The Aggregate Cost of Systematic Forecast Errors*

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Abstract

This paper estimates the aggregate cost of forecast errors made by firm managers. Using firm-level data on managerial expectations of future sales, we document that, consistent with underreaction to new information, managerial forecast errors are positively correlated with past forecast errors or past forecast revisions. We then investigate the effect on allocative efficiency and total output implied by this forecasting bias, in the context of a quantitative steady-state model of heterogeneous firms in general equilibrium. We find significant aggregate output and welfare losses relative to a full-information rational expectation benchmark; perhaps more surprisingly, large aggregate gains can also be achieved by simply replacing observed managerial forecasts with “optimal forecasts” that can easily be estimated from the data.

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1. Introduction

A growing number of papers document that managers make systematic errors in forecasting future outcomes, and that these errors correlate with real firm decisions. Ben-David et al. (2013) provide evidence that CEOs have miscalibrated 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. These recent findings echo earlier studies in behavioral corporate finance. For instance, CEO overconfidence tends to correlate with excess investment (Malmendier and Tate, 2005) and expansive acquisitions (Malmendier and Tate, 2008). In a large sample of entrepreneurs, optimism correlates with excessive short-term leverage (Landier and Thesmar, 2009). The question remains, however, as to whether the significant relationship between forecast errors and firm decisions, which has been documented in these firm-level studies, is significant from a quantitative standpoint. Do observed forecasting biases lead to significant distortions in firms behavior? How much do these distortions matter in general equilibrium? Our paper addresses these questions.

The first step of our analysis provides simple regression-based evidence on systematic forecasting biases by managers. This first step is similar in spirit to recent contributions in the macroeconomics and finance literature that directly use expectations 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)) and show that managerial forecasting errors are highly persistent – consistent with short-term underreaction– with an autoregression coefficient of .17. Concerned by the fact that guidance may be affected by strategic considerations, we replicate this finding using analyst expectation data instead and report similar estimates, consistent with earlier findings by Bouchaud et al. (2018).

The second step of our analysis is the introduction of non-rational expectations into an otherwise standard general equilibrium model with heterogeneous firms. To give a role to
(non-rational) expectations, the only real friction in the model comes from time-to-build for capital investment. In our baseline model, aggregate output and productivity can be simply expressed as a function of three moments of the distribution of log-forecast errors for sales: the unconditional mean and variance of sales log-forecast errors, as well as the covariance between log-forecast errors and log-productivity. In particular, aggregate TFP solely depends on the variance of sales log-forecast errors, a result reminiscent of Hsieh and Klenow (2009) and David et al. (2016). Intuitively, a larger dispersion in forecast errors generates ex post misallocation of capital across firms as firms end up with a capital stock, which does not correspond to the optimal level given their realized productivity. Aggregate output depends on aggregate TFP through the dispersion of log-forecast errors, but also on two additional terms (Sraer and Thesmar (2018)): mean log-forecast error (if firms are optimistic on average, output will be higher); the covariance of log-forecast error and log-productivity (if high productivity firms are on average more optimistic, output will be higher).

We then use this model to quantify the TFP and output losses attributable to predictable expectation errors. We do so by comparing the actual economy, where the three sufficient statistics described above are equal to their estimated values, to a counterfactual economy with a different process for expectation formation. We use two different approaches to construct these counterfactual economies.

In the first approach, we add additional structure by postulating a structural behavioral model of expectation formation. The model builds on Bordalo et al. (2017a) in that it allows current forecasts to depend on current and past innovations to TFP, but differs from their model in that it allows for both over- and under-reaction to news. We estimate this belief-formation model using our expectation data, which then allows us to structurally estimate the production parameters of the economy (persistence and volatility of TFP shocks) using COMPUSTAT data on sales. We then define as our first counterfactual an economy with the estimated production parameters but where managers hold rational expectations. Quantitatively, we find that, relative to this counterfactual, aggregate TFP in the actual
economy is .2% lower and aggregate output 1% lower. The intuition for the larger effect on output is that in the estimated model of belief formation, optimistic managers tend to be less productive on average.

In our second approach, we do not attempt to construct a rational expectation counterfactual, but instead consider an economy where managers use “optimal forecasts” instead of the forecasts we observe in the data. These optimal forecasts are estimated by optimally projecting future sales on managerial forecasts as well as additional forecasting variables that the econometrician can observe. To avoid potential look ahead bias, we run these forecasting regressions on the first part of our sample and then use these forecasting rules in the second half of the sample. This approach does not rely on a specific model of expectation formation and accommodates non-bayesian models such as Bordalo et al. (2017a) and Bouchaud et al. (2018) but also deviations from common knowledge as in Woodford (2003) and Coibion and Gorodnichenko (2015). Relative to an economy where managers use these forecasting rules, we find that aggregate TFP is 2% lower and output 5% lower in the actual economy. Intuitively, relative to actual forecasts, these empirical forecasts lead to both a lower dispersion in forecast errors. This reduces the dispersion of forecast errors and increases the correlation between forecasted and realized productivity.

The main contributions of this paper are to (1) provide a tractable framework to quantify the aggregate effect of predictable forecast errors by managers and (2) apply this framework using guidance data as a measure of managerial expectations for publicly-traded firms and production data from COMPUSTAT. In this sense, our paper builds on the recent literature that uses expectations data to measure forecast error predictability, but takes it one step further by incorporating such predictability into a quantitative, steady-state, model with heterogenous firms. Coibion and Gorodnichenko (2015) document that past revisions positively predict forecast errors in macroeconomic forecasts, arising 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, suggesting over-reaction. Bordalo et al. (2018) document over-reaction in macro and financial variables among professional forecasters. Using data on household expectations of inflation, Malmendier and Nagel (2016) find evidence consistent with “experience effects”, in the sense that pre-birth data is heavily discounted. In the case of sales forecasts by managers and analysts, we find consistent evidence of significant under-reaction to new information.

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 develops the intuition that near-rational errors lead to first-order distortions in household savings decisions. On the empirical side, David et al. (2016) use a steady-state production model similar to the one in our paper, but use it to quantify the steady-state efficiency gains from improved allocative efficiency due to the stock market. In contrast, our paper is concerned with informational inefficiencies arising through 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 heterogenous firms and distorted expectations; it derives simple aggregation formulas that allows us to map sufficient statistics of the distribution of forecast errors on to aggregate effects; it then describes the two approaches we take for measurement: (1) putting structure on expectation formation and (2) construct “optimal” forecasts from the data. Section 4 implements these two approaches in the data. Section 5 concludes.
2. Evidence on Managerial Biases

2.1. Data and Summary Statistics

We collect data on firms’ expectations from the IBES Guidance dataset, which collects forecasts announced by firm management. In the following, we first present the summary statistics of the guidance data, then analyze its informativeness, and finally study predictable forecast errors. We also supplement this analysis with analyst forecast data from IBES: we find that management forecast is more informative than analyst forecast, both for predicting actual sales and for explaining investment activities.

