The Micro and Macro of Managerial Beliefs

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Abstract

This paper studies how biases in managerial beliefs affect managerial decisions, firm performance, and the macroeconomy. Using a new survey of US managers, I establish three facts. (1) Managers are not overoptimistic: sales growth forecasts on average do not exceed realizations. (2) Managers are overprecise: they underestimate future sales growth volatility. (3) Managers overextrapolate: their forecasts are too optimistic after positive shocks and too pessimistic after negative shocks. To quantify the implications, I estimate a dynamic general equilibrium model in which managers of heterogeneous firms use a subjective beliefs process to make forward-looking hiring decisions. Overprecision and overextrapolation lead managers to overreact to firm-level shocks and overspend on adjustment costs, destroying 2.1 to 6.8 percent of the typical firm's value. Pervasive overreaction leads to excess volatility and reallocation, lowering consumer welfare by 0.5 to 2.3 percent relative to the rational-expectations equilibrium. These findings suggest overreaction could amplify asset-price and business-cycle fluctuations.

JEL Codes: G31, G32, G4, D25, D84, M54, E7

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1 Introduction

This paper examines how firm managers form their beliefs about future own-firm outcomes, and quantifies how decisions based on those beliefs impact firm performance, resource reallocation, and the macroeconomy. These questions are fundamental for dynamic corporate finance and macroeconomics. If managers have non-rational expectations—i.e., if their beliefs are not consistent with the firm's objective risks—they could make decisions that destroy firm value. Pervasive departures from rational expectations could also affect cross-firm resource allocation and shift the economy away from its welfare-maximizing equilibrium.

My paper's goal is to estimate how—and by how much—managerial decisions differ from what we would observe if managers indeed had rational expectations. This agenda raises an additional question: What features allow a quantitative model to capture how managers form their beliefs and how those beliefs affect their decisions? This question is largely still open because, for decades, the predominant assumption has been that managers—as well as consumers, workers, etc.—have rational expectations. So, until recently, few studies examined manager beliefs empirically (see, e.g., Manski, 2018 and Shleifer, 2019) or considered quantitative models featuring beliefs.

Recent work in behavioral corporate finance provides mounting evidence that at least some firm managers have non-rational expectations. Those who appear more versus less rational also make different decisions, as documented in the review by Malmendier and Tate (2015) and the papers cited therein. These results accompany a wave of empirical work using survey data on managerial beliefs and attitudes, including Graham, Harvey, and Puri (2013,2015), Ben-David, Graham, and Harvey (2013), Gennaioli, Ma, and Shleifer (2016), Ho et al. (2016), and Bachmann et al. (2018). Survey data appears increasingly useful for learning about beliefs and developing new modeling approaches, for example models with extrapolative expectations such as Bordalo, Gennaioli, and Shleifer (2018).[1]

My paper builds on this work and answers the above questions by developing new, survey-based measures of the extent to which US managers have biased or non-rational beliefs. Specifically, I find managers underestimate the volatility and overestimate the persistence of future own-firm sales. Building on this evidence, I estimate a dynamic equilibrium model in which managers of heterogeneous firms use a subjective beliefs process to make forward-looking hiring decisions subject to firm-specific risk and adjustment costs. The estimated model captures a range of stylized facts about how managers form their expectations and how those expectations relate to the firm's hiring policies. Thus, my structural estimation

[1] Researchers have also begun to examine the role of beliefs elsewhere in financial economics; for example, in portfolio choices in Giglio, Maggiori, Stroebel, and Utkus (2019); in the mid-2000s housing boom and bust in Kaplan, Mitman, and Violante (2020); and risk premiums in Maxted (2019).

approach reveals how biases in manager beliefs impact firms' dynamic behavior.

In the estimated model, biased managers overreact to shifts in profitability and overspend on adjustment costs. This overreaction results in wasted resources, excess firm volatility and reallocation, and diminished firm value. Because managerial biases are pervasive, so are these effects, which push the macroeconomy away from its welfare-maximizing, rational-expectations equilibrium. My paper focuses on the effects of overreaction in the absence of economy-wide shocks, but my findings suggest, more broadly, that overreaction stemming from managerial beliefs could also amplify asset-price and business cycle dynamics.

My evidence about managerial beliefs comes from the Atlanta Fed / Chicago-Booth / Stanford Survey of Business Uncertainty (SBU) developed by Altig et al. (2020). The SBU surveys a panel of US managers (typically CEOs or CFOs) monthly and elicits subjective probability distributions about future own-firm sales and employment. Responses are confidential and collected by a Federal Reserve Bank, so managers have few motives to misreport their beliefs. Because the SBU elicits subjective distributions, I observe managerial expectations (i.e., forecasts) for year-ahead sales and employment growth, as well as the uncertainty around those expectations. I then test whether managerial expectations and uncertainty are empirically consistent with outcomes, documenting three key facts summarized in Figure 1.

First, managers do not appear to be *overoptimistic*: sales growth expectations on average do not exceed realizations. We can see this in Figure 1a, which shows the empirical distribution of forecast errors about future sales growth, also superimposing the error distribution implied by manager beliefs. Both are roughly symmetric and centered around zero, meaning the average forecast error is close to zero (by construction for the subjective distribution). This result is consistent with Bachmann and Elstner (2015) and Boutros et al. (2020), who separately examine survey data from Germany and the United States.

Second, managers are *overprecise*. They underestimate the volatility of future own-firm sales growth, which they reveal by overestimating their forecasts' accuracy. In Figure 1a, manager subjective beliefs imply a forecast error distribution that centers tightly around zero, but, empirically, errors are widely dispersed and large in magnitude. This isn't because managers have trouble expressing uncertainty in the SBU. Figure 1b reveals a positive relationship between managerial subjective uncertainty and absolute forecast errors. But those errors are about 15 percentage points larger empirically than what we would expect from manager beliefs, resulting in the vertical gap between the subjective and empirical absolute errors in Figure 1b. This second fact builds on Ben-David et al. (2013), who find US managers underestimate the volatility of S&P 500 returns.

Third, managers *overextrapolate* from current conditions, which we can see in Figure 1c. If a manager's firm experiences high sales growth in the current quarter, their sales growth expectations for the next four quarters tend to be overoptimistic. If, instead, the firm experiences shrinking sales, they tend to be overpessimistic. Managers, thus, appear to overestimate the persistence of recent business developments. Many studies in the forecasting literature find evidence of overextrapolation, for example, La Porta (1996), Bordalo et al. (2020), and Deng (2021) among analysts, and Rozsypal and Schlafmann (2017) among US households.

To understand how these features of managerial beliefs impact individual firms and the macroeconomy, I build a dynamic general equilibrium model with heterogeneous firms subject to firm-specific risk. Managers forecast their firm's future profitability using a subjective beliefs process that can differ in its long-run mean, persistence, and conditional volatility from the objective profitability process. These three features correspond to the three key facts I document in the SBU data, and which are summarized in Figure 1.

Managers use their beliefs process to make forward-looking hiring decisions subject to adjustment costs. These costs represent resources firms devote to expanding, such as costs of posting and filling new vacancies (see, e.g. Davis, Faberman, and Haltiwanger, 2013, and Gavazza, Mongey, and Violante, 2018), as well as costs of downsizing quickly, including those associated with labor unrest (see, e.g., Krueger and Mas, 2004, Mas, 2008, and Gruber and Kleiner, 2012). Because they represent real expenditures that reduce the firm's free cash flows, adjustment costs make manager mistakes expensive, as resources spent on unnecessary adjustments are wasted. Empirically, they also help the model fit the joint dynamics of firm-level sales and employment.

I estimate the model targeting three broad features of the SBU data: (1) The degree of managerial optimism, overprecision, and overextrapolation; (2) the link between managerial beliefs and decisions, as well as beliefs and outcomes; and (3) the joint dynamics of sales and employment growth. Although the model is highly overidentified, it fits a number of targeted and untargeted features of the data. Indeed, a key contribution of this paper is to show how a dynamic model with a managerial beliefs process fits a range of empirical patterns involving managerial beliefs and decisions. My paper thus builds on work with behavioral models of firms that typically did not have the data to estimate such models (e.g., Fuster, Hebert, and Laibson, 2010; Hackbarth, 2008; Kim, 2018; and Benigno and Karantounias, 2019).

I use the estimated model to quantify the costs of managerial biases and point to why they arise. The typical firm's value would be 2.1 to 6.8 percent higher, depending on the model specification, if it hired a manager with rational expectations. At the macro level, consumer welfare would be 0.5 to 2.3 percent higher if all managers had rational expectations. For comparison, Taylor (2010) estimates CEO entrenchment costs 3 percent of firm value, and Krusell et al. (2009) quantify the welfare cost of business cycles at 0.1 to 1.5 percent.

Managerial overprecision and overextrapolation reduce firm value and consumer welfare because they lead to overreaction. Managers believe profitability shocks are persistent and stable, so they react more strongly and are more willing to pay adjustment costs than they would if they knew shocks are transitory and volatile. Thus, biased managers generate excess volatility and pay too many adjustment costs, which wastes real resources. Pervasive overreaction also has aggregate effects because it distorts prices and allocations relative to the welfare-maximizing, rational-expectations equilibrium.

The interplay between beliefs and reallocation frictions in my model builds on Asker, Collard-Wexler, and de Loecker (2014) and David and Venkateswaran (2019), who argue adjustment costs materially affect dynamic behavior and resource misallocation. Thus, my paper contrasts with Bachmann and Elstner (2015), who find smaller implications of managerial optimism using a frictionless model. Ma, Ropele, Sraer, and Thesmar (2020) find smaller implications in a model with adjustment costs and managers who *under*react to shocks. Their model, thus, implies too little rather than too much reallocation and no excess spending on adjustment costs.

More broadly—because managerial beliefs lead to overreaction—beliefs could also amplify asset-price and business-cycle fluctuations. Quantifying this mechanism goes beyond the scope of this paper, but a similar logic operates in the literature on beliefs and credit cycles, in particular, Bordalo et al. (2021). Not coincidentally, an emerging behavioral macro/finance literature focuses much of its attention on beliefs and how they shape consumer and firm behavior and asset prices (e.g., Gabaix, 2014, 2016, 2019; Bordalo et al., 2019; Carroll et al., 2020; Coibion et al., 2018; Coibion et al., 2020; and Zorn, 2020).

These broader implications matter because managerial overprecision and overextrapolation are pervasive features of beliefs. They are prevalent among managers of small, large, public, and private firms, and regardless of whether the CEO is a major shareholder or part of a major shareholding family. Indeed, I find similar degrees of overprecision and modestly more overextrapolation among firm managers who may have the strongest incentives to overreact (e.g., Terry, 2017 and Terry, Whited, and Zakolyukina, 2019). These patterns support the external validity of my results and expand on earlier work (e.g., Malmendier and Tate 2005, 2008) that argued *some* managers are biased, but perhaps not the typical manager.

In the rest of this paper, I document three key facts about managerial beliefs in Section 2. Section 3 develops a general equilibrium model in which managers of heterogeneous firms use a subjective beliefs process to make forward-looking hiring decisions. Section 4 describes how I solve and estimate the model by targeting beliefs, decisions, and outcomes. Section 5 quantifies the impact of managerial beliefs on firm value and the macroeconomy. Section 6 goes through robustness and extensions, and Section 7 concludes.

2 Facts About Managerial Beliefs

This section uses data from the Atlanta Fed/Chicago-Booth/Stanford Survey of Business Uncertainty (SBU) to document three key facts about managerial beliefs regarding their own firms' future sales growth. Specifically,

1. Managers are not overoptimistic. Sales growth expectations on average do not exceed realizations.

2. Managers are overprecise. They underestimate sales growth volatility.

3. Managers overextrapolate. They tend to overestimate their firm's future performance when the firm is growing, and underestimate when it is shrinking.

Additionally, managerial beliefs as reported in the SBU are consistent with future sales and employment outcomes, with managerial hiring plans, and with the firm's current employment growth (i.e., net hiring). These facts validate the SBU data and support my analysis of managerial optimism, overprecision, and overextrapolation. Below, I also use these empirical relationships between beliefs, decisions, and outcomes to discipline managerial behavior in my quantitative model.

2.1 The Survey of Business Uncertainty

My data on managerial beliefs come from the Atlanta Fed/Chicago-Booth/Stanford Survey of Business Uncertainty (SBU), a monthly panel survey fielded by the Federal Reserve Bank of Atlanta. Here, I provide an overview of the SBU data, but interested readers should refer to Altig et al. (2020) for full details about the survey's development and methodology.

The SBU surveys high-level firm managers of US firms monthly via email. The most common job title in the SBU is "CFO (or other finance)," accounting for nearly 70 percent of panel members, followed by "CEO" and "Owner" with just under 20 and 10 percent each. Appendix Figure A.1 shows the breakdown in job titles in more detail. A team of research assistants at the Atlanta Fed recruit respondents over the phone. They remain in the panel as long as they are willing to continue participating.

Figure 2 shows the SBU's questionnaire for own-firm sales growth. The survey first asks managers to report their firm's current sales level and its sales growth over the past 12 months. Then, it asks for a *five-point, subjective probability distribution* for future sales growth, looking four quarters ahead. Respondents provide five potential outcomes, corresponding to a lowest, low, middle, high, and highest scenario for four-quarters-ahead sales growth. Then, they assign a probability to each scenario. The survey also asks a similar set of questions about the firm's employment 12 months into the future, shown in appendix Figure A.3.

