\mathbb{F}}_{it-1} [p_{it} y_{it}] \right) \\ &= \ln(p_{it} y_{it}) - \ln(\mathbb{F}_{it-1} [p_{it} y_{it}]) - \zeta_{it} \\ &= -\frac{\Phi}{\alpha\theta} (\gamma\rho\omega_{it-1} + \lambda\psi_{it}) + \frac{\Phi}{\alpha\theta} \omega_{it} - \frac{1}{2} \left( \frac{\Phi}{\alpha\theta} \right)^2 \sigma_{\omega}^2 - \zeta_{it}, \end{aligned}$$

where  $\zeta_{it}$  is the “noise” introduced by managers in their reported forecasts.

The variance of log-sales forecast errors in the data is therefore given by:

$$\text{Var}[\widehat{FE}_{it}] = \sigma_{\zeta}^2 + \left(\frac{\Phi}{\alpha\theta}\right)^2 \left((1 + \gamma^2\rho^2)\sigma_{\omega}^2 + \lambda^2\sigma_{\psi}^2\right)$$

The covariance of date- $t$  and date- $t-1$  reported log-sales forecast errors writes:

$$\text{Cov}[\widehat{FE}_{it}, \widehat{FE}_{it-1}] = -\left(\frac{\Phi}{\alpha\theta}\right)^2 \gamma\rho\sigma_{\omega}^2$$

Distorted beliefs lead to persistence in forecast errors. An unusually large innovation  $\omega_{it-1}$  implies a positive forecast error today. For an agent over-weighting such unusually large realization (i.e.  $\gamma > 0$ ), this large innovation means a high forecast for date  $t$  sales, which leads, on average, to a negative forecast error at date  $t$ .

A regression of reported log-sales forecast at date  $t$  on reported log-sales forecast at date  $t - 1$  leads to a regression coefficient  $\kappa_1$ :

$$\kappa_1 = -\frac{\left(\frac{\Phi}{\alpha\theta}\right)^2 \gamma\rho\sigma_{\omega}^2}{\sigma_{\zeta}^2 + \left(\frac{\Phi}{\alpha\theta}\right)^2 \left((1 + \gamma^2\rho^2)\sigma_{\omega}^2 + \lambda^2\sigma_{\psi}^2\right)}$$

The covariance of log-productivity innovations (as measured by the econometrician) and reported log-sales forecast errors is:

$$\text{Cov}[\omega_{it} + \psi_{it}, \widehat{FE}_{it}] = \left(\frac{\Phi}{\alpha\theta}\right) \left(\sigma_{\omega}^2 - \lambda\sigma_{\psi}^2\right)$$

A regression of date  $t$  log-productivity innovations on date- $t$  reported log-sales forecast leads to a regression coefficient  $\kappa_2$ :

$$\kappa_2 = \frac{\left(\frac{\Phi}{\alpha\theta}\right) \left(\sigma_{\omega}^2 - \lambda\sigma_{\psi}^2\right)}{\sigma_{\zeta}^2 + \left(\frac{\Phi}{\alpha\theta}\right)^2 \left((1 + \gamma^2\rho^2)\sigma_{\omega}^2 + \lambda^2\sigma_{\psi}^2\right)}$$

Finally, from the formula for log-sales forecast, note that:

$$\mathbb{F}_{it-1} [p_{it}y_{it}] = \left(\frac{\Phi}{R}\right)^{\frac{\Phi}{1-\Phi}} \frac{\Omega^{\frac{1}{1-\Phi}}}{1 - (1 - \alpha)\theta} \left(\mathbb{F}_{it-1} \left[e^{\frac{\Phi}{\alpha\theta}v_{it}}\right]\right)^{\frac{1}{1-\Phi}} = \frac{R}{\alpha\theta}k_{it}$$

Therefore, the sales to capital ratio is related to the true log-sales forecast in the following way:

$$\ln(p_{it}y_{it}) - \ln(k_{it}) = \ln(p_{it}y_{it}) - \ln(\mathbb{F}_{it-1} [p_{it}y_{it}]) + \ln\left(\frac{\alpha\theta}{R}\right)$$

Since we observe only reported log-sales forecast:

$$\ln(p_{it}y_{it}) - \ln(k_{it}) = \ln(p_{it}y_{it}) - \ln(\widehat{\mathbb{F}}_{it-1}[p_{it}y_{it}]) + \zeta_{it} + \ln\left(\frac{\alpha\theta}{R}\right)$$