We focus on forecasts of fiscal year total sales, which is one of the most popular forecast item. The forecast horizon ranges from nowcast (same as fiscal year end quarter) to about 30 quarters; forecast horizon longer than 12 quarters is rare. In most specifications, we restrict to forecasts made in the first fiscal quarter, about total sales of that fiscal year. Comprehensive data coverage starts from 2003.

We focus on US non-financial firms (SIC outside of 6000 to 6999). Every year there are about 900 unique firms in this sample, which we will refer to as the guidance sample. We winsorize outliers at the 1% level.

Table 1 Panel A provides summary statistics for firms in the guidance sample, and Panel B reports statistics for firms in the contemporaneous full Compustat sample. Firms in the guidance sample are larger and generally more profitable.

We also include in Panel A summary statistics of forecast errors (together with contemporaneous consensus analyst forecast errors). Here we restrict to forecasts made at the beginning of the first fiscal quarter about sales in the given fiscal year. The errors are computed as log actual sales minus log forecasts. We do not find that the forecast errors are systematically upward or downward biased.
2.2. Forecast Informativeness

We begin by examining the informativeness of firm forecasts measured through guidance data. First, we show they are very consistent with firm forecasts collected by the Duke University CFO survey. Second, we show firm forecasts of sales are very predictive of actual sales. Third, we show firm forecasts have strong explanatory power of 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.\(^1\) In 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 the overall forecasts are very 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*

We then analyze the informativeness of firms’ sales forecasts for actual sales. Here we restrict to forecasts made in the first fiscal quarter, to keep a fixed forecast horizon. We run predictive regressions with actual sales in fiscal year \(t\) on the left hand side, sales forecasts of year \(t\) made in the first quarter on the right hand side along with control variables.

\(^1\) 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.
Table 2 shows that firms’ sales forecasts are very predictive of actual sales. We sequentially add controls that include contemporaneous (consensus) analyst sales forecasts, lagged sales, beginning-of-year $Q$, beginning-of-year log assets. In columns (5) to (8), we also add year fixed effects, industry fixed effects (Fama-French 12 industries), industry-year fixed effects, and firm fixed effects.\(^2\) In all cases, firms’ sales forecasts have strong predictive power for actual sales. The results suggest that the sales forecasts are very informative.

**Expectations and Investment**

We also analyze the informativeness of sales forecasts for explaining investment activities. We run regressions with capital expenditures in fiscal year \(t\) on the left hand side, sales forecasts of year \(t\) made in the first quarter on the right hand side along with control variables (e.g. beginning-of-year $Q$, contemporaneous and lagged cash flows, lagged capital expenditures, beginning-of-year log assets, etc.).

Table 3 shows that firms’ sales forecasts have strong predictive power for capital expenditures, beyond the control variables.\(^3\) The results are consistent with (Gennaioli et al., 2015), who document that managers earnings expectations have strong explanatory power for investment activities. Moreover, Table 3 suggests that when firm forecasts are included, analyst forecasts do not have additional explanatory power for investment activities. The evidence further points to the informativeness of firm forecast data.

### 2.3. Persistence of Forecast Errors

In the following, we document the predictability of firms’ sales forecasts. We first show positive auto-correlation of forecast errors:

\[
Error_{it} = cst + \beta Error_{i,t-1} + \epsilon_{it}
\]

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\(^2\)We need to be careful with adding firm fixed effects given our panel is relatively short.

\(^3\)One concern could be potential reverse causality: when firms are investing a lot, managers would expect sales to increase. Note that capital expenditures capture long-term capital investments, which are unlikely to pay off immediately. In addition, if we were to switch the left-hand side and right-hand side variables (i.e. use capital expenditures to explain sales forecast), then the coefficient is more than 2.5 ($1 of capital expenditure immediately turns into $2.5 of sales) which is unreasonably large.
where $\text{Error}_t$ is log actual sales of fiscal year $t$ minus log forecast (made in first fiscal quarter). We perform this test using both firm guidance data and contemporaneous analyst forecast data (if guidance and analyst forecast are both available). Figure 2 provides a binned scatter plot of this regression using managerial guidances. It shows that the relationship is monotonic and reasonable linear.

Table 4, Panel A, reports the regression results. Column 1 uses firm-level data and column 2 uses analyst data. We find $\beta \approx 0.17$ in both guidance and analyst forecast data, which is statistically significant. The quantitative interpretation of this estimate does, however, require a structural model which we describe in Section 3.

2.4. Link between Error and Revisions

We then document the link between forecast error and forecast revisions, drawing on the regression specification from (Coibion and Gorodnichenko, 2015). The intuition of this test is that if forecasters underreact to information, then when they revise up (down) their forecasts in response to good (bad) news, the revision would be insufficient and the actual would be systematically higher (lower) than the forecasts; vice versa.

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, here 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 thus regress the sales forecast error on forecast revisions:
log sales$_{it}$ − log $F_{t-h}$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 $h$ no less than 2 quarters), and $k$ is the time when the previous forecast of sales$_{it}$ is made.

Table 4, Panel B reports the results. We find a coefficient of around 0.34 in both guidance and analyst forecast data, which is statistically significant.

In summary, we find that firm forecasts are very informative, but they do display systematic stickiness biases. The two specifications explored in Table 4 indicate that managers seem to be underreacting to new information. This 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 output and TFP.

3. The Model

3.1. Macroeconomic Framework

Time is discrete and the economy is in steady state. At each date $t$, a continuum of monopolists produce imperfectly substitutable intermediate goods in quantities $y_{it}$ at a price $p_{it}$. There is a perfectly competitive final good market, which aggregates intermediate inputs according to a CES technology:

$$Y = \left(\int y_{it}^\theta \, di\right)^{\frac{1}{\theta}},$$

(1)

where we omit the $t$ subscript for aggregate output because the economy is assumed to be in steady state. We use the final good as the numeraire. 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.