SBU responses are confidential and collected by a Federal Reserve Bank, so managers have no clear incentive to misreport their beliefs. Although the survey is complex, Altig et al. (2020) find only small and statistically insignificant evidence that participants' responses change as they acquire experience with the survey. This result stands in contrast to evidence from consumer expectations surveys whereby participants "learn" from continued participation (see, e.g., Binder, 2019, and Kim, 2020).

I follow Altig et al. (2020) by focusing on moments of managers' subjective five-point distributions. I use the mean of the distribution (i.e., the inner product of the vector of potential outcomes and the vector of probabilities) to measure manager expectations or forecasts. To measure subjective uncertainty, I use the mean absolute deviation of the subjective distribution. This moment captures the magnitude of forecast errors managers expect to make, with higher values corresponding to higher uncertainty. (See Section A.2 in the Online Appendix for more details on how I construct these subjective moments from the raw SBU data.) My analysis below tests whether these measures of managerial expectations and uncertainty appear consistent with corresponding outcomes in the survey data.

Appendix Table A.1 reports summary statistics for my sample of SBU responses. The survey has been fielded since October 2014, and I use data from all survey waves up to and including May 2019. Altig et al. (2020) report that in the first half of 2018, about 40 percent of invitations resulted in a survey response, adding up to about 300 responses each month. Recruitment for the survey is continuous, with the aim of replacing panel members who drop out, and thereby maintaining consistent sample sizes across months.

The sample of firms in the SBU is broadly representative of the US private non-farm sector in employment-weighted terms. The survey oversamples larger and older firms, as well as firms in cyclical, highly capital-intensive sectors like durables manufacturing. These sample properties arise partly because small and young firms are relatively scarce in the survey's Dunn & Bradstreet sampling frame, partly due to deliberate over-sampling of larger enterprises that carry more weight in the macroeconomy, and partly due to higher response rates among larger firms. In Section A.1 of the Online Appendix, I reproduce figures from the appendix to Altig et al. (2020) showing the share of employment by firm size, sector, age, and region in the SBU in comparison with the universe of firms in US Census data.

2.2 Managerial Beliefs Predict Outcomes, Hiring Plans, and Current Hiring

To start my analysis, I document that beliefs reported in the SBU predict firm-level outcomes and decisions. These results serve two purposes. First, they validate the SBU data and lend credence to my maintained assumption that the beliefs reported in the survey are the beliefs managers use to make forward-looking decisions. Second, they are key empirical benchmarks for any dynamic model featuring managerial beliefs and decisions. So, it is worth documenting them before building and estimating such a model as I do in Sections 3 and 4 below.

Figure 3a shows managerial sales growth expectations or forecasts for the next four quarters are highly predictive of actual sales growth. This fact is also a key result of Altig et al. (2020). The left panel of Figure 3a shows the relationship in the raw panel data, and the right panel shows the result holds within firm; namely, after controlling for firm and date fixed effects. Hiring plans—i.e., managerial forecasts for the firm's employment growth over the next 12 months—also predict the firm's actual employment growth, as we can see in Figure 3b. Again, the relationship holds in both the raw panel data and when we focus on within-firm variation. Appendix Table A.2 expands on this analysis by showing managerial forecasts have stronger predictive power than a range of observable characteristics. R-squareds, in fact, rise by 5 to 7 percentage points after including subjective forecasts as predictors for future sales and employment growth. These results suggest managers embed private information they have about business prospects into their survey responses.

Managerial forecasts predict outcomes, but do they also predict choices? I examine this question in Table 1 and Figures 4 and A.2. Sales growth forecasts and uncertainty respectively predict more positive and more negative hiring plans (i.e., employment growth expectations for the next 12 months), as we see in columns 1 and 2 of Table 1 and Figures 4a and 4b. Both relationships hold in the raw panel data and after controlling for firm and time effects. Uncertainty about sales also predicts uncertainty about the firm's future employment growth, as columns 3 and 4 and Figure 4c show. This relationship is present, again, in both the raw panel and after controlling for firm and time effects. Altogether, subjective first and second moments appear to be informative about managers' hiring plans.

The final two columns of Table 1 test whether beliefs can also predict the firm's current hiring decision (i.e., its current employment growth). Higher managerial forecasts for year-ahead sales growth predict more current hiring, controlling for sales growth uncertainty and irrespective of including firm and time effects. Sales growth uncertainty over the next year has a hard time predicting the firm's current net hiring in the raw panel data (column 5), but it predicts lower current hiring when we include the firm and time effects (column 6). So, more uncertain firms don't have lower employment growth on average, but the average firm does have lower employment growth when it faces more uncertainty. My structural estimation exercise in Section 4.2 focuses the latter within-firm relationship, linking managerial uncertainty to hiring decisions. Appendix Figure A.2 visualizes the relationships between net hiring, expectations, and uncertainty studied in columns 5 and 6.

Having established that managerial beliefs have predictive power for outcomes, hiring plans, and current hiring decisions, I now turn to whether beliefs appear consistent with realized outcomes in the SBU.

2.3 Fact 1: Managers are Not overoptimistic

I find no evidence that managers are systematically optimistic about their own firm's future sales growth. Table 2 displays the mean forecast for sales growth (looking four quarters ahead), the mean realized sales growth, and finally the mean forecast-minus-realized sales growth, pooling observations from all firms and survey waves. Looking at the top row of the table, columns 1 and 2 show the mean forecast and mean realization are not far from each other, at 0.040 and 0.054. In column 3, I estimate a mean forecast error of -0.014 with a firm-clustered standard error of 0.006, statistically different from zero with ninety-five percent confidence.

From this evidence alone, managers appear mildly pessimistic, but the result is not robust. Using two-way clustered standard errors by both firm and date to account for common shocks across firms, the mean forecast error is no longer statistically significant. In the bottom panel of the table, I also find the employment-weighted mean forecast error is much closer to zero than the unweighted mean and not significant even with firm-clustered standard errors. When I extend the sample period by a few months, say, as far as February 2020, I estimate the average forecast-minus-realized sales growth is smaller in absolute value at -0.0025 (0.0060) and not significant. This last result in particular suggests the apparent pessimism in Table 2 is a one-off feature of that particular sample. Altogether, it is hard to argue that managers are systematically pessimistic.

2.4 Fact 2: Managers are Overprecise

Managers responding to the SBU are overprecise: they underestimate their firm's sales growth volatility and overestimate the accuracy of their forecasts. Figure 1a illustrates this fact by comparing two distributions. The blue bars (with the solid outline) show the empirical distribution of forecast-minus-realized sales growth in the SBU data. The orange bars (with the dotted outline) show the distribution of forecast-minus-realized sales growth that would arise if realizations were drawn independently from each manager's five-point subjective probability distribution. Both histograms are scaled so that the sum of the heights of the bars equals one, and hold fixed the width of the bars at 0.05.

The subjective distribution of forecast errors is much less dispersed in Figure 1a, indicating managers' actual forecast errors are empirically larger than they expect ex ante. Under the null hypothesis that managers have rational expectations and shocks to sales growth are drawn independently across firms, the two distributions should be identical, however. This clear difference in dispersion rejects that hypothesis, at least as it concerns second moments. By contrast, Figure 1a confirms Fact 1 that managers are not overoptimistic, as both distributions are roughly symmetric and centered around zero (by construction for the subjective distribution).

Table 3 quantifies the discrepancy in the magnitude of subjective versus empirical errors. Managers' subjective distributions would imply a mean absolute forecast error of 0.035. The empirical mean absolute forecast error is 0.183, however, with a standard error of 0.007 (clustered by firm). Thus, there is an "excess absolute forecast error" of about 0.148, that is statistically different from zero even with two-way firm and date clustered errors.

It is tempting to think that overprecision arises because managers are unable to express uncertainty in the SBU data. However, their subjective uncertainty strongly predicts future sales growth volatility. The binned scatter plot with the blue dots in Figure 1b shows this upward-sloping relationship, which implies higher ex-ante uncertainty is associated with higher ex-post volatility. This finding is also one of the key results in Altig et al. (2020).

Figure 1b also reveals the extent of managerial overprecision by showing the uncertainty–absolute-errors relationship is shifted upward relative to what we would see if sales growth realizations were drawn from managers' subjective distributions. The binned scatter plot with the orange triangles shows the subjective relationship, in which the conditional mean of absolute errors is (by construction) equal to subjective uncertainty and follows the 45-degree line. The empirical and subjective plots are roughly parallel, but a vertical gap of about 0.15 separates them, corresponding to the degree of overprecision. Thus, managers appear to underestimate the *level* of uncertainty, even if they can perceive and express differences in firm-level volatility in their survey responses.

The above evidence suggests managers are overprecise, but we have reasons to be cautious. In particular, measurement error in realized sales growth might inflate absolute forecast errors, generating the above patterns even in the absence of overprecision. I explore this possibility using my quantitative model, by estimating the amount of measurement error in the SBU's employment and sales data and find it is not enough to account for the measured degree of managerial overprecision. (See Section 4 for more details about the estimation.) Section A.4 of the Online Appendix also argues measurement error in sales is unlikely to be the driving factor. The reason is my observed empirical forecast errors are about as large as professional forecasters' errors for publicly traded firms' sales, also from a four quarter horizon. Thus, measurement error in the SBU is unlikely to be so severe as to be the main reason why managers appear overprecise.

2.5 Fact 3: Managers Overextrapolate

Managers in the SBU overextrapolate. Their forecasts tend to exceed realizations when they are made during high-performing quarters, and vice versa. Figure 1c uses a binned scatter plot to trace the relationship between forecast-minus-realized sales growth for quarters t to $t + 4$, against the firm's sales growth from quarters $t - 1$ to t. We can see a positive relationship, so managerial forecast errors are predictable from the firm's recent past sales growth. This pattern is consistent with overextrapolation, whereby managers overestimate how much future business conditions will resemble today's.

Table 4, explores this pattern further. Column 1 reports the estimate from the raw panel regression corresponding to Figure 1c. Firms growing one standard deviation above average in quarter t overestimate their firm's subsequent sales growth between quarters t and $t + 4$ by about 0.062, or about 3.8 times the absolute value of the mean and 23 percent of the standard deviation of the dependent variable. Column 2 reports results from an employment-weighted specification, resulting in a slightly smaller slope coefficient. Column 3 adds time fixed effects, and column 4 adds sector-by-time effects. The coefficients barely move, so the relationship is not a result of common macro or sector-specific shocks. In columns 5 and 6 I use firm and time fixed effects and weight by employment in 6. Again, the estimated coefficient barely moves relative to column 1.

As with managerial overprecision, overextrapolation could be driven by measurement error in realized sales growth. Transitory measurement error, for example, would mechanically generate a negative correlation between past sales growth from quarter $t - 1$ to t and subsequent sales growth from t to $t + 4$. In the quantitative portion of the paper, I estimate the degree of measurement error in the survey data and find that—as with overprecision—measurement error alone cannot explain the pattern in Figure 1c. In Section A.5 of the Online Appendix, I additionally show sales growth forecasts are predictable from a measure of past sales growth that is unlikely to be contaminated by transitory measurement error.

I also explore the nature of managerial overextrapolation more deeply in the Online Appendix. I regress the forecast error covering sales growth from quarter t to $t + 4$ on the error covering $t-4$ to t and find a statistically significant coefficient of -0.179 (0.067), consistent with overextrapolation.[2] Ma et al. (2020) find, instead, that forecast errors are *positively* autocorrelated in an Italian survey and US public firms' guidance, implying managers *underestimate* the persistence of shifts in sales. I suspect this difference between our papers arises from differences in data collection, cleaning, and statistical model specifications rather than differences across our samples. The reason is that Bordalo et al. (2021) and Deng (2021) also examine US public firms' guidance and analyst forecasts and find evidence of overextrapolation, consistent with my results.

The Online Appendix (Section A.5.4) also argues overextrapolation cannot explain the large discrepancy between subjective and objective absolute errors I document in Fact 2. Overextrapolation mechanically increases absolute forecast errors because it biases conditional means. Yet, firms with small recent sales growth shocks (for whom extrapolation has a negligible effect on absolute errors) still make forecast errors that are larger than they expect by about 0.12.

2.6 Heterogeneity and Learning

Facts 1 to 3 above describe the average manager in the SBU data. But individual managers are likely heterogeneous in their optimism, overprecision, and overextrapolation. I would ideally like to estimate these traits at the individual level, but because the SBU is a young survey and a short panel, I am unable to do so precisely.

Instead, Figure 5 tests for differences in managerial optimism, overprecision, and overextrapolation across firm sizes, time periods, and sectors, or across firms with particular principal-agent relationships. Small firms that are likely poorly managed and unproductive could have more biased managers, for example, or biases might be concentrated among firms for which certain types of agency conflicts are more severe.

Figure 5 reveals, however, that managerial biases appear similar across firms, time periods, and industries. (Table 4 already showed my measure of overextrapolation holds across firms in the same survey wave.) The smallest 10 percent of firms (by sales) do appear more pessimistic and more overprecise at first glance, but these patterns are easily explained. Small firms likely appear pessimistic because they grew particularly fast during the later phases of the recent economic expansion. Their larger excess absolute forecast errors in Figure 5b stem, in turn, from small firms' higher volatility. Indeed, managers underestimate

[2] The negative autocorrelation implies that firms that are ex-post too optimistic in the four quarters ending in t make forecasts that are too pessimistic looking forward from t to $t+4$. Including firm and date fixed effects the coefficient increases to -0.317 with a standard error of 0.052. Section A.5.2 of the Online Appendix describes the full exercise and discusses how this dynamic panel estimator might be biased.

their absolute forecast errors by about 80 percent regardless of size. Managerial optimism, overprecision, and overextrapolation also look similar across firms that are public versus private, or across firms whose CEOs are major shareholders (or part of a family of major shareholders) versus not. Thus, Facts 1 to 3 appear to reflect widespread psychological phenomena and have external validity.