As a result, a regression of the log-sales-to-capital ratio on the reported log-sales forecast error should have a coefficient of:

$$\hat{\kappa}_3 = 1 - \frac{\sigma_\zeta^2}{\widehat{\text{Var}}[\widehat{FE}_{it}]}$$

## C.2. Derivation of model with time-to-build in labor

With time-to-build in labor and capital, the firm maximizes:

$$\max_{k_{it}, l_{it}} A\mathbb{F}_{t-1}[e^{v_{it}}] \left(k_{it}^\alpha l_{it}^{1-\alpha}\right)^\theta - wl_{it} - Rk_{it}$$

The first-order condition in labor implies:

$$l_{it} = \left(\frac{(1-\alpha)\theta}{w} A\mathbb{F}_{t-1}[e^{v_{it}}]\right)^{\frac{\Phi}{\alpha\theta}} k_{it}^\Phi$$

And the first-order condition in capital leads to:

$$\frac{\alpha\theta}{R} A\mathbb{F}_{t-1}[e^{v_{it}}] \left(\frac{(1-\alpha)\theta}{w} A\mathbb{F}_{t-1}[e^{v_{it}}]\right)^{\frac{(1-\alpha)\Phi}{\alpha}} k_{it}^{\Phi-1} = 1 \Rightarrow k_{it} = \left(\frac{\alpha\theta}{R}\right)^{\frac{1}{1-\Phi}} \left(\frac{(1-\alpha)\theta}{w}\right)^{\frac{(1-\alpha)\theta}{1-\theta}} (A\mathbb{F}_{t-1}[e^{v_{it}}])^{\frac{1}{1-\theta}}$$

And labor demand is simply:

$$l_{it} = k_{it} \left(\frac{(1-\alpha)\theta}{w}\right) \left(\frac{R}{\alpha\theta}\right) = \left(\frac{\alpha\theta}{R}\right)^{\frac{\theta}{1-\theta}} \left(\frac{(1-\alpha)\theta}{w}\right)^{\frac{1-\alpha\theta}{1-\theta}} A^{\frac{1}{1-\theta}} (\mathbb{F}_{t-1}[e^{v_{it}}])^{\frac{1}{1-\theta}}$$

Therefore, the firm revenue is simply:

$$p_{it}y_{it} = Ae^{v_{it}} k_{it}^{\alpha\theta} l_{it}^{(1-\alpha)\theta} \propto e^{v_{it}} (\mathbb{F}_{t-1}[e^{v_{it}}])^{\frac{1}{1-\theta}}$$

## C.3. Derivation of model with CES production function

## C.4. Proof of Proposition 2

We first take capital as given, and maximize profit with respect to labor given wage. We obtain:

$$\pi_{it} = (1 - \theta(1 - \alpha))Y^{1-\phi} e^{\frac{\phi z_{it}}{\alpha}} k^\phi \left(\frac{(1-\alpha)\theta}{w}\right)^{\frac{1-\alpha}{\alpha}\phi}$$

where  $\phi = \frac{\theta\alpha}{1-\theta(1-\alpha)}$ .

We then take the forecast  $F$  of the above expression, and maximize it with respect to capital  $k_{it}$ . We obtain the following formula for the revenue productivity of capital:

$$\alpha\theta\frac{p_{it}y_{it}}{k_{it}} = (r + \delta) \frac{e^{\frac{\Phi z_{it}}{\alpha}}}{\underbrace{F_{t-1}e^{\frac{\Phi z_{it}}{\alpha}}}_{\equiv 1 + \tau_{it}}}$$

Time to build acts like a wedge  $\tau_{it}$  between the effective cost of capital and the frictionless cost of capital. This wedge has a rational and bias component. Given that the mean of  $z$  is zero and that the innovation on  $z$  is  $\ll 1$ , we rewrite the log wedge as:

$$\ln(1 + \tau_{it}) = \frac{\Phi}{\alpha}z_{it} - \ln\left(\mathbb{F}_{t-1}\left[e^{\frac{\Phi}{\alpha}z_{it}}\right]\right) = \ln(p_{it}y_{it}) - \ln(\mathbb{F}_{t-1}[p_{it}y_{it}]) = FE_{it}$$

In other words, the log-sales forecast error acts as a capital wedge for the firm. Based on this observation, we can use the formula in [Sraer and Thesmar \(2018\)](#) to calculate log TFP when the log-sales forecast is log-normally distributed (so that productivity and the log-sales forecast errors are jointly log-normally distributed), or alternatively, when variations in the log-sales forecast errors and productivity are small around their respective mean, so that we can consider a 2nd order Taylor expansion around these means. This directly provides the formula in [Proposition 2](#).