Each firm $i$ has Cobb-Douglas technology: $y_{it} = e^{z_{it}} k_{it}^{\alpha} l_{it}^{1-\alpha}$. Log productivity $z_{it}$ is stochastic and follows an AR1 process:

$$z_{it} = \rho z_{it-1} + u_{it}$$

with innovation volatility $\sigma_u$. $z$ has unconditional expectation of 0, and we assume that the innovation is normally distributed (or, equivalently that $u_{it}$ is small). Productivity shocks are idiosyncratic and there is no aggregate uncertainty. There is a single labor market from which all firms hire. $w$ is the wage, which firms take as given. As in Sraer and Thesmar (2018), we assume that households have GHH preferences in leisure and consumption and psychological discount rate $r$. In steady state without uncertainty, this ensures that the cost of funding is $r$ and the labor supply is given by $L_0 w^{\epsilon}$ where $\epsilon$ is the constant wage elasticity.

Labor is frictionlessly chosen once current period productivity is known, but there is time-to-built capital. Capital $k_{it}$ is chosen at date $t-1$ when only $z_{it-1}$ is known. Capital goods are final goods – so their price is 1. When used in production, they depreciate at rate $\delta$, so that the rental cost of capital is $r + \delta$.

We note $F_{t-1} x_{it}$ the forecast of variable $x_{it}$ as of period $t-1$. We do not model how this forecast is made at this stage but simply assume that it satisfies the following two properties:

$$F_{t-1} \kappa x_{it} = \kappa F_{t-1} x_{it}$$
$$F_{t-1} x_{it-1} = x_{it-1}$$

Denote $\phi = \frac{\alpha \theta}{1-\theta(1-\alpha)}$ the effective returns to scale in capital. Then, log sales can be written as:

$$\log p_{it} y_{it} = \left( (1-\theta) \log Y + (1-\alpha) \theta \log \frac{\alpha \theta}{w} \right) + \frac{\phi}{\alpha} z_{it} + \phi k_{it}$$
where we note that capital stock $k_{it}$ is known as of $t - 1$.

Let us define an arbitrary set of conditioning variables. This allows us to define the log bias in sales expectations as:

$$
\log(b_{it-1}) = \log F_{t-1} p_{it} y_{it} - \log E_{t-1} p_{it} y_{it}
= \log F_{t-1} e^{\phi_{zt}} - \log E_{t-1} e^{\phi_{zt}}
$$

which can be measured using (1) data on sales forecasts and (2) assumptions about the information set available to managers.

We finally clear the product and the labor market, and characterize aggregate production and log TFP in the following proposition:

**Proposition 1** (Bias distribution and production losses). Let $\mu_b$, $\sigma^2_b$ and $\sigma_{zb}$ the unconditional mean, variance and covariance of the log bias with productivity.

Then, the output and TFP losses of non-zero biases (i.e. the differences between an economy with biases and an economy without biases) are given by:

$$
\Delta \log Y = \frac{\alpha(1 + \epsilon)}{1 - \alpha} \left( \mu_b + \frac{1}{2} \frac{\theta}{1 - \theta} (\alpha \sigma^2_b + 2 \sigma_{zb}) \right) \quad (2)
$$

$$
\Delta \log(TFP) = -\frac{\alpha}{2} \left( 1 + \frac{\alpha \theta}{1 - \theta} \right) \sigma^2_b \quad (3)
$$

*Proof*. See Appendix C.1

Proposition 1 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 $\alpha \theta$. When the realization of productivity is lower than expected (for a rational reason or because of bias), the firms has too much capital compared to the frictionless benchmark where there is no time to build. Hence, the marginal productivity of capital is lower than $r + \delta$ in this case. Following Hsieh and Klenow (2009), we call this the “wedge” although in our particular set-up this wedge has a structural interpretation:
The forecast error. Starting from this observation, we can use the formulas derived in Sraer and Thesmar (2018) (among others) which connect log output and TFP with the first two moments of wedges. We then decompose wedges into a rational term (which exists even without bias) and a bias. This leads to the formulas in proposition 1.

Formulas (2-3) can be interpreted with the same intuitions as in the misallocation literature. Only the dispersion of biases has the power to generate TFP losses. When all firms have the same bias, there is no misallocation of input across firms since marginal productivity are equalized across firms. Output is, however, affected by two other moments of the distribution of biases. An positive average bias leads firms to invest too much relative to rational expectation, which in turn, leads to an increases in production. A rise in the covariance between bias and productivity also increase aggregate production, as productive firms become relatively more optimistic.

An empiricist who would observe forecast bias at the firm-level would be able to compute efficiency and output losses by estimating the three moments of the bias distribution in Formulas (2-3). However, this requires observation, at the firm-level, of both subjective and rational forecasts. While data on subjective forecasts can be sometimes be found, one cannot observe firm-level rational expectation forecasts. One solution is then to bring additional structure to the updating process. This is the route we follow in the next section.

3.2. Distorted Expectations Formation

Inspired by Bordalo et al. (2017a), we assume that agents make forecasts using the following conditional density for $z_{it}$:

$$h_t^\gamma (z_{it}) = h(z_{it}|z_{it-1}) \left( \frac{h(z_{it}|z_{it-1})}{h(z_{it}|p_{z_{it-2}})} \right)^\gamma$$

(4)

where $h(z_{it}|z_{it-1})$ is the actual density of $z_{it}$ conditional on $z_{it-1}$. Hence, in this model, agents use a distorted density when making their forecasts. Bordalo et al. (2017a) assume $\gamma > 0$
so that \( \gamma \) captures the strength of the representativeness bias. When \( \gamma \) is large, the agent overweights “exceptional” past realizations (such that \( z_{it-1} - \rho z_{it-2} \) is large) when making her forecast. We extend their formulation to \( \gamma < 0 \). This is mostly done for empirical purposes but could be interpreted as a form of inattention (Mankiw and Reis, 2002) or belief in excessive mean-reversion Rabin (2002).