Appendix Table A.3 shows additionally that Facts 1 to 3 don't appear significantly related to the number of previous survey responses the manager has completed. This pattern is first-pass evidence that managers don't appear to learn about the firm's risks as they get further into their tenure, broadly consistent with the main result in Boutros et al. (2020). They examine data from the Duke CFO Survey and show managers update their beliefs about future S&P 500 returns volatility in response to realized returns, but not by enough to eliminate overprecision over time. Boutros et al. (2020) argue managers update their beliefs consistent with Bayes' rule, but overprecision persists because they have very strong priors. A similar mechanism might be behind the persistent managerial optimism, overprecision, and overextrapolation I find in Table A.3.

3 A General Equilibrium Model of Employment Dynamics with a Managerial Beliefs Process

This section develops the dynamic general equilibrium model with heterogeneous firms that I use to study how managerial beliefs impact managerial decisions and thus firm behavior and macro outcomes. The model builds on the standard setup in Hopenhayn (1992) and Hopenhayn and Rogerson (1993), which I extend by giving managers a subjective beliefs process for future firm-level shocks.

3.1 Technology and Environment

Time is quarterly and there is a unit mass continuum of firms[3] with access to a decreasing-returns-to-scale revenue production function in labor n_t and a Hicks-neutral idiosyncratic shock z_t:

$$y(z_t, n_t) \;\; = \;\; z_t n_t^{\alpha}.$$

[3]To keep notation light, I do not use subscripts to index firms. Instead, I use lower case letters for quantities pertaining to individual firms, and upper case letters for aggregate quantities. General equilibrium prices w_t and r_t are lower-case despite being the same for all firms in the economy.

The returns-to-scale parameter, α, belongs to the unit interval $(0, 1)$. I am agnostic about the specific sources of decreasing returns, which could include imperfect competition or limits to managerial attention and span of control, following Lucas (1978).

Each firm's idiosyncratic shock z_t follows a log-normal autoregressive Markov process:

$$\log(z_{t+1}) \quad = \quad \mu + \rho \log(z_t) + \sigma\varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim \mathcal{N}(0, 1). \tag{1}$$

This stochastic process represents firm-level "profitability" or "business conditions," since z captures fluctuations in both the firm's demand and supply (see Foster et al., 2008). I focus on a stationary shock process to capture the mean reversion in sales levels I estimate in the SBU data. There is no aggregate risk.

Firms hire labor in a competitive market and pay the economy-wide equilibrium wage w_t, taking it as given. Each firm's operating income in quarter t is its revenue minus its wage bill:

$$z_t n_t^{\alpha} - w_t n_t.$$

Every firm in the model has a manager who makes hiring and firing decisions on a quarterly basis. The manager observes the firm's current idiosyncratic shock z_t, and then decides how many workers to hire or lay off, choosing the firm's labor for the following quarter:

$$n_{t+1} \quad = \quad (1 - q)n_t + h_t.$$

The firm's workforce next quarter, n_{t+1}, includes labor already working at the firm less exogenous separations (occurring with a rate q) plus net hiring or layoffs h_t. I assume managers choose n_{t+1} under uncertainty about next quarter's profitability shock, z_{t+1}. These dynamics capture real-world lags in searching for, interviewing, and training new employees, as well as lags between management's decision to lay off workers and the actual reduction in employment.

Hiring and firing workers incurs adjustment costs, which capture the real costs of posting vacancies, extra hours spent by human resources searching and interviewing candidates, and the cost of training new hires. They also include real costs associated with layoffs, such as revenue lost as the firm rebalances duties across the remaining workers. Accordingly, I interpret labor adjustment costs as real resource expenditures that reduce firm cash flows. This treatment follows Davis, Faberman, and Haltiwanger (2013) and Gavazza, Mongey, and Violante (2018), who among others report evidence that firms actively spend resources when they are looking to grow, as well as Krueger and Mas (2004), Mas (2008), and Gruber and Kleiner (2012), who show layoffs and upset workers can materially affect firms' operations.

I allow for convex and non-convex components labor adjustment costs. The convex portion is quadratic in the gross rate of hiring and scales with firm size, whereas the non-convex portion consists of a fixed share of the firm's current wage bill if the firm makes any net hires or layoffs:

$$AC(n_t, n_{t+1}; w_t) \;=\; \lambda n_t \left(\frac{n_{t+1} - (1-q)n_t}{n_t}\right)^2 + F w_t n_t \mathbf{1}\left(n_{t+1} \neq n_t\right). \tag{2}$$

The literature has long debated the form of adjustment cost functions (see, e.g., Cooper and Haltiwanger, 2006, and Bloom, 2009). My hybrid specification follows standard practice for firm-level data that aggregates several establishments, product lines, and divisions belonging to the same firm, where convex costs are appropriate, as well as studies that find lumpy labor adjustments consistent with non-convexities.[4]

Each firm in the model obtains cash flow $\pi(z_t, n_t, n_{t+1}; w_t)$ in quarter t, equal to its operating income less hiring and firing costs. Cash flows thus depend on the firm's current profitability z_t, labor n_t, the manager's labor choice for next quarter n_{t+1}, and the equilibrium wage w_t:

$$\pi(z_t, n_t, n_{t+1}; w_t) \;=\; z_t n_t^{\alpha} - w_t n_t - AC(n_t, n_{t+1}; w_t).$$

3.2 Managerial Beliefs

Firm-level profitability z_t follows a log-normal autoregressive process, shown in equation (1). Managers in the model observe their firms' current profitability z_t, but use the following beliefs process to forecast z_{t+1}:

$$\log(z_{t+1}) \;=\; \tilde{\mu} + \tilde{\rho}\log(z_t) + \tilde{\sigma}\varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim \mathcal{N}(0,1). \tag{3}$$

The parameters $\tilde{\mu}$, $\tilde{\rho}$, and $\tilde{\sigma}$ distort managers' optimism, their sense of persistence, and their uncertainty about future profitability relative to the objective process in equation (1). If $\tilde{\mu} > \mu$, managers on average overestimate $\log(z_{t+1})$ and are overoptimistic. If $\tilde{\rho} > \rho > 0$, they overestimate the persistence of firm-level profitability, meaning they overextrapolate.

[4]See Hamermesh (1995), Abowd and Kramarz (2003), Rota (2004), Caballero et al. (1997), Varejão and Portugal (2007), and Cooper and Willis (2009) for similar models featuring various types of labor adjustment frictions, many of which identify non-convexities in labor adjustment frictions.

If $\tilde{\sigma} < \sigma$, managers are overprecise or too sure about the future because they underestimate how risky innovations to $\log(z_t)$ really are.

This explicit specification for managerial beliefs is the main innovation in my model, which I have tailored to capture my empirical findings from Section 2; namely, that managers are not overoptimistic, but they are overprecise and overextrapolate. Although I assume a reduced form beliefs process, Section 2.3.5 of Gabaix (2019) micro-founds a similar process from inattention. My specification is also consistent with the intuition behind the diagnostic expectations framework developed and used by Bordalo et al. (2018, 2020, 2021). They micro-found extrapolative expectations by arguing people exaggerate the probability of representative events, in particular those resembling current conditions. My specification captures this intuition when $\tilde{\rho} > \rho$ and $\tilde{\sigma} < \sigma$, because managers overestimate the probability of $\log(z_{t+1})$ remaining close to $\log(z_t)$ in both a first- and second-moment sense. I abstract from managerial learning for simplicity, but also because Appendix Table A.3 fails to find a relationship between the degree of optimism, overprecision, or overextrapolation and the number of times a manager has previously responded to the SBU.

3.3 Managerial Decisions

I assume firm managers are risk neutral and are compensated with a share $\theta \in (0, 1]$ of their firm's equity, abstracting from agency frictions. (Section 6.2 examines how robust my quantitative results are to a plausible relaxation of this assumption.) Thus, managers aim to maximize the net present value of their firms' cash flows. Because they use their subjective beliefs process to forecast future profitability and make hiring decisions, however, managers actually optimize their *subjective* valuation of the firm.

In quarter t, each manager observes her firm's current profitability z_t and labor n_t, the current market wage w_t, and the risk-free rate r_{t+1}. The manager then chooses next quarter's labor n_{t+1}, incurring adjustment costs $AC(n_t, n_{t+1}; w_t)$, to solve the following problem:

$$\tilde{V}(z_t, n_t; w_t, r_{t+1}) \quad = \quad \max_{n_{t+1}>0} \left[\begin{array}{c} \pi(z_t, n_t, n_{t+1}; w_t) \\ +\frac{1}{1+r_{t+1}} \tilde{\mathbf{E}}_t[\tilde{V}(z_{t+1}, n_{t+1}; w_{t+1}, r_{t+2})] \end{array} \right], \tag{4}$$

where the operator $\tilde{\mathbf{E}}_t[\cdot]$ computes the conditional expectation across realizations of z_{t+1} under the manager's beliefs process. The solution to the functional equation above, $\tilde{V}(z_t, n_t; \cdot)$, thus, denotes the manager's *subjective* value of the business.

The key tradeoff in the manager's problem is between adjusting the firm's labor today in response to the latest profitability shock, z_t, and spending on adjustment costs. Responding to shocks brings the firm closer to its optimal static scale and increases the manager's future valuation of the business. But responding also entails spending on adjustment costs and reducing current cash flows $\pi(\cdot)$. Biases in manager beliefs can distort this tradeoff, and thus lead to value-destroying decisions.

3.4 Objective Firm Value

I use $V(z_t, n_t; \cdot)$—without the tilde superscript—to denote the *objective* value of a firm with profitability z_t and labor n_t. Namely, $V(z_{t,} n_t; \cdot)$ represents the expected net present value of cash flows, forecasting future shocks under the *objective* stochastic process in (1) and taking the hiring policy of the firm's manager as given.

Let $n_{t+1} = \kappa(z_t, n_t; w_t, r_{t+1})$ be the manager's choice for next quarter's labor as a function of the firm's idiosyncratic states and equilibrium prices, namely, the optimal policy from (4). The firm's objective value, $V(z_t, n_t; \cdot)$, thus, satisfies the following functional equation:

$$V(z_t, n_t; w_t, r_{t+1}) \quad = \quad \left[\begin{array}{c} \pi(z_t, n_t, \kappa(z_{t,} n_t; w_t, r_{t+1}); w_t) \\ + \frac{1}{1+r_{t+1}} \mathbf{E}_t[V(z_{t+1}, \kappa(z_{t,} n_t; w_t, r_{t+1}); w_{t+1}, r_{t+2})] \end{array} \right], \tag{5}$$

In contrast to the manager's problem, equation (5) uses the objective expectations operator $\mathbf{E}_t[\cdot]$ to forecast the firm's continuation value.

In general, $V(z_t, n_t; \cdot)$ differs from the managers' subjective valuation of the firm $\tilde{V}(z_t, n_t; \cdot)$. They are identical when the managerial beliefs process coincides with the objective shock process—i.e., when managers have rational expectations. In most cases, $V(z_t, n_t; \cdot)$ is also less than the value generated by a rational manager.

3.5 Household

An infinitely-lived representative household consumes the output of the firms in the model and supplies their labor.

The household owns a "mutual fund" that holds the remaining share $1 - \theta \in [0, 1)$ of the equity of the firms in the economy. (Recall that each manager owns a share $\theta \in (0, 1]$ of the firm she runs.) The mutual fund provides the household with lump-sum capital income equal to

$$(1 - \theta)\Pi_t \quad = \quad (1 - \theta) \int_{\mathcal{Z},\mathcal{N}} \pi\left(z, n, \kappa(z, n; w_t, r_{t+1}); w_t\right) \phi_t(z, n) \mathrm{d}z\mathrm{d}n, \tag{6}$$

where $\phi_t(z, n)$ is the measure of firms in the economy with profitability z and labor n in quarter t. Again, $\kappa(z, n; \cdot)$ is the hiring policy of a manager whose firm has profitability z and labor n in quarter t.

The household can also save and borrow using a zero-net-supply, risk-free bond B_{t+1}. Because the economy has no aggregate risk and the mutual fund is perfectly diversified against firm idiosyncratic risk, the household doesn't face any uncertainty.

The representative household maximizes its lifetime utility from consumption and leisure,

$$\max_{C_t, N_t, B_{t+1}} \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\gamma}}{1-\gamma} - \chi \frac{N_t^{1+\eta}}{1+\eta} \right],$$

subject to its budget constraint

$$C_t + B_{t+1} \quad = \quad w_t N_t + (1 + r_t) B_t + (1 - \theta) \Pi_t.$$

The household's optimality conditions are the usual inter-temporal Euler equation and intra-temporal labor-leisure tradeoff:

$$\frac{1}{(1 + r_t)} \quad = \quad \beta \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma} \tag{7}$$

$$w_t \quad = \quad \chi C_t^{\gamma} N^{\eta}. \tag{8}$$

I deliberately keep the household and its optimization problem simple to focus my analysis on managerial decisions and firm outcomes. However, these optimality conditions help pin down equilibrium prices and allocations, and so affect my estimates of the aggregate costs of managerial overprecision and overextrapolation.

3.6 Equilibrium

I focus on stationary general equilibria in which prices clear markets, taking as given managerial beliefs. Formally, these are temporary equilibria as in Molavi (2019), which extends the setup in Grandmont (1977) and Woodford (2013).

A stationary general equilibrium is a set of prices $\{w, r\}$, consumption, labor supply, and saving choices by the household $\{C, N^S, B\}$, subjective firm valuations $\tilde{V}(z_t, n_t; w, r)$ by managers, and a stationary distribution of firms $\phi : \mathcal{Z} \times \mathcal{N} \rightarrow [0, 1]$ such that:

1. $\tilde{V}(z_t, n_t; w, r)$ solves each manager's optimization problem in (4).
2. The household's consumption C, labor supply N^S, and savings B satisfy its optimality conditions in (7) and (8) and its budget constraint.

3. The distribution of firms $\phi(z,n)$ is invariant across quarters and is consistent with managers' hiring decisions and exogenous fluctuations in firms' idiosyncratic profitability, namely,

$$\begin{aligned}\phi_{t+1}(z,n) &= \phi_t(z,n) \quad \forall z,n,t\\ \phi(z',n') &= \int_{\mathcal{Z},N}\phi(z,n)\cdot Pr(z'|z)\cdot \mathbf{1}(n'=\kappa(z,n;w,r))\mathrm{d}z\mathrm{d}n, \quad \forall z',n'.\end{aligned}$$

4. The labor and risk-free bond markets clear:

$$\begin{aligned}N^S &= \int_{\mathcal{Z},\mathcal{N}} n\cdot\phi(z,n)\mathrm{d}z\mathrm{d}n\\ B &= 0, \quad \text{in zero net supply by assumption.}\end{aligned}$$

Here, $Pr(z'|z) = Pr(z_{t+1} = z'|z_t = z)$ stands for the conditional density of idiosyncratic shocks z_{t+1} under the *objective* driving process from equation (1). Once again, $n_{t+1} = \kappa(z_t, n_t; w_t, r_{t+1})$ is the employment chosen by a manager whose firm has profitability and labor (z_t, n_t), facing equilibrium prices w_t and r_{t+1}. The above definition extends naturally to the case where the economy is in transition to its aggregate steady state.

Although redundant for equilibrium, the aggregate output market also clears. Output is firm-level sales less adjustment cost expenditures, and is equal to consumer spending plus managerial compensation, or, alternatively, the sum of labor income and firm profits:

$$\begin{aligned}Y &= \int_{\mathcal{Z},\mathcal{N}} [zn^\alpha - AC(n,\kappa(z,n;w,r);w)]\cdot\phi(z,n)\mathrm{d}z\mathrm{d}n \qquad (9)\\ &= C+\theta\Pi\\ &= wN+\Pi.\end{aligned}$$

My model abstracts from aggregate risk and instead focuses on how managerial beliefs about firm-specific shocks affect managerial decisions and (stationary) aggregate outcomes. Thus, managerial biases matter as long as they alter cross-firm labor allocations, the household's labor-leisure tradeoff, and the amount of resources ultimately spent on consumption versus adjustment costs. I make this abstraction primarily because the time period over which I have evidence on beliefs covers late 2014 to mid-2019, when the US economy experienced historically low aggregate volatility. This empirical setting lends itself to focusing on managers' own-firm expectations and micro-to-macro effects of resource misallocation. Richer models and sample periods with higher macro volatility could reveal even larger effects of managerial biases, particularly if managers are biased about aggregate shocks.

4 Model Solution and Estimation

I quantify how managerial beliefs, adjustment costs, and profitability fluctuations impact firm behavior by estimating the model from Section 3 using SBU data. This section describes: (1) how I solve managers' dynamic problem and compute the aggregate steady state of the model given a set of parameters, and (2) the structural estimation exercise I use to obtain the model's key parameters.

4.1 Computing the Stationary General Equilibrium

Solving and simulating economic models in which agents have non-rational beliefs imposes few constraints relative to standard rational-expectations modeling. In my setting, I simply need to use the managerial beliefs process to obtain firms' dynamic hiring policies, but use the objective process to track actual fluctuations in firm profitability and employment.

Here, I sketch out the algorithm I use to compute the economy's stationary equilibrium. For full details, see Section C.1 of the Online Appendix. To begin, I use the household's inter-temporal Euler equation in (7) to pin down the stationary risk-free rate: $r = 1/\beta - 1$. Then, I iterate through the following steps:

1. Starting with a guess for the stationary wage w, I solve managers' problem from equation (4) using value-function iteration aided by Howard's improvement algorithm over a discretized (z, n) state space. Here, I use the manager's belief process from equation (3) to forecast the firm's future profitability.

2. I compute the stationary distribution $\phi(z, n; w, r)$ of firms that arises from: (1) the managerial policy function $n_{t+1} = \kappa(z_t, n_t; w, r)$ obtained in step 1, and (2) the *objective* process for firm profitability from equation (1). I compute $\phi(\cdot)$ numerically using a non-stochastic simulation algorithm based on Young (2010). This procedure is conceptually equivalent to simulating a long panel of firms, but it avoids the need to draw random numbers that introduce simulation error.

3. Using the stationary distribution $\phi(\cdot; w, r)$, I compute the household's implied consumption $C = wN^D + (1 - \theta)\Pi$, where $N^D = \int_{\mathcal{Z}\times\mathcal{N}} n \cdot \phi(z, n; w, r)\mathrm{d}z\mathrm{d}n$ is aggregate labor demand and $(1 - \theta)\Pi$ is the household's total capital income (see equation 6). Then, I find the household's desired labor supply N^s given C and w according to its intra-temporal labor-leisure tradeoff in (8). If $\|N^D - N^S\| < \varepsilon$, for a pre-specified tolerance ε, the labor market clears and I have found the economy's stationary equilibrium. Otherwise, I update the guess for the wage w and go back to step 1.

4.2 Estimation

I estimate the model from Section 3 using a minimum-distance estimation procedure that chooses model parameters to match an array of moments from the SBU's firm-level data.

Prior to estimation, I calibrate several parameters based on prior literature or on normalizations. Table 5 shows these calibrated parameters, most of which pertain only to the household's problem and do not directly affect manager decisions. The main exception is the household's discount factor β, which, again, maps to the risk-free rate. I normalize the objective mean of the firm profitability process, μ, to zero, and set the exogenous separation rate for labor q to 30 percent annually, following Shimer (2005). For the share of firm equity owned by managers, θ, I consider several values ranging from 5 percent (an estimate for publicly-traded companies in Nikolov and Whited, 2014) to 50 percent. My choice of θ does not affect my estimates of the model's other parameters because θ drops out of the managers' problem in (4). In Section 5, I consider how θ affects my general equilibrium counterfactuals by changing the household's capital income and labor-leisure tradeoff.

I estimate the remaining parameters of the model by finding a vector ϑ of parameters that minimizes the weighted distance between a vector of moments from my model's stationary distribution $m(\vartheta)$ and corresponding moments computed from SBU microdata, $m(X)$, with the weights given by an appropriate matrix W:

$$\min_{\vartheta} \quad [m(\vartheta) - m(X)]' W [m(\vartheta) - m(X)]. \tag{10}$$

The vector of parameters ϑ includes the persistence and volatility of shocks in the objective driving process from equation (1), ρ and σ; the parameters of the managerial beliefs process from equation (3)—$\tilde{\mu}$, $\tilde{\rho}$ and $\tilde{\sigma}$—; the elasticity of revenue with respect to labor, α; and the two adjustment costs parameters, λ and F.

Because the key tradeoff for managers in the model is between adjusting the firm's labor and paying adjustment costs, I estimate three specifications of the model featuring different adjustment cost functions. The first focuses on convex adjustment costs, estimating λ and setting $F = 0$. The second focuses on fixed adjustment costs, now estimating F and setting $\lambda = 0$. The third includes both types, estimating λ and F jointly with the other parameters.

My estimation targets 19 moments, which broadly correspond to three features of the SBU data:[5]

1. The extent of managerial optimism, overprecision and overextrapolation (3 moments), essentially Facts 1 through 3 from Section 2.

[5] My approach of using survey evidence on beliefs contrasts with Alti and Tetlock (2014), who use asset-pricing anomalies to estimate a similar model.

2. The links between managerial expectations and uncertainty with outcomes, hiring plans, and hiring decisions (12 moments based on my analysis from Section 2.2.)

3. The joint dynamics of sales and employment growth (4 moments), including:

   - The variance-covariance matrix of employment growth (i.e., net hiring) in quarter t, and sales growth between quarters $t-1$ and t (3 moments);
   - The covariance of sales growth between quarters $t-1$ and t with sales growth between quarters t and $t+4$ (1 moment). This moment is informative about the persistence of firm-level shocks.

Table 7 shows the full list of targeted moments, sorted into the three groups above. See Section C.4 in the Online Appendix for more details on how I construct the model and data moments, and details about the estimation procedure.

I use a simulated annealing algorithm to undertake the numerical minimization problem in equation (10), with the aim of finding a global rather than a local minimum. For my choice of W, I use the efficient weighting matrix, namely, the inverse of the firm-clustered variance-covariance matrix of data moments $m(X)$. Bazdresch, Kahn, and Whited (2017) show the efficient weighting matrix has desirable small-sample properties in minimum-distance estimations of dynamic firm models.

Although there is no one-to-one mapping from moments to parameters, certain moments are particularly informative about certain parameters. Here, I provide a heuristic description of what simulated moments vary most strongly with a given parameter, based on comparative statics exercises. Section C.4 of the Online Appendix also reports the sensitivity of my estimated parameters to moments, following Andrews, Gentzkow, and Shapiro (2017).

The moments in the first group, involving optimism, overprecision, and overextrapolation, vary with the gap between corresponding parameters in the objective and subjective stochastic processes, namely, $\tilde{\mu}$ and μ, $\tilde{\sigma}$ and σ, and $\tilde{\rho}$ and ρ. The moments from the second group discipline the link between managerial beliefs, decisions, and outcomes. Among them, the covariance between sales growth expectations and hiring plans (i.e., employment growth expectations) increases with the revenue elasticity of labor α and decreases with the convex adjustment cost parameter λ. In the third group, the variance of quarterly sales growth increases with the true standard deviation of firm-level shocks, σ. The (negative) covariance between sales growth from $t-1$ to t and sales growth from t to $t+4$ increases towards zero with the true persistence of shocks, ρ, and with the adjustment cost parameters, which make the firm's labor more persistent. The covariance of employment and sales growth declines with both λ and F. Higher adjustment costs mean the firm's employment responds more sluggishly to shocks.

The two types of adjustment costs are separately identified by the fact that F induces Ss-like hiring policies but λ does not, so they affect certain model moments differently. Increasing F, for example, generates larger forecast errors as the manager makes lumpy adjustments in response unexpectedly large and mean-reverting shocks. These lumpy adjustments also help the hybrid model reconcile a low covariance of employment and sales growth with relatively high mean reversion in sales, which the convex model has a hard time fitting jointly. More broadly, I find λ and F have Andrews, Gentzkow, and Shapiro (2017) sensitivities of different sign with respect to several target moments, which gives me further confidence they are separately identified.

4.2.1 Measurement error

As part of my estimation, I acknowledge the SBU may have nontrivial measurement error, since it is a self-reported survey and it collects discrete approximations of managers' subjective distributions. To address the first issue, I assume measured sales and employment *levels* have multiplicative log-normal i.i.d, error $\xi \sim \log \mathcal{N}(0, \sigma_\xi^2)$. To address the second, I also assume manager expectations and subjective uncertainty about future sales and employment growth are measured with i.i.d. error $\nu \sim \mathcal{N}(0, \sigma_\nu^2)$.

I estimate the variances σ_ξ^2 and σ_ν^2 of both types of measurement error along with the other economic parameters for several reasons. First, doing so aids in the estimation by adding flexibility for the model to fit the data and addresses a likely source of misspecification. Namely, the firm's labor choice in the model is continuous and probably aligns more closely with total work hours, but in the data I only observe employment. Allowing labor to be mis-measured in the model addresses this discrepancy. Second, measurement error in sales growth inflates the moments that quantify the extent of overprecision and overextrapolation in the data (see my discussion of Facts 2 and 3 in Section 2 above). Omitting measurement error from the model, thus, would bias me towards estimating stronger overprecision and overextrapolation. Finally, the novelty of the SBU data makes the magnitude of its measurement error interesting in its own right.

To gain intuition for what moments identify σ_ξ^2 and σ_ν^2, note that they each amplify some of the variances I target in my estimation. By definition, the variances of measured employment and sales growth in the model increase with σ_ξ^2. Four variances increase with σ_ν^2, namely, those pertaining to subjective expectations and uncertainty for each of sales and employment. The model in practice underestimates most of these variances when I restrict σ_ξ^2 and σ_ν^2 both to be zero, so the parameters are identified by increasing the model-implied variances towards their empirical counterparts. Additionally, σ_ξ^2 makes the covariance of past ($t-1$ to t) and future (t to $t+4$) sales growth more negative, and both σ_ξ^2 and σ_ν^2 increase average absolute forecast errors, because they introduce noise to forecast and realized sales. Each of the measurement error parameters affect multiple moments, so both are effectively subject to overidentifying restrictions. Appendix B provides more details on how measurement error affects model moments.

After including the two measurement error parameters, my estimation fits 19 data moments with 9 or 10 parameters, depending on the specification, so the estimation is overidentified by 9 or 10 degrees of freedom.