Using this density, it is straightforward to compute the log forecast error, bias and equilibrium. The following proposition summarizes everything:

**Proposition 2** (Aggregate Impact of Distorted Forecasts). Assume that managers make forecasts according to the density described in equation (4). \( \gamma \) measures the extent of expectation distortions. Then:

1. The sales forecast error is given by:

\[
\log F_{t-1}p_{it}y_{it} - \log p_{it}y_{it} = \left(-\frac{\phi}{\alpha} u_{it} + \frac{1}{2} \left(\frac{\phi}{\alpha}\right)^2 \sigma_u^2 \right) + \frac{\phi}{\alpha} \gamma \rho u_{it-1}
\]

In particular, the univariate regression coefficient of error on lagged error is given by

\[
-\frac{\gamma \rho}{1 + \gamma^2 \rho^2}
\]

2. The log bias is given by:

\[
\log F_{t-1}p_{it}y_{it} - \log E_{t-1}p_{it}y_{it} = \frac{\phi}{\alpha} \gamma \rho u_{it-1}
\]

which is zero when \( \gamma = 0 \)

3. Log output and TFP losses from \( \gamma \neq 0 \) are given by:

\[
\Delta \log Y = \frac{1}{2} \frac{\theta}{1 - \theta} \frac{1 + \epsilon}{1 - \alpha} \left(\phi^2 \rho^2 \gamma^2 + 2 \phi \rho \gamma \right) \sigma_u^2
\]

\[
\Delta \log(TFP) = -\frac{\rho^2 \phi^2 \gamma^2}{2 \alpha} \left(1 + \frac{\alpha \theta}{1 - \theta}\right) \sigma_u^2
\]

which are equal to zero when \( \gamma = 0 \)
This proposition shows how to estimate the aggregate cost of distorted expectations, provided they are described by the density (4). Point 1. in Proposition 2 uses the density of forecasts to derive the expectation formation process of future sales, which we are able to observe in the data. Expectation error is made of two parts. The first two terms in brackets correspond to the log “rational error”, whose expectation is non zero due to the fact that productivity is log-normal. The second term is conditionally non zero and reflect the actual expectation distortion. Assume for instance $\gamma < 0$, the agent is on average optimistic when the innovation is negative (underreaction to negative shocks). This second term is exactly the log bias that we present in Point 2. of Proposition 2. The distribution of log bias is what generates TFP losses in equations (2-3). Looking at the formula for the log forecast error, it appears that regressing it on its lagged value yields a coefficient of $-\frac{\gamma \rho}{1+\gamma \rho^2}$. Provided we can estimate $\rho$ separately using production data, the regression coefficient can directly help us infer $\gamma$. In particular, if forecast errors are positively autocorrelated —as is the case in our data— $\gamma$ is then negative. This is the case of under-reaction.

Point 3. in Proposition 2 presents the equation that permit the measurement of output and TFP losses due to expectation distortions $\gamma$. TFP loss is a function of $\gamma^2$. It does not depend on over- vs under- reaction. What matters is only the discrepancy between optimal and actual investment. Production loss is however, sensitive to the sign of $\gamma$. A positive $\gamma$ leads to higher production in aggregate. This is because, with overreaction, high productivity firms tend to overestimate future productivity, and therefore overinvest. On average, production is higher, even though aggregate productivity is lower: There is more investment than in the case where $\gamma = 0$.

Using these formulas, it is possible to estimate the cost of biases, provided the econometrician estimates $\gamma$, the deviation from rational expectations, but also production parameters such as $\rho$ and $\sigma_u^2$. In Section 4, we will jointly estimate actual productivity dynamics and expectation biases by matching data on productivity dynamics and expectation errors.
3.3. Model-Free approach

A downside of the previous approach is that it imposes more structure than needed on the expectation formation model. Not only did we assume that the distorted density (4) is a good description of expectation formation, but we have also assumed away the possibility that managers have private information about future productivity: in the setting of Section 3.2, there is no distinction between the information set of the manager and that of the econometrician.

In this section, we relax this assumption, but to do so, we focus on an different counterfactual: instead of comparing the actual economy with one where managers hold rational expectations, we instead consider a counterfactual economy where managers make forecasts that are empirically derived to minimize forecast errors using two sources of information: (1) the empirically observed forecast in the guidance data and (2) additional information about the firm.

More precisely, we consider forecasting rules based on the following set of observables: managerial forecasts, realizations, and additional variables $X_{it}$ (other accounting variables, industry or macroeconomic variables, etc.). These forecasting rules then optimally combine these observables to form the following forecast $F^o$ of future productivity:

$$F^o_t e^{\hat{\phi} z_{it}} = E \left( e^{\hat{\phi} z_{it}} | F_{t-1} e^{\hat{\phi} z_{it}}, X_{i,t-1} \right)$$

The forecast $F^o$ may differ from the managerial forecast $F_{t-1} e^{\hat{\phi} z_{it}}$ for two reasons. First, the manager may not be rational. For instance, an inattentive manager may underreact to private information, which would lead the optimal forecaster to scale up the subjective forecast to reach the empirically efficient forecast. Second, the conditioning variables $X_{i,t-1}$ may not belong to the manager’s information set. This is the case in models of noisy information like Woodford (2003), where each manager receives a noisy signal of an aggregate outcome, but does not observe the signal of others.
What would be the effect on aggregate outcomes if managers used the econometrician’s forecast $F^o$ instead of their subjective forecasts $F$? Since both forecasts can be observed in the data, these aggregate effects can be directly computed by applying our aggregation formulas and using the two sets of sufficient statistics computed with the two different forecasts. We summarize this approach in the following proposition:

**Proposition 3 (Aggregate Impact of Non Optimal Forecast).** Define the “optimal” forecast as the projection of sales on past subjective forecast and other conditioning variables.

$$F^o_{t-1} = E\left( sales_{it} | F_{t-1} sales_{it}, X_{i,t-1} \right)$$

which can be estimated from the data. We then construct the log forecast error of the manager and the log forecast error of the “optimal” forecaster:

$$u^o_t = \log sales_{it} - \log F^o_{t-1} sales_{it}$$
$$u^m_t = \log sales_{it} - \log F_{t-1} sales_{it}$$

which can both be estimated from the data. We note $\Delta \mu_F$, $\sigma^2_F$ and $\sigma_zF$ the differences in means, variances and covariances with log productivity between optimal and actual forecasts. Then, compared to a situation where managers use the econometric forecasts $F^o_t$, the log output and TFP losses are given by:

$$\Delta \log Y = \frac{\alpha(1+\epsilon)}{1-\alpha} \left( \Delta \mu_F + \frac{1}{2} \frac{\theta}{1-\theta} \left( \alpha \Delta \sigma^2_F + \Delta \sigma_zF \right) \right)$$  \hspace{1cm} (7)$$

$$\Delta \log(TFP) = -\frac{\alpha}{2} \left( 1 + \frac{\alpha \theta}{1-\theta} \right) \Delta \sigma^2_F$$  \hspace{1cm} (8)$$

**Proof.** Similar to Proposition 1, whose proof connects output and TFP with the moments of forecast errors. \hfill \square

This proposition is equivalent to 1, but the reference point differs. We now compute
TFP and output loss compared to a situation where the econometrician would first collect each manager’s forecast, and then replace each forecast with her own forecast $F^o$ made from individual forecasts and additional variables. This approach allows us to directly use the data and abstract from a specific expectation formation model. In contrast, proposition 1 compares actual TFP and output with an economy with managers forming fully information expectations. The present approach can only use information available to econometrician and information available to the managers.