4.3 Estimation Results

Tables 6 and 7 show the results from my structural estimation of the model. The first shows the estimated parameters and their standard errors for all three specifications. The second shows all 19 targeted moments in the data and each of the three estimated specifications of the model. It also reports t-statistics for the null hypothesis that each pair of model and data moments are identical, bolding those that are statistically significant with 95 percent confidence. The bottom of Table 7 also reports the value of the econometric criterion at the estimated parameters for each specification.

4.3.1 Assessing the model's fit

Table 7 shows the specifications with convex and hybrid (convex and fixed) adjustment costs fit the data well. The model is overidentified by 10 and 9 degrees of freedom, respectively, in these specifications, and yet only 3 moments in the convex, and 2 in the hybrid specification are statistically different between the model and the data. Moreover, each of those statistically different pairs of moments are the same order of magnitude. The econometric criterion attains similar values in these two specifications, respectively 94.0 and 87.1. It is slightly lower for the hybrid specification due to the extra free parameter.

The specification with only fixed adjustment costs, by contrast, fits the data relatively poorly. Many more moments are statistically significantly different between the model and the data, and the econometric criterion has a much higher minimum at 204.7 than in the other two specifications. Based on their better fit to the data, I focus my analysis below on the two specifications with convex and hybrid adjustment costs.

Figure 6 shows how my two preferred specifications of the model fit three key non-targeted relationships: (1) the link between labor productivity and the firm's employment growth, essentially the "empirical policy function" proposed in Bazdresch, Kahn, and Whited (2017) as a benchmark for dynamic models; (2) the autocorrelation of non-overlapping forecast errors, namely, those covering $t-4$ to t and t to $t+4$; and (3) the positive relationship between uncertainty in t and the absolute change in sales growth forecasts documented in Altig et al. (2020).

Each subfigure of 6 uses a bin-scatter plot to represent the joint distribution of each pair variables in both the model and the data. To conform with the lack of persistent cross-firm heterogeneity and aggregate shocks in the model, I remove firm and date fixed effects from the SBU data variables before constructing each bin-scatter in Figure 6. Figure 6b represents a dynamic panel relationship, so I additionally plot a bin-scatter for the raw panel data, showing it is similarly steep without removing the fixed effects. Figure 6a also plots two versions of the relationship in the model, with and without considering measurement error in sales and employment, to see how this shapes the model-implied empirical policy function.

Both of the preferred specifications of the model fit the positive relationship between labor productivity and hiring decisions, shown in Figure 6a. Accounting for measurement error in the model, in particular, helps both specifications fit the steepness of the relationship in the middle 85 percent of the distribution of labor productivity.[6] Similarly, both specifications of the model fit the (negative) autocorrelation of non-overlapping forecast errors, as we can see in Figure 6b. Although this moment is not targeted in the estimation, it reflects the degree of managerial overextrapolation, which my estimation targets with the (positive) covariance between sales growth from $t-1$ to t and forecast-minus-realized sales growth from t to $t+4$. Thus, it is reassuring—if not surprising—that the model fits two moments related to overextrapolation even though only one is targeted. Finally, both versions of the model generate a positive relationship between subjective uncertainty in quarter t and the absolute revision to year-ahead sales growth expectations between t and $t+1$, but the relationship is much flatter than in the data, as Figure 6c shows. This discrepancy is likely due to the simple idiosyncratic profitability process in the model. A richer model with stochastic volatility, for example, might generate bigger expectations revisions when firms face shocks to their idiosyncratic volatility.

Looking at the model's fit of targeted and untargeted moments in Table 7 and Figure 6, it's altogether clear that it captures many, if not all, interesting features of the data. This result is one my paper's key contributions, namely, showing how a canonical dynamic model of managerial decision-making augmented with a managerial beliefs process captures many

[6] Ilut, Kehrig, and Schneider (2018) find firms are quick to hire and slow to fire, but Figure 6a appears to show roughly symmetric responses around mean productivity, and my estimated model captures this relative symmetry. The absence of these dynamics in my data could be due to higher frequency [the SBU is quarterly but the Census data that Ilut, Kehrig, and Schneider (2018) focus on is annual] and differences in the two samples. In particular, my SBU sample consists of larger, well-established firms for which the exit margin that might generate quick-to-fire dynamics is plausibly absent.

stylized facts about manager beliefs, decisions, and firm outcomes.

4.3.2 Estimates of the economic parameters

Table 6 shows the specifications with convex and hybrid (convex and fixed) adjustment costs estimate parameters with reasonable economic magnitudes. For example, the revenue-elasticity of capital, α, is between 0.8 and 0.9, comparable to estimates of the returns to scale of revenue production functions in macroeconomics. Assessing the magnitude of the adjustment cost parameters, which govern the key tradeoff in the model, is harder because they are model and context dependent. Still, the 3.9 percent fixed adjustment cost in the hybrid specification is comparable to the magnitude of fixed adjustment costs in Bloom (2009). It also seems intuitive for the convex only specification to find higher convex costs than the hybrid specification, which has an additional tool to match the same data moments.

In comparison, the specification with fixed adjustment costs finds parameter estimates that are less plausible, as we see in Table 6, on top of fitting the data relatively poorly. In particular, the degree of decreasing returns to scale is much stronger (α equals 33 percent), and the magnitude of fixed adjustment costs is much larger than in the hybrid specification at 26 percent. These implausible estimates further support my decision to focus on the convex and hybrid specifications in my quantitative analysis.

4.3.3 Implied magnitude of pessimism, overprecision, and overextrapolation

My estimates of the subjective stochastic process are consistent with my interpretation of the evidence from Section 2. Consistent with Fact 1, managers in the estimated model appear only mildly pessimistic. My estimate for $\tilde{\mu}$ is -0.003 in both the convex and hybrid specifications, implying managers underestimate the mean innovation to $\log(z_t)$ by about 2.5 percent of its true standard deviation, σ. Consistent with Fact 2, managers are overprecise. They believe the volatility of shocks to business conditions $\tilde{\sigma}$ is about 36 to 38 percent as large as the true volatility σ in the hybrid and convex specifications, respectively. Consistent with Fact 3, managers overextrapolate. They believe the autocorrelation of $\log(z)$, $\tilde{\rho}$, is between 0.90 and 0.91, but the true autocorrelation, ρ, is 0.75 and 0.85 in the hybrid and convex specifications. These estimates imply managers believe the half-life of innovations to $\log(z)$ is about 7.4 quarters, relative to a true half-life of 2.4 or 4.4 quarters.

These estimates of the beliefs process also suggest measurement error in sales cannot solely Facts 2 and 3 in the data. Even though I estimate nearly 10 percent measurement error in sales and employment levels, I still find $\tilde{\rho} > \rho$ and $\tilde{\sigma} < \sigma$ by economically significant magnitudes.

The main difference across my two preferred specifications is the hybrid estimates a lower objective autocorrelation ρ, implying a stronger degree of overextrapolation. The reason is the fixed adjustment cost component of the hybrid specification generates lumpiness in managers' hiring policies, so labor responds relatively strongly to large profitability shocks and relatively weakly to small shocks. Lumpiness thus helps the model match the degree of mean reversion in the sales data with a lower estimate for ρ (because labor reacts to surprisingly mean-reverting shocks), and also match the low covariance of sales and employment growth (because the combined adjustment costs lead to small reactions to small shocks). Convex adjustment costs, instead, generate smooth and sluggish labor adjustments, so the tradeoff to fitting the degree of mean reversion and the employment-sales growth covariance is steeper. On balance, the estimation settles at a higher estimate for ρ in the convex specification, implying more modest overextrapolation.

5 Micro and Macro Costs of Biases in Managerial Beliefs

I quantify how managerial beliefs impact firm value and aggregate outcomes by computing two types of counterfactuals on my estimated model:

1. I ask how much the typical firm's value would increase if it hired a manager with rational expectations.

2. I ask how aggregate outcomes differ in an economy in which managers have rational expectations relative to outcomes in my estimated economy.

The first counterfactual holds equilibrium prices constant, whereas the second allows them to adjust when all managers' beliefs and decision rules change. Section C.5 of the Online Appendix shows these quantitative results are robust to modest changes in some of the key parameters of the model.

Since managers in the model use a reduced-form beliefs process (see equation 3), giving a manager rational expectations (setting $\tilde{\mu} = \mu$, $\tilde{\sigma} = \sigma$, and $\tilde{\rho} = \rho$) amounts to ridding them of the underlying psychological frictions (e.g., inattention or representativeness) that distort their beliefs to begin with. Below, I also consider counterfactuals where I only rid managers of overprecision (i.e., set $\tilde{\sigma} = \sigma$ and leave $\tilde{\rho}$ unchanged) or overextrapolation (i.e., set $\tilde{\rho} = \rho$ and leave $\tilde{\sigma}$ unchanged). My aim in those cases is to test how individual features of manager beliefs matter, but the interpretation is admittedly less clear.

My counterfactuals hold constant other features of managerial decision-making, the firm's business and its access to capital, and the relationship between managers and shareholders. In particular, changing managers' beliefs does not change their ability or the firm's long-run firm profitability. If, in reality, biased managers have higher ability or are more effective leaders (see, e.g., Goel and Thakor, 2008, and Bolton et al., 2012), my counterfactuals will overestimate the benefits of hiring managers with rational expectations. Alternatively, biased managers might be less able, or more likely to make catastrophic decisions that do not arise in my model. There are plausible arguments for both cases. Because my model also abstracts from financial frictions, my counterfactuals hold constant the firm's access to investor funding and focus on how manager beliefs change the way they take-up business opportunities. A model with richer manager-investor relationships could also explore the impact of manager beliefs on that dimension, for example, building on Malmendier and Tate (2005).

5.1 Managerial Beliefs and Firm Value

Table 8 shows how the value of the typical firm would change if we replaced its biased manager with another who knows (at least some of) the true parameters of the firm-level shock process in equation (1). Each row computes the average difference in percentage terms between the objective firm value generated by managers who use my estimated beliefs process and the value generated by a counterfactual manager with different beliefs, specified in each row of the table.

For the typical firm, hiring a manager with rational expectations (for whom $\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, and $\tilde{\mu} = \mu$) raises firm value by 2.1 or 6.8 percent in the convex and hybrid models, respectively. The larger firm-value impact with hybrid adjustment costs is consistent with more severe overextrapolation in that case but similar degrees of overprecision across the two specifications. (In both cases, $\tilde{\sigma}$ is about 60 percent smaller than σ, but $\tilde{\rho}$ is 7 versus 20 percent larger than ρ in the convex versus the hybrid adjustment costs specifications.) Still, both estimates of the firm-value cost of biases are comparable in magnitude to other estimates of managerial misbehavior or entrenchment. Terry (2017) quantifies the firm-value cost of managerial short-termism at about 1 percent, and Taylor (2010) estimates the cost of CEO entrenchment at 3 percent. Wu (2018) argues managerial dividend smoothing leads to a 2 percent loss in firm value.

Table 8 also suggests overextrapolation and overprecision are the key reasons why managers destroy value, whereas managerial pessimism has a small marginal impact. Hiring a manager who does not overextrapolate and isn't overprecise ($\tilde{\rho} = \rho$ and $\tilde{\sigma} = \sigma$), but slightly understates the mean innovation to $\log(z_t)$ ($\tilde{\mu} = -0.003$), raises value by 2.0 or 6.6 percent, almost as much as hiring a rational manager.

Comparing now whether overprecision or overextrapolation individually affect firm value by more, the table shows hiring a manger who is not overprecise ($\tilde{\sigma} = \sigma$) increases value by 1.4 percent in the convex specification but only 0.9 percent in the hybrid version. Instead, hiring a manager who does not overextrapolate ($\tilde{\rho} = \rho$) increases firm value by 0.8 percent in the convex model and 5.4 percent with hybrid adjustment costs. These differences stem, again, from whether overprecision or overextrapolation is relatively more severe in each specification.

5.2 Managerial Beliefs and the Macroeconomy

Table 9a shows my headline results on how biases in managerial beliefs affect macroeconomic outcomes. Each entry in the table reports the percent difference between long-run consumer welfare or GDP in a counterfactual economy in which managers have rational expectations (for whom $\tilde{\mu} = \mu$, $\tilde{\sigma} = \sigma$, and $\tilde{\rho} = \rho$) relative to an economy in which managers use the estimated (biased) beliefs process to forecast future shocks.

Aggregate consumer welfare is larger in the rational expectations economy by 0.50 to 2.3 percent in consumption-equivalent terms. GDP (gross output less adjustment costs, as in equation 9) is also higher by 0.3 to 1.1 percent, but only marginally so for the hybrid specification when managers have 50% equity. For comparison, recent estimates of the cost of business cycles amount to about 1 percent in consumption equivalent terms after considering the impact of long-term unemployment in Krusell et al. (2009). In Terry (2017), the welfare cost of managerial short-termism is 0.4 percent of consumption.

A key determinant of the welfare impact of biases is the share of managerial equity θ. More managerial equity means less initial capital income for the representative consumer, and therefore higher marginal utility from making managers rational and thus making the economy work better.[7] Table 9a shows this relationship by computing welfare gains under three values for θ, ranging from 0.05 to 0.50. The lower value corresponds to the equity share managers hold in publicly traded firms, estimated by Nikolov and Whited (2014). I choose 0.5 as a reasonable upper bound for θ, because nearly 60 percent of SBU firms have CEOs who are major shareholders or part of a major shareholding family. Lower values of θ are more conservative, so I focus on the lower bound of 5 percent for the rest of my analysis.

General equilibrium forces are a crucial element of the results in Table 9a. Section C.6 of the Online Appendix corroborates this argument by computing a version of Table 9a that considers an economy with rational managers but holds prices constant at their original values from the equilibrium with biased managers. That exercise predicts implausibly large losses in consumer welfare and gains in aggregate output. Thus, without the discipline of general

[7] Appendix Table A.4 also explores the impact of θ on equilibrium conditions more fully.

equilibrium, comparing long-run outcomes across economies in which all firm managers have rational versus non-rational expectations does not make much sense.

5.3 Managerial Overprecision and Overextrapolation Lead to Overreaction

Beliefs matter for firm value and aggregate outcomes because overextrapolation and overprecision lead managers to overreact to shocks. Overextrapolative managers overestimate the persistence of shocks, so they hire or lay off too many workers in response. Overprecise managers perceive certainty about the firm's future profitability, so they are too willing to pay the adjustment costs associated with responding to shocks.

Figure 7 illustrates how beliefs lead to overreaction in both specifications of the model. Each panel plots the positive relationship between labor productivity (essentially, the marginal product of labor) and net hiring, similar to the top panel of Figure 6 in two economies. The solid blue curves represent the baseline economy with biased managers, and the dashed orange curves represent the counterfactual economy in which they have rational expectations.. To focus on variation stemming only from managerial decisions, the figure ignores measurement error in sales and employment. Overreaction is evident in the steeper relationship in the economy with biased managers, who hire or lay off more workers in response to shifts in labor productivity. In fact, the right panel suggests rational managers barely react to transitory shocks when facing the combination of fixed and convex adjustment costs I estimate for the hybrid specification.

Managerial overreaction generates excess volatility and reallocation, as I document in Table 9b. Depending on the adjustment costs specification, within-firm employment volatility is 33 to 82 percent lower in the rational-expectations economy, or 27 to 55 percent lower if we consider the impact of measurement error. Reallocation[8] is also 60 to 97 percent lower and dispersion in the marginal product of labor (a measure of static misallocation, as in Hsieh and Klenow, 2009) is 3.5 percent higher when managers have rational expectations. Firms in the rational-expectations economy are, accordingly, further from their optimal static scale.

Based on these statistics, biased managers appear to be better at (re)allocating labor across firms, which would typically result in higher welfare (e.g., Decker et al., 2020). In my model, it does not because reallocation is costly and biased managers overestimate its benefits. When they overreact to shocks, managers over-spend on adjustment costs, destroying firm value and lowering consumer welfare. We can see this over-spending in the last column of

[8] I measure the rate of reallocation as the employment-weighted average of absolute firm-level employment growth rates, following Davis and Haltiwanger (1992). Because I focus on stationary equilibria with no aggregate employment growth, reallocation and excess reallocation are the same in my model economy.

Table 9b, which shows the rational-expectations economy spends 1.2 to 2.3 fewer percentage points of GDP on reallocation (i.e., adjustment) costs. This feature of my model contrasts with Ma et al. (2020), who find smaller effects of managerial biases in a closely related paper. They find managers *underestimate* the persistence of temporary shocks, which implies no over-spending on adjustment costs and too little rather than too much reallocation.

Table 9c illustrates the relationship between overprecision and overextrapolation on one hand and static misallocation and welfare on the other by comparing counterfactual economies in which managers are not overprecise ($\tilde{\sigma} = \sigma$) , do not overextrapolate ($\tilde{\rho} = \rho$), or both together. In particular, the table shows there is an optimal degree of dispersion in marginal products, which arises when managers have rational expectations. Too little dispersion (as in the baseline case) or too much both lower welfare.

A natural implication of these results is that managerial beliefs could play a role in amplifying aggregate fluctuations. If managers overreact to firm-specific shocks, they might also overreact to industry or economy-wide shocks. Overreaction to firm-specific shocks could even generate large responses to macroeconomic impulses on its own. Several papers in the behavioral macro literature propose this mechanism, at least as far back as Fuster, Hebert, and Laibson (2010). More recently Bordalo, Gennaioli, and Shleifer (2018) and Bordalo, Gennaioli, Shleifer, and Terry (2021) have proposed models of credit cycles with a similar intuition. Yet, *how much* amplification managerial beliefs generate and what mechanisms are required to sustain that amplification is still unclear.

6 Model Robustness and Extensions

This section considers how my key quantitative results from Section 5 change when I introduce taxes, agency frictions, monitoring and dismissal to discipline managers, and when I extend my model to have both labor and capital. I also reestimate the model on subsamples of the SBU to test for sorting and heterogeneity in the degree of overextrapolation and overprecision. For brevity and simplicity, I focus on extensions of the model specification that has only convex adjustment costs throughout.

6.1 Taxing Layoffs to Counteract Managerial Overreaction

The insight that managerial beliefs lead to costly overreaction raises the question of whether any policies can mitigate it and improve consumer welfare. Figure 8a demonstrates how a tax levied on firms that fire or lay off workers can improve welfare by tempering hiring and layoffs in response to shocks. Many real-world policies resemble such a tax, including experience-rated unemployment insurance taxes in the US (see, e.g., Guo, 2020), and several policies that are common in Europe and make layoffs costly (see Horobin and Walker, 2017).

With the tax, firm cash flows become

$$\pi(z_t, n_t, n_{t+1}; w_t, \tau_f) \quad = \quad z_t n_t^{\alpha} - w_t n_t \cdot (1 + \tau_f \mathbf{1}(n_{t+1} < n_t)) - AC(n_t, n_{t+1}). \qquad (11)$$

I assume the government has a balanced budget and transfers the tax revenue lump sum to the household (see Appendix C.1 for details).

Figure 8a plots the difference in welfare between an economy with the tax relative to the baseline economy with biased managers, as a function of the tax rate. The horizontal line near the top shows the potential welfare gains from moving to an economy with rational managers, at 0.5 percent of consumption. A firing tax increases welfare by as much as 0.3 percent—closing about 60 percent of the welfare gap with the rational-expectations economy. Subsidizing firing (e.g., with a tax credit on firms that downsize) instead lowers consumer welfare, as we can see in the region with a negative tax rate.

This exercise shows how an implementable policy can mitigate the macroeconomic costs of managerial overreaction without changing managerial psychology or beliefs, which may be difficult or impossible. Additionally, it demonstrates how the impact of public policies can depend on the nature of beliefs.[9] Conventional wisdom says that suppressing resource reallocation lowers productivity and welfare (see, e.g., Decker et al., 2020), but the opposite is true in my model because managers overreact. I admittedly abstract from many features of reality that could overturn this result in practice, but the broader point about understanding how beliefs interact with policy stands.

6.2 Agency: Managers Who Want to"Live the Quiet Life"

My baseline model abstracts from agency conflicts between managers and shareholders. Here, I examine how things change when I relax this assumption in the spirit of Bertrand and Mullainathan (2003), who find unsupervised managers prefer a "quiet life," for example avoiding big decisions like plant openings and closures.

Specifically, I suppose a fraction $\psi \in [0, 1]$ of the adjustment costs managers face are purely psychological, and do not represent real resource costs for the firm and the economy, whereas the remaining $1 - \psi$ do. This friction misaligns manager and shareholder incentives in at least two ways, both of which are consistent with preferring a quiet life as in Bertrand

[9]Section C.7 of the Online Appendix expands on this point by showing the welfare cost of taxation is higher when managers are overprecise and overextrapolate, and, similarly, that managerial overreaction is more costly in the presence of distortionary taxes.

and Mullainathan (2003). First, managers overly dislike adjusting the firm's labor, so they underreact to shocks. Managerial overprecision and overextrapolation could thus be desirable to counteract managerial inertia. Second, adjustment costs scale with firm size, so managers prefer keeping the firm smaller than shareholders might like. This preference will make the mild managerial pessimism (recall that $\tilde{\mu} = -0.003$) and overprecision I estimate from the SBU data more costly, because both of them also induce managers to limit the firm's size.[10]

Figure 8b shows the impact on firm value of hiring a manager who has rational expectations (left) and the difference in consumer welfare (right) between the equilibria of the baseline and rational-expectations economies, in both cases as a function of the share ψ of adjustment costs that are psychological to the manager. At $\psi = 0$ the firm value and welfare gains coincide with the results from Section 5, but as ψ increases, managerial preferences for a smaller firm amplify the impact of beliefs on firm value (left). Manager preferences against responding to shocks instead dampen (and even eliminate) the welfare costs of beliefs in general equilibrium (right). These mixed results suggest agency frictions and managerial beliefs interact in less than obvious ways, so future work should pay attention to identifying and estimating belief and agency frictions jointly.

6.3 Monitoring and the Threat of Managerial Dismissal

Just as my baseline model abstracts from agency frictions, it does not feature a mechanism allowing shareholders to monitor and control managers. In particular, shareholders could undo the impact of beliefs by credibly threatening to dismiss a biased manager whose hiring policies deviate from what they would prefer.

To address this question, I consider an extended version of my model where, at the end of quarter t, shareholders dismiss the firm's manager with probability $\Omega(z_t, n_t, n_{t+1}; \omega)$, namely, depending on the firm's current profitability and labor, as well as the manager's choice for next period's labor. The parameter $\omega \geq 0$ governs the strength of the monitoring mechanism, so $\partial\Omega(z_t, n_t, n_{t+1}; \omega)/\partial\omega > 0$. I assume managers are still compensated with an equity stake in the firm, which they lose if they are dismissed. Taking this possibility into account, managers maximize a modified version of the problem in equation 4, but now discount future cash flows by a factor of $\frac{1-\Omega(z_t,n_t,n_{t+1};\omega)}{1+r_{t+1}}$. See Appendix C.2 for details on the specific functional form of the dismissal probability.

Figure 8c shows how rational shareholders can reduce the impact of managerial biases on the firm's value (left) and overall welfare (right) by increasing ω, namely, by dismissing

[10] I model managerial overprecision as an underestimate of the volatility of innovations to $\log(z_{t+1})$, so managers' subjective forecast of future profitability, $\widetilde{\mathbf{E}}[z_{t+1}]$, understates the objective forecast $\mathbf{E}[z_{t+1}]$ through a Jensen's inequality mechanism.

misbehaved managers more often. For $\omega = 0$, the firm value and welfare impact of biases coincide with those from Section 5. As ω increases, the rational shareholders successfully nudge managers toward implementing their desired policy, eliminating the impact of managerial biases when ω is large enough.

This exercise suggests monitoring and managerial dismissal can be powerful weapons, but it abstracts from real-world frictions that probably make them less effective in practice. Shareholders are unlikely to have rational expectations, for starters. Indeed, La Porta (1996) and Rozsypal and Schlafmann (2017) show equity analysts and consumers overextrapolate. It also seems unrealistic for outside shareholders to delegate the running of the firm to a manager and then seek to micromanage her every move. More likely, shareholders delegate to the manager owing to her superior ability and knowledge of firm fundamentals. Finally, if rational shareholders were able to monitor effectively, we might expect the degree of overprecision and overextrapolation to correlate with the strength of the monitoring mechanism. Yet, in Sections 2.6 and 6.5, I find modest differences between firm managers who likely face different amounts of shareholder scrutiny.

6.4 A Model with Capital and Labor

My model and quantitative analysis focuses on how managerial biases impact employment dynamics and abstract from capital investment because the SBU doesn't have quality data on firm balance sheets, assets, and capital expenditures. Biases surely impact investment decisions as well, but whether this impact would amplify or dampen the impact of biases on firm value and welfare is not obvious.

To explore how abstracting from capital investment might affect my quantitative results, I consider an extended model featuring both capital and labor as factors of production, both of them subject to adjustment costs. In Appendix C.3, I provide more details about this two-factor model and explain how I calibrate its parameters based on my estimates of the baseline labor-only model and investment moments from the literature.

Figure 8d compares the firm value (left) and welfare (right) impact of managerial biases in my estimated model with labor only and convex adjustment costs against three calibrations of the two-factor model. The first uses a baseline set of labor and capital adjustment costs parameters, and the other two increase or decrease them together by 10 percent. The two-factor model provides smaller firm-value gains from hiring an unbiased manager, but they are of a similar magnitude to the baseline. Welfare gains from moving to the rational-expectations equilibrium are also similar across the two.[11] Furthermore, managerial overprecision and

[11]The firm-value and welfare implications of biases both decrease modestly in the two-factor model when we increase or decrease the adjustment costs parameters. This finding suggests my baseline calibration of

overextrapolation lead to overreaction in the two-factor model as they do in the labor-only model. Indeed, the correlation between sales growth from $t-1$ to t and investment and employment growth in t are both lower, respectively, by 13 and 48 percent when managers have rational expectations relative to when they are overprecise and overextrapolate.

6.5 Heterogeneity Across Subsamples

I revisit the question of whether overprecision and overextrapolation are particularly severe or particularly costly for certain firms by re-estimating my model on subsamples of SBU firms. Managers of small firms that are typically less productive and less well-managed could be more biased, for example. Alternatively, firms with dispersed shareholders and professional managers, including publicly traded firms, could incentivize them to react to short-term fluctuations, as suggested by Terry (2017) and Terry, Whited, and Zakolyukina (2019). The question is whether we see stronger biases and more overreaction in such firms, or some other form of sorting that links firm characteristics and managerial biases.

Table 10 shows parameter estimates and quantifies the gain in firm value from hiring a rational manager for six subsamples of my SBU data. Columns (1) and (2) compare firms with above- and below-median employment. Columns (3) and (4) compare publicly traded and private firms. Columns (5) and (6) compare firms with insider CEOs (who are major shareholders or part of a family of major shareholders) against firms with outside CEOs. (See appendix Figure A.4 for a screenshot of the ownership questions I use to classify firms in columns 3 to 6.)