4. Structural Estimation

In this section, we offer two structural estimations of the TFP and output losses of non optimal expectation formation. The first section focuses on the distorted expectation formation model (4). We jointly estimate the key structural parameters needed to use the aggregation formulas (in particular the expectation distortion parameter $\gamma$). The second section uses the model free approach and computes the dispersion of the discrepancy between forecasts and optimal forecasts in order to compute the TFP and output losses.

4.1. Distorted Expectations Formation

4.1.1. Moments and Calibrated Parameters

We want to compute TFP and output losses as given by equations (5-6). We will set $\alpha = .3$ and set $\theta = .8$ (Broda and Weinstein, 2006). We however explore sensitivity to $\theta$.

We need to estimate three parameters: $\rho$, $\sigma_u$ and $\gamma$. The first moment is the regression coefficient of the log forecast error on sales on its lag. Given the log forecast error expression in proposition 2, it is given by:

$$\beta_{fe_t \text{ on } fe_{t-1}} = -\frac{\rho \gamma}{1 + \rho^2 \gamma^2}$$
which allows to jointly identify $\gamma$ and $\rho$.

The second and third moments are computed by regressing the log solow residual:

$$\tilde{z}_{it} = \frac{1 - \theta(1 - \alpha)}{\theta} \log p_{it}y_{it} - \alpha \log k_{it}$$

on its lag. The second moment we seek to match is the autoregression coefficient. The third moment is the variance of the error term. These two moments pin down $\sigma^2_u$ and $\rho$. In doing this, we follow David et al. (2016).

### 4.1.2. Estimation Method and Results

We estimate $\rho$, $\sigma_u$ and $\gamma$ by matching the three moments described above: regression coefficient of log forecast error on its past, regression coefficient of log Solow residual on its past and volatility of innovation. We estimate $\sigma_u$ and $\rho$ as the autoregression coefficient and innovation volatility of an AR(1) process fitted on the Solow residual. We then estimate the expectation parameter $\gamma$ so that $-\frac{\rho^2 \gamma}{1 + \rho^2 \gamma}$ matches the autoregression coefficient of log forecast errors of managerial guidances as in Table 4. We estimate the standard errors of these three parameter estimates by bootstrapping the sample used to estimate the three moments.

Estimation results are reported in Table 5, Panel A. A priori, guidance data are a better measure of managerial expectations, so we use analyst data as a robustness check. Our estimates for $\sigma_u$ and $\rho$ are respectively .04 and .41. These estimates have orders of magnitude consistent existing literature. The estimate of $\gamma$ is negative ($-.41$), consistently with the idea that managers under-react to news. It is statistically significant at 1%, reflecting the fact that the initial autoregression coefficient on log forecast error is itslef precisely estimated in Table 4.

Panel B of Table uses structural equations (5-6) to back out the effect of non-zero $\gamma$ on aggregate output and TFP. Consistent with stronger underreaction with analyst data, the effect is much stronger with analyst data. TFP loss is a modest -.15% but output loss is
significant: -1.3%. Since our structural parameters are estimated with standard errors, we are in a position of defining confidence bands around our point estimate. Our output estimates are quite precise, with a confidence band of [1.1; 1.7] when using managerial guidances.

Figure 3 explores the sensitivity of our estimate of $TFP$ to the elasticity of substitution $\theta$. Given the relatively small estimate based on managerial guidances, the sensitivity is modest on the range explored. Estimates based on analyst data display are more pronounced sensitivity. Moving from .8 to .85 (corresponding to a mark-up of 15%) would increase TFP losses from under-reaction from -.75% to -1.5%.

4.2. Model Free Approach

With this approach, we need to compute the moments of the difference between actual forecasts and “optimal” forecasts. We compute optimal forecasts by fitting the following equation to the data:

\[ sales_{it} = \exp(a + bF_{t-1}sales_{it} + cX_{it-1}) + \epsilon_{it} \]  \hspace{1cm} (10)

where $F_{t-1}sales_{it}$ is the date t-1 managerial forecast for sales at date t, and $X_{it-1}$ is a set of additional variables designed to account for (1) possible under- or over-reaction to variables belonging to the information set of the manager and (2) possible under-reaction to variables outside of the manager’s information set. Mechanism (1) arises when managers are not rational while mechanism (2) is still consistent with rational expectation.. We do not attempt to disentangle these two mechanisms in the data. We then estimate this equation, so that we can compute the “optimal” log forecast error as:\footnote{We estimate Equation 10 using the procedure GLM in Stata.}
\[ u_t^o = \log \text{sales}_{it} - \log F_{t-1}^o \text{sales}_{it} \]
\[ = \log \text{sales}_{it} - \hat{a} - \hat{b} F_{t-1} \text{sales}_{it} - \hat{c} X_{it-1} \]

We then use this formula to compute the mean and variance if \( u_t^o \). To compute the covariance between the log-optimal forecast and log productivity, we simply retrieve log productivity via equation (9). We then compute the same three moments for the managerial log-forecast error. We can directly observe it from the data, so the procedure is more direct. We can then compute the set of differential moments \( \Delta \mu_F, \Delta \sigma^2_F \) and \( \Delta \sigma_zF \), which we then plug into equations (7-8).

We try several sets of forecasting variables, and report the results in Table 6. Panel A report the differential log-forecast error moments between actual and optimal forecasts. In Panel B, we plug these differential moments into formulas (7-8). Each column corresponds to a different model for the optimal forecast. Each time, the optimal forecast equation is estimated on the first part of the sample, and results are presented on the second part. In column 1, we use past log sales (\( \log \text{sales}_{i,t-1} \)) as only forecasting variable. In particular, note that this model does not make use of the manager’s specific forecast \( F_{t-1} \text{sales}_{it} \) (i.e. we set \( a = 0 \)). In column 2, we add the manager’s forecast. In columns 3 and 4, we add further variables \( X_{i,t-1} \) to augment the forecasting power of the “optimal” forecast: the average growth forecast in the sic12 industry to which the firm belong (column 3);\(^5\) the sample-wide average forecast (column 4). The idea behind using these two controls is a potential lack of common knowledge as in Woodford (2003). Firms observe private signals but ignore signals that other firms observe, and are relevant to their own forecasts. Using such variables may help improve the optimal forecast.