Table 10 reveals overprecision and overextrapolation are present in all subsamples, suggesting my analysis and methodology have external validity. They also argue against strong sorting mechanisms, whereby some firms successfully avoid hiring biased managers, for example, because their value is more sensitive to manager behavior. Indeed, the degree of overprecision, namely, the ratio between $\tilde{\sigma}$ and σ, is similar in all subsamples at around 40 percent, except for firms with outside CEOs, who appear more overprecise with a ratio of 31 percent. The degree of overextrapolation (the difference between $\tilde{\rho}$ and ρ) is somewhat larger among small firms, firms with outside CEOs, and, to a lesser extent, publicly traded firms. In each of those cases, the firm-value impact of biased managers is modestly larger. These patterns suggest a plausible link between overprecision and overextrapolation, on one hand, and firm productivity, managerial ability, and incentives on the other. But the relatively small differences across subsamples, in particular, between public and private firms for

the two-factor model is near a knife-edge where larger adjustment costs constrain biased managers in a way that makes their policies more similar to rational managers', but smaller adjustment costs also reduce the costs of managerial overreaction.

which incentives and monitoring are almost surely different, suggests these mechanisms are unlikely to explain the prevalence or degree of managerial biases altogether. More broadly, the ubiquity of managerial biases suggest they should be a first-order concern for economists modeling firm behavior under uncertainty. It also alleviates concerns that my quantitative results could be confounded by managers and firms matching on beliefs.

7 Conclusion

This paper uses a new survey of US managers to study how their beliefs affect firm behavior, performance, and macroeconomic outcomes. I make four key contributions.

First, I document new evidence about US managers' beliefs. Whereas managers are not overoptimistic about future sales growth, they underestimate sales growth volatility and overestimate the persistence of business fluctuations; namely, managers are overprecise and they overextrapolate.

Second, I extend a canonical heterogeneous firm model to accommodate a managerial beliefs process and fit it to an array of new data moments, including several that relate beliefs to decisions and outcomes.

Third, my estimated model reveals biased managers overreact to profitability shocks, lowering firm value by 2.1 to 6.8 percent and consumer welfare by 0.5 to 2.3 percent. Overreaction is costly because managers spend too many resources responding to volatile, transitory shifts in profitability, thereby wasting those resources. This insight comes with the broader implication that beliefs could also amplify asset-price and business-cycle fluctuations.

Fourth, I show there are feasible policy instruments that can diminish managerial overreaction and improve consumer welfare. Changing how managers think is not necessary to mitigate the impact of their non-rational beliefs. This analysis highlights the policy relevance of understanding how manager beliefs relate to decisions and other frictions in the economy.

Altogether, my paper stresses the importance of managerial beliefs by showing overprecision and overextrapolation are pervasive and consequential for the micro- and macroeconomy even during periods of macro stability. It also raises questions. For example, why do firms hire and retain, or at least have difficulty identifying (and avoiding hiring) biased managers? Do they actively promote and select managers who exhibit decisiveness and confidence (see, e.g., Goel and Thakor, 2008, Kaplan, Klebanov, and Sorensen, 2012, and Kaplan and Sorensen, 2017)? How do managerial beliefs interact with the business cycle and with massive shocks such as the COVID-19 pandemic? These questions are beyond the scope of my paper, but they carry more weight now that we know more about the micro and macro of managerial beliefs.

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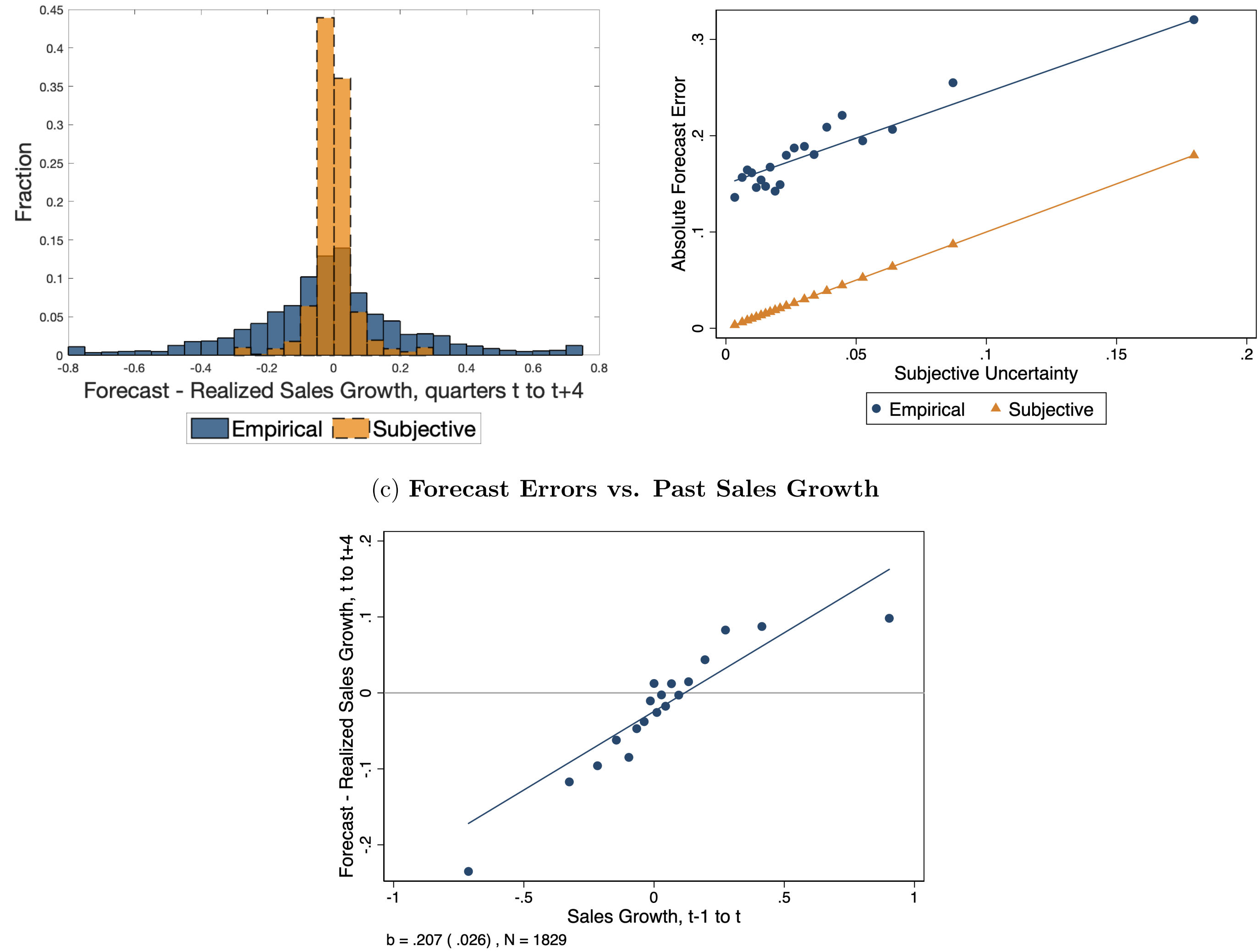
Figure 1: **Features of Managerial Forecast Errors**



(a) **Subjective vs. Empirical Error Distributions**

(b) **Abs. Forecast Errors vs. Uncertainty**

(c) **Forecast Errors vs. Past Sales Growth**

Notes: Figure 1a plots the empirical distribution of forecast errors and the distribution of forecast errors we would see if sales growth realizations were drawn independently from each SBU respondent's subjective probability distribution. I scale both distributions so that the sum of the heights of the bars is equal to one, and fix the width of the bars to 0.05. Figure 1b shows two binned scatter plots of absolute forecast errors against ex-ante subjective uncertainty (measured as the mean absolute deviation of the subjective distribution). The blue circles plot the average empirical absolute forecast error against 20 quantiles of subjective uncertainty, while the orange triangles plot the average forecast error we would expect to see if sales growth realizations were drawn independently from each respondent's subjective probability distribution. Figure 1c shows a binned scatter plot of actual forecast errors for sales growth between t and $t+4$ on the vertical axis against realized sales growth between quarters $t-1$ and t, i.e., in the quarter just prior to the survey response. Data are from the SBU and the sample period includes all months between 10/2014 to 5/2019. A forecast error observation consists of a response in quarter t with a well-formed subjective probability distribution for sales growth, looking 4 quarters ahead, for which I also observe realized sales growth between quarters t and $t+4$. $N = 2,580$ for Figures 1a and 1b, and $N = 1,829$ for Figure 1c.

Figure 2: **Sales Questions in the Survey of Business Uncertainty**

SBU Survey of Business Uncertainty

FEDERAL RESERVE BANK of ATLANTA | CHICAGO BOOTH | Stanford University

For the current quarter, what would you estimate the total dollar value of your **SALES REVENUE** will be?

$ 5,000,000

Looking back, over the last 12 months, what was your approximate percentage **SALES REVENUE** GROWTH rate?

5 %

Next - 2 of 7

SBU Survey of Business Uncertainty

FEDERAL RESERVE BANK of ATLANTA | CHICAGO BOOTH | Stanford University

Looking ahead, from now to four quarters from now, what approximate percentage **SALES REVENUE** growth rate would you assign to each of the following scenarios?

The LOWEST percentage sales revenue growth rate would be about:	-2	%
A LOW percentage sales revenue growth rate would be about:	0	%
A MIDDLE percentage sales revenue growth rate would be about:	4	%
A HIGH percentage sales revenue growth rate would be about:	6	%
The HIGHEST percentage sales revenue growth rate would be about:	10	%

SBU Survey of Business Uncertainty

FEDERAL RESERVE BANK of ATLANTA | CHICAGO BOOTH | Stanford University

Please assign a percentage likelihood to the **SALES REVENUE** growth rates you entered. (Values should sum to 100%)

LOWEST: The likelihood of realizing a **-2%** sales revenue growth rate would be:	10	%
LOW: The likelihood of realizing a **0%** sales revenue growth rate would be:	20	%
MIDDLE: The likelihood of realizing a **4%** sales revenue growth rate would be:	40	%
HIGH: The likelihood of realizing a **6%** sales revenue growth rate would be:	20	%
HIGHEST: The likelihood of realizing a **10%** sales revenue growth rate would be:	10	%
Total	100	%

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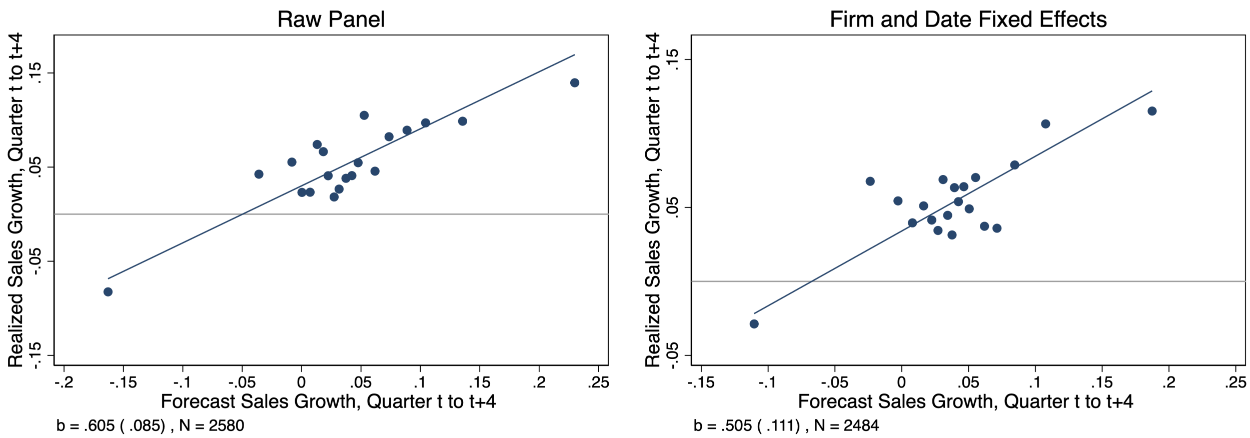
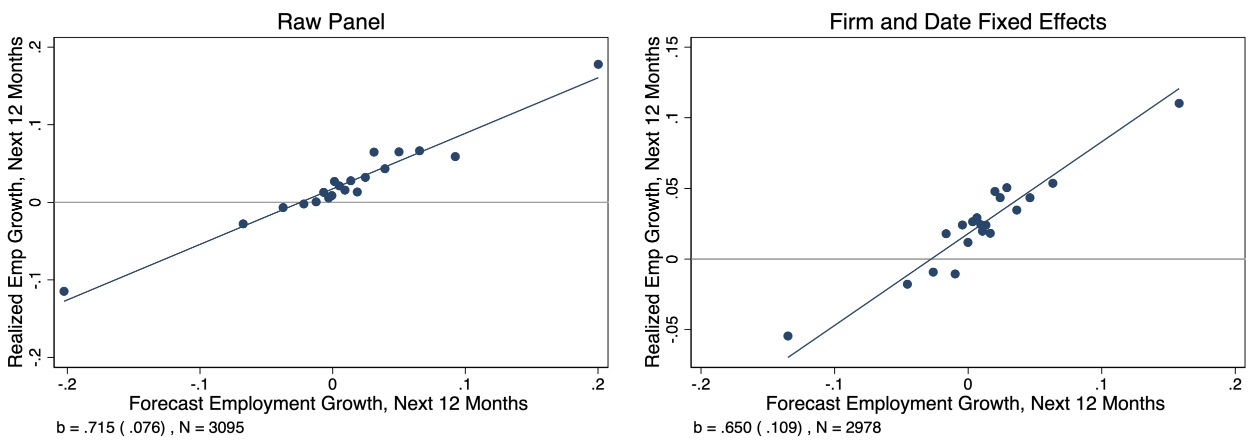
Notes: Sales growth questions in the Survey of Business Uncertainty as they have appeared since September 2016. In months prior to September 2016, the SBU asked for sales growth beliefs in levels rather than growth rates. See the Online Appendix for those earlier questions. The rates of sales growth assigned to the five scenarios and their associated probabilities shown in this example correspond to the mean outcome and probability vectors across all responses between October 2014 and May 2019.