Results in Table 6 show estimated TFP cost of suboptimal expectation formation some-

---

\(^5\) We make sure this average forecast does not include the forecast of the firm itself.
where between 1.5% and 2%. "optimal" forecasts based only on past sales lead to large aggregate TFP gains of about 1.3% (column 1). Adding managerial information in the form of the current forecast improves these TFP gain from 1.3% to 1.9% (column 2). The extra-forecasting variables included in column 3 and 4 do not generate any additional TFP gains. This rather large effect on TFP from using past-sales based forecast comes from the fact that, in the cross-section, past sales forecast future sales better than managerial forecasts. As a result, forecasts based on past sales do a better job at forecasting the cross-section of future sales than managers’ actual forecasts, and thus lead to a significantly larger reduction in the dispersion of the forecast bias.

4.3. Measurement error of Forecast

In this last section, we explore the effect of forecast measurement error on our estimates of TFP losses. While we have shown that forecasts have an informative content (they predict future sales, futures investment, correlate with analyst forecasts as well as CFO surveys), it may still be the case that they also contain noise. Some of this noise may be come from the fact that managers may communicate strategically with markets, or simply because their may be an honest gap between what they say and what they mean. This Section proposes an approach to estimate the size of this noise by looking at an additional moments from the data: the relationship between investment and sales forecasts. We then explore the quantitative impact of this noise on our estimates.

Assume the forecast is measured with error. Then, the measured forecast is given by:

\[ \hat{F}_{tsales_{t+1}} = \hat{F}_{tsales_{t+1}} + v_{t+1} \]

where we assume \( v \) to be i.i.d., of variance \( \sigma_v^2 \) and independent of the true forecast. The firm subscript \( i \) is omitted.

First, notice that we can measure \( \sigma_v^2 \) by looking at the empirical sensitivity of investment
to sales forecasts. In our model:

$$\log k_{t+1} = cst + \log F_t sales_{t+1}$$

differentiating, writing $k_{t+1} = k_t (1 - \delta) + i_{t+1}$ and taking a first order approximation in $i_{t+1}/k_t$ we obtain:

$$\frac{i_{t+1}}{k_t} = cst + (1 - \delta) \left( \log F_t sales_{t+1} - \log F_{t-1} sales_t \right)$$

This equation can be estimated on actual data through linear regression. Let $\hat{\gamma}_{\text{inv}}$ be the estimated coefficient. Given measurement error $v$, straightforward algebra leads to:

$$\sigma_v^2 = \frac{1}{2} \left( 1 - \frac{\hat{\gamma}_{\text{inv}}}{1 - \delta} \right) \sigma_{Fg}^2$$

This model attributes to measurement error the gap between $1 - \delta$ (the theoretical regression coefficient) and $\hat{\gamma}_{\text{inv}}$ (the empirical coefficient).

This observation allows us to compute the bias induced by expectation measurement error on our estimates. Let us look at both approaches separately.

**Structural approach**

The structural approach consists of regressing the forecast error on its lag. Note the log forecast error:

$$f_{e_{t+1}} = \log sales_{t+1} - \log F_t sales_{t+1}$$

so that the measured standard error is $\hat{f}_{e_{t+1}} = f_{e_{t+1}} - v_{t+1}$

The empirical autoregression coefficient is given by:
\[
\hat{\beta}_{\text{auto}} = \frac{\text{cov} (\hat{f}_{e,t+1}, \hat{f}_t)}{\text{var} (\hat{f}_t)} = \frac{\text{var} (\hat{f}_t) - \sigma^2_{\hat{f}}}{\text{var} (\hat{f}_t)} \cdot \frac{\text{cov} (f_{e,t+1}, f_t)}{\text{var} (f_t)}
\]

Hence, the moment condition is now:

\[
\frac{\gamma \rho}{1 + (\gamma \rho)^2} = -\hat{\beta}_{\text{auto}} \times \frac{1}{1 - \frac{1}{2} \left(1 - \frac{\hat{\gamma}_{\text{inv}}}{1 - \delta}\right) \frac{\sigma^2_{\hat{F}_g}}{\sigma^2_{\hat{F}_e}}}
\]

Given that \(\hat{\beta}_{\text{auto}} = -.17\), \(\hat{\gamma}_{\text{inv}} = .37\), and \(\delta = .05\), we obtain that the RHS is .26. This leads to \(\hat{\gamma}_\rho = .28\) (instead of .18 without error term correction). This increases the TFP loss to 26bp (0.3%).

“Model free” approach

We use the variance of observed log forecast errors in this method. The true variance is given by:

\[
\sigma^2_{f_e} = \sigma^2_{\hat{f}_e} - \frac{1}{2} \left(1 - \frac{\hat{\gamma}_{\text{inv}}}{1 - \delta}\right) \frac{\sigma^2_{\hat{F}_g}}{\sigma^2_{\hat{F}_e}}
\]

which leads to 3.3% instead of 4.4%. The measurement error is approximately 1/3 of the variance of the true error. Comparing to the optimal forecast, this puts the loss to 1.24% instead of 1.95%.

5. Conclusion

This paper estimates the aggregate cost of forecast errors made by firm managers. We start with firm-level data on managerial expectations of future sales. We document that their forecast errors are predictable, either with past forecast errors, or past forecast revisions. Such predictability is consistent with underreaction to new information. We confirm this analysis with data on analyst forecasts both at consensus and individual level. We then
investigate the quantitative implications of these predictable errors for allocative efficiency and output. We write down a standard steady-state model of heterogeneous firms in general equilibrium. There is a one period time to build, so that managers need to forecast future productivity when making their investment decisions. This model connects forecast error predictability with TFP and output losses. Given the statistical properties of managerial forecast errors in our data, aggregate losses from deviation from full information rationality are found to be sizable.
References


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: TFP Loss as a function of $\theta$
## B. Tables

### Table 1: Summary Statistics

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<th>p50</th>
<th>p75</th>
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<td>0.01</td>
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<td>0.05</td>
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<td>6.99</td>
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Note: Summary statistics of the guidance sample and the contemporaneous full Compustat sample. Firm forecast data are from IBES Guidance dataset (covers 2003 to 2015), 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. We winsorize outliers at the one percent level.
Table 2: Predicting Actual Sales

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Note: Panel regression

\[
sales_{it}/assets_{i,t-1} = \alpha + F_{i,t-1}sales_{it}/assets_{i,t-1} + X'_{it}\gamma + \epsilon_{it}
\]

Note: $sales_{it}$ is sales of firm $i$ in fiscal year $t$ (normalized by lagged assets), $F_{i,t-1}sales_{it}$ 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, 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. $R^2$ does not include fixed effects. Standard errors are clustered by both firm and time.
Table 3: Predicting Capital Expenditures

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<td>(0.00643)</td>
<td>(0.00629)</td>
<td>(0.00639)</td>
<td>(0.00635)</td>
<td>(0.00632)</td>
<td>(0.00784)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>L.cash flow</strong></td>
<td>-0.00310</td>
<td>-0.00508</td>
<td>-0.00318</td>
<td>-0.00288</td>
<td>-0.00197</td>
<td>0.00665**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00617)</td>
<td>(0.00665)</td>
<td>(0.00629)</td>
<td>(0.00626)</td>
<td>(0.00635)</td>
<td>(0.00334)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>log(L.asset)</strong></td>
<td>-0.000711*</td>
<td>-0.000837**</td>
<td>-0.00596</td>
<td>-0.000930**</td>
<td>-0.000798*</td>
<td>-0.00759***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000387)</td>
<td>(0.000398)</td>
<td>(0.000380)</td>
<td>(0.000431)</td>
<td>(0.000411)</td>
<td>(0.00134)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Constant</strong></td>
<td>0.0282***</td>
<td>0.0279***</td>
<td>0.00792**</td>
<td>0.00891***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00275)</td>
<td>(0.00279)</td>
<td>(0.00316)</td>
<td>(0.00317)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Fixed effects**

<table>
<thead>
<tr>
<th></th>
<th>No</th>
<th>No</th>
<th>No</th>
<th>Year</th>
<th>Industry</th>
<th>Ind-Year</th>
<th>Firm</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Obs</strong></td>
<td>7,575</td>
<td>7,032</td>
<td>7,430</td>
<td>6,904</td>
<td>7,430</td>
<td>7,430</td>
<td>6,976</td>
</tr>
<tr>
<td><strong>R²</strong></td>
<td>0.044</td>
<td>0.046</td>
<td>0.625</td>
<td>0.624</td>
<td>0.625</td>
<td>0.601</td>
<td>0.603</td>
</tr>
</tbody>
</table>

Standard errors in parentheses, clustered by firm and time

*** p<0.01, ** p<0.05, * p<0.1

Note: Panel regression

\[
capx_{it}/assets_{i,t-1} = \alpha + F_{i,t-1} sales_{it}/assets_{i,t-1} + X'_{it} \gamma + \epsilon_{it}
\]

Note: \( capx_{it} \) is capital expenditures of firm \( i \) in fiscal year \( t \) (normalized by lagged assets), \( F_{i,t-1} sales_{it} \) 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, \( capx \) 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. \( R^2 \) does not include fixed effects. Standard errors are clustered by both firm and time.
Table 4: Stickiness of Forecast Errors

<table>
<thead>
<tr>
<th></th>
<th>(1) Firm</th>
<th>(2) Analyst</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A. Forecast Error on Lagged Forecast Error</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>L.forecast error</td>
<td>0.166***</td>
<td>0.175***</td>
</tr>
<tr>
<td></td>
<td>(0.0274)</td>
<td>(0.0309)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.00664</td>
<td>-0.00850</td>
</tr>
<tr>
<td></td>
<td>(0.00445)</td>
<td>(0.00518)</td>
</tr>
<tr>
<td>Obs</td>
<td>6,314</td>
<td>5,616</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.027</td>
<td>0.030</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel B. Forecast Error on Forecast Revision</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forecast revision</td>
<td>0.330***</td>
<td>0.349***</td>
</tr>
<tr>
<td></td>
<td>(0.0409)</td>
<td>(0.0347)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.00723**</td>
<td>-0.00532*</td>
</tr>
<tr>
<td></td>
<td>(0.00282)</td>
<td>(0.00304)</td>
</tr>
<tr>
<td>Obs</td>
<td>8,949</td>
<td>7,673</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.021</td>
<td>0.034</td>
</tr>
</tbody>
</table>

Standard errors in parentheses, clustered by firm and time

*** p<0.01, ** p<0.05, * p<0.1

Note: In Panel A, the left-hand-side is forecast error (log actual sales minus log sales forecast made in first quarter) of fiscal year $t$; the right-hand-side is forecast error of year $t - 1$. The firm forecasts come from IBES guidance dataset, and the analyst forecasts use data from IBES analyst dataset. In Panel B, the left-hand-side is forecast error associated with forecast about fiscal year $t$ sales in a given time; the right-hand-side is the log change since the last forecast of fiscal year $t$ sales (forecast revision).
Table 5: TFP and Output Losses From Distorted Expectations

<table>
<thead>
<tr>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Estimation Result</td>
</tr>
<tr>
<td>$\hat{\gamma}$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$\hat{\rho}$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$\hat{\sigma}_u^2$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>Panel B: Macro Estimate: $\gamma = \hat{\gamma}$ vs $\gamma = 0$</td>
</tr>
<tr>
<td>$\hat{\log Y}$</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$\hat{\log TFP}$</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

Note: We report here the results of our structural estimation using the distorted expectation model of Bordalo et al. (2017a). Persistence and innovation volatility are computed by fitting an AR1 model on the Solow residual. $\hat{\gamma}$ is estimated by SMM by matching the autoregression coefficient of log forecast errors of managerial guidances from Table 4. Standard error are obtained by bootstrapping on the estimation sample.
Table 6: Model Free Approach: 
TFP and Output Observed vs Optimal Forecasts

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A: Moments: Observed - Optimal</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>∆(\hat{\mu}_F)</td>
<td>-2.0</td>
<td>-6.8</td>
<td>-6.7</td>
<td>-6.4</td>
</tr>
<tr>
<td></td>
<td>(2.2)</td>
<td>(2.2)</td>
<td>(2.2)</td>
<td>(2.2)</td>
</tr>
<tr>
<td>∆(\hat{\sigma}^2_F)</td>
<td>4.0</td>
<td>5.9</td>
<td>6.0</td>
<td>5.9</td>
</tr>
<tr>
<td></td>
<td>(1.5)</td>
<td>(1.5)</td>
<td>(1.5)</td>
<td>(1.5)</td>
</tr>
<tr>
<td>∆(\hat{\sigma}_{zF})</td>
<td>-2.2</td>
<td>-0.8</td>
<td>-0.9</td>
<td>-0.8</td>
</tr>
<tr>
<td></td>
<td>(0.9)</td>
<td>(0.8)</td>
<td>(0.8)</td>
<td>(0.8)</td>
</tr>
<tr>
<td>Panel B: Macro Estimates: Observed - Optimal</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>∆(\hat{\log TFP})</td>
<td>-1.3</td>
<td>-1.9</td>
<td>-2.0</td>
<td>-1.9</td>
</tr>
<tr>
<td></td>
<td>(0.5)</td>
<td>(0.5)</td>
<td>(0.5)</td>
<td>(0.5)</td>
</tr>
<tr>
<td>∆(\hat{\log Y})</td>
<td>-5.4</td>
<td>-4.1</td>
<td>-4.4</td>
<td>-3.9</td>
</tr>
<tr>
<td></td>
<td>(1.4)</td>
<td>(1.1)</td>
<td>(1.2)</td>
<td>(1.1)</td>
</tr>
</tbody>
</table>

Note: All numbers multiplied by 100 (log percentage points). We report here the estimation of output and TFP net gain coming from observed, compared to optimal forecast. A positive number corresponds to a positive difference between observed forecasts and hypothetical optimal forecasts. Optimal forecasts are computed via estimating the following model:

\[
sales_{it} = \exp (a + bF_{t-1}sales_{it} + cX_{it-1}) + \epsilon_{it}
\]

via the GLM procedure in STATA. Once \(a,b,c\) are estimated, we compute the three relevant moment of the log forecast error \((\log sales_{it} - a - b\log F_{t-1}sales_{it} - cX_{it-1})\). We then do the same for the observed managerial log forecast errors \((\log sales_{it} - \log F_{t-1}sales_{it})\). We report the value of the differences in Panel A. In panel B, we plug these differences into aggregation formulas (7-8). Each column corresponds to a model for the estimation of optima forecasts. Column 1 only uses past log sales. Column 2 adds managerial forecasts. Column 3 further adds average forecast of growth in sic 12 industry. Column 4 instead adds the average growth forecast at the macro level. In all regressions, we first estimate the forecasting model on the first part of the sample (until 2008), and estimate the moments on the second part of the sample (starting in 2009). Standard error are obtained by bootstrapping on the estimation sample.
C. Proofs

C.1. Proof of Proposition 1

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

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

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

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

\[ \alpha\theta p_{it}y_{it} = (r + \delta)\frac{e^{\frac{\phi z_{it}}{\alpha}}}{F_{t-1}e^{\frac{\phi z_{it}}{\alpha}}} \equiv \log(1 + \tau_{it}) \]

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:

\[ \log(1 + \tau_{it}) = \frac{\phi}{\alpha}u_{it} - \frac{\phi^2}{2\alpha^2}\sigma_u^2 + \log E_{t-1}e^{\frac{\phi z_{it}}{\alpha}} - \log F_{t-1}e^{\frac{\phi z_{it}}{\alpha}} \]

Based on this observation, we can use the formula in Sraer and Thesmar (2018) to calculate log output and log TFP as functions of the moments of the distribution of log wedges. These moments are given by:

\[ \mu_{\tau} = -\frac{\phi^2}{2\alpha^2}\sigma_u^2 + \mu_b \]
\[ \sigma_{\tau}^2 = \left(\frac{\phi}{\alpha}\right)^2\sigma_u^2 + \sigma_b^2 \]
\[ \sigma_{z\tau} = \frac{\phi}{\alpha}\sigma_u^2 + \sigma_{zb} \]

where \( \mu_b, \sigma_b^2 \) and \( \sigma_{zb} \) are the mean, variance and covariance with \( z \) of the distribution of log biases:

\[ \log b_{it-1} = \log E_{t-1}e^{\frac{\phi z_{it}}{\alpha}} - \log F_{t-1}e^{\frac{\phi z_{it}}{\alpha}} \]

C.2. Proof of Proposition 2

The log distorted distribution is given by:
\[
\log h_{t-1}^\gamma(z_{it}) = \text{cst} - \frac{1}{2\sigma_u^2} \left( (1 + \gamma)(z_{it} - \rho z_{it-1})^2 - \gamma (z_{it} - \rho^2 z_{it-2})^2 \right)
= \text{cst}' - \frac{1}{2\sigma_u^2} \left( z_{it}^2 - 2z_{it} \left( (1 + \gamma)\rho z_{it-1} - \gamma \rho^2 z_{it-2} \right) \right)
= \text{cst}'' - \frac{1}{2\sigma_u^2} \left( z_{it} - \left( (1 + \gamma)\rho z_{it-1} - \gamma \rho^2 z_{it-2} \right) \right)^2
\]

Managers use the distorted density in order to forecast \( e^{\hat{z}_{it}} \). The forecast thus writes as:

\[
\log F_{t-1} e^{\hat{z}_{it}} = \log \int e^{\hat{z}_{it}} h_{t-1}^\gamma(z) dz
= \frac{\phi}{\alpha} \left( (1 + \gamma)\rho z_{it-1} - \gamma \rho^2 z_{it-2} \right) - \frac{\phi^2}{2\alpha^2 \sigma_u^2}
= \frac{\phi}{\alpha} \left( \rho z_{it-1} + \gamma \rho u_{it-1} \right) - \frac{\phi^2}{2\alpha^2 \sigma_u^2}
\]

and the forecast error:

\[
\log F_{t-1} e^{\hat{z}_{it}} - \frac{\phi}{\alpha} z_{it} = \frac{\phi}{\alpha} (-u_{it} + \gamma \rho u_{it-1}) - \frac{\phi^2}{2\alpha^2 \sigma_u^2}
\]

which is the formula in the proposition, item 1.

Item 2. on the log bias follows directly from the fact that:

\[
\log E_{t-1} e^{\hat{z}_{it}} = E_{t-1} \log e^{\hat{z}_{it}} + \frac{1}{2} \text{var}_t \log e^{\hat{z}_{it}}
= \frac{\phi}{\alpha} \rho z_{it-1} + \frac{\phi^2}{2\alpha^2 \sigma_u^2}
\]

Item 3. comes from injecting the log bias variance and covariance into (2-3)