Figure 3: **Sales and Employment Growth Forecasts Predict Outcomes**

(a) **Sales Growth Forecasts Predict Sales Growth**



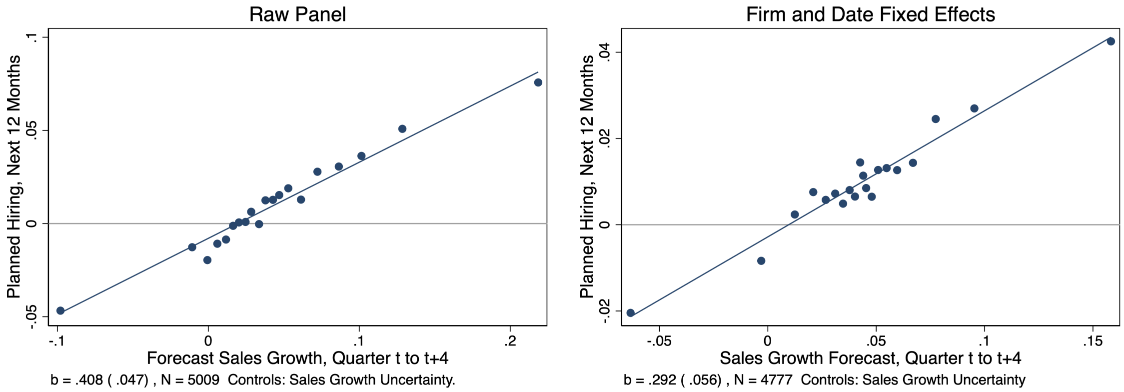
(b) **Hiring Plans Predict Actual Hiring**



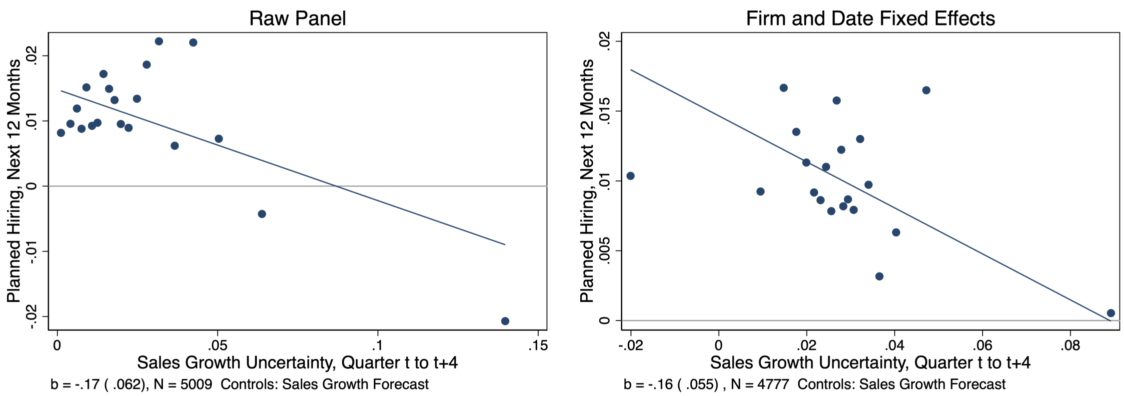
Notes: Figure 3a shows binned scatter plots of managerial sales growth forecasts for the next four quarters on the horizontal axis against realized sales growth over those four quarters. The left panel shows the relationship in the raw panel data, and the right panel controls for firm and date fixed effects. Figure 4b shows managerial hiring plans (forecasts for employment growth) for the next 12 months against actual employment growth. The left panel shows the relationship in the raw panel data, and the right controls for firm and date fixed effects. The reported estimates and standard errors below each figure refer to the underlying microdata regression. Data are from the SBU with the sample period covering 10/2014 to 5/2019. An observation corresponds to an individual firm's response to the SBU questionnaire in a given month.

Figure 4: **Sales Growth Forecasts and Uncertainty Predict Planned Hiring**

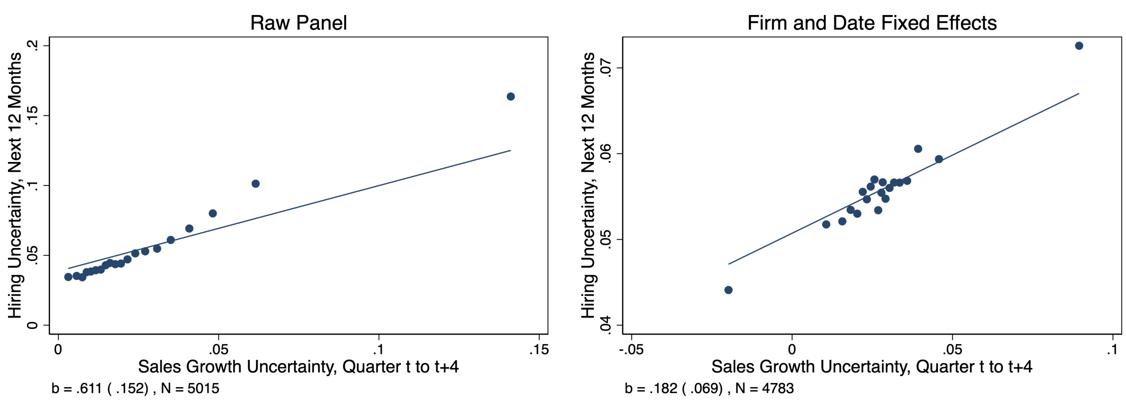
(a) **Sales Forecasts Predict Hiring Plans**



(b) **Sales Uncertainty Predicts Hiring Plans**



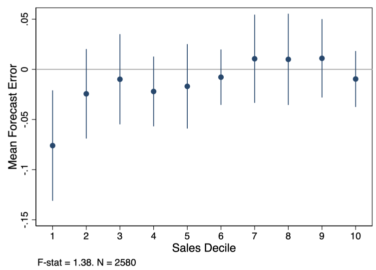
(c) **Sales Uncertainty Predicts Hiring Uncertainty**



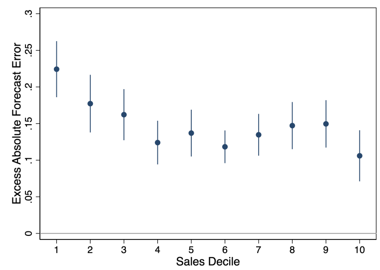
Notes: The top figure shows binned scatter plots of planned hiring over the next 12 months (i.e. the managers' expectation of the firm's employment growth) on the vertical axis against sales growth forecasts for the next four quarters, controlling for sales growth uncertainty over the same horizon. The top-left figure shows the relationship in the raw panel data and the right figure controls for firm and date fixed effects. The middle figure shows binned scatter plots of planned hiring again on the vertical axis, now against the manager's subjective uncertainty for sales growth over the next four quarters, and controls for the sales growth forecast. The middle-left figure shows the relationship in the raw panel data and the middle-right figure controls for firm and date fixed effects. The bottom figure shows binned scatter plots now of hiring uncertainty (managers' subjective mean absolute deviation for employment growth over the next 12 months) against sales growth uncertainty on the horizontal axis. Again, the raw panel data are on the left, and the right controls for firm and date fixed effects. The reported estimates and standard errors refer to each of the underlying population regressions. Data are from the SBU with the sample period covering 10/2014 to 5/2019. An observation corresponds to an individual firm's response to the SBU questionnaire in a given month.

Figure 5: **Heterogeneity in Optimism, Overprecision, and Overextrapolation**

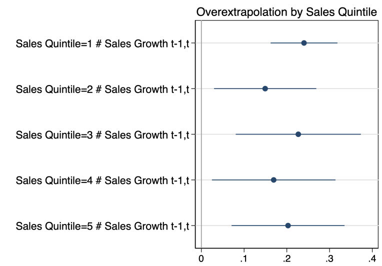
(a) **Optimism by Size**



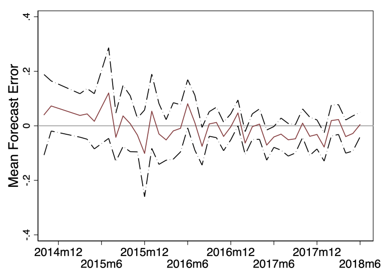
(b) **Overprecision by Size**



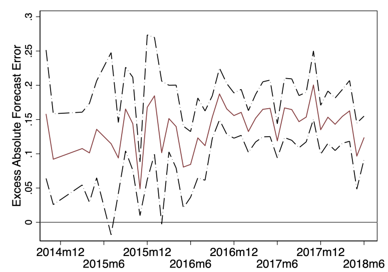
(c) **Overextrapolation by Size**



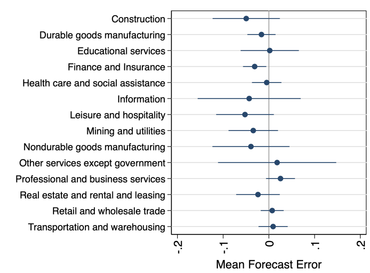
(d) **Optimism Across Time**



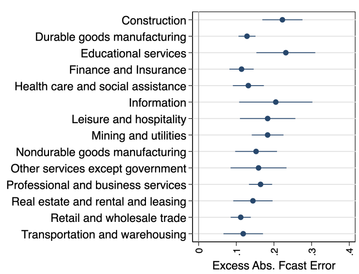
(e) **Overprecision Across Time**



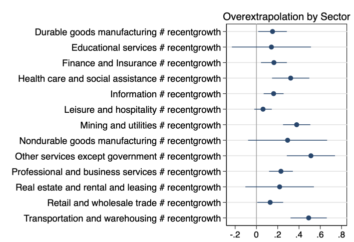
(f) **Optimism by Sector**



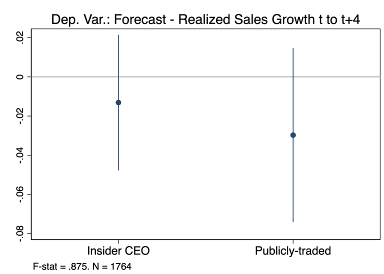
(g) **Overprecision by Sector**



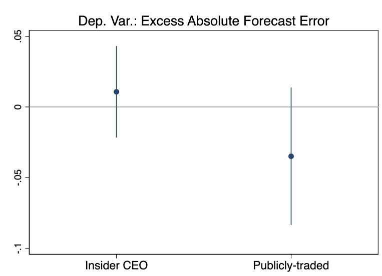
(h) **Overextrap. by Sector**



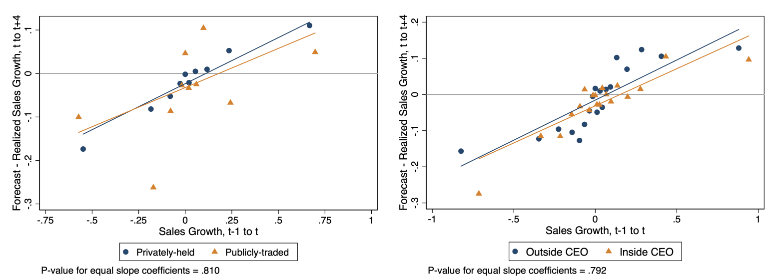
(i) **Optimism by Ownership**



(j) **Overprecision Ownership**



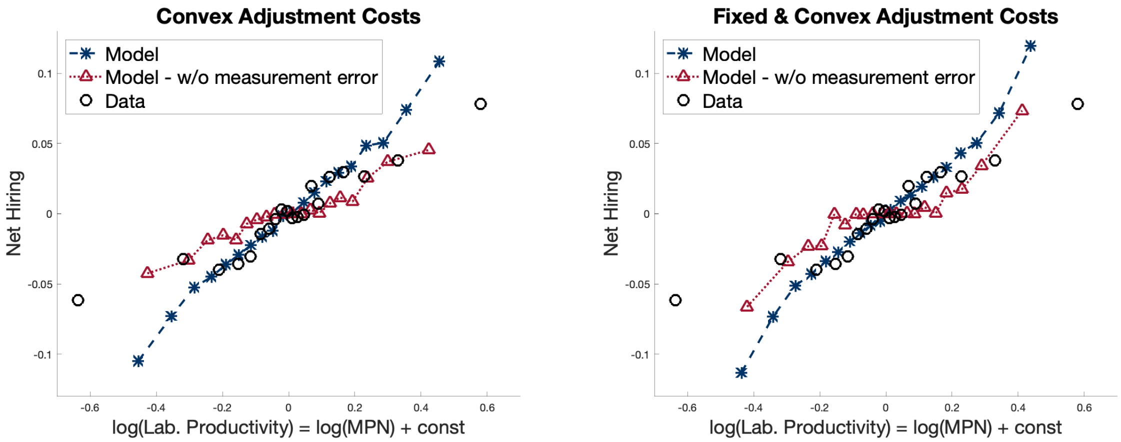
(k) **Overextrapolation by Ownership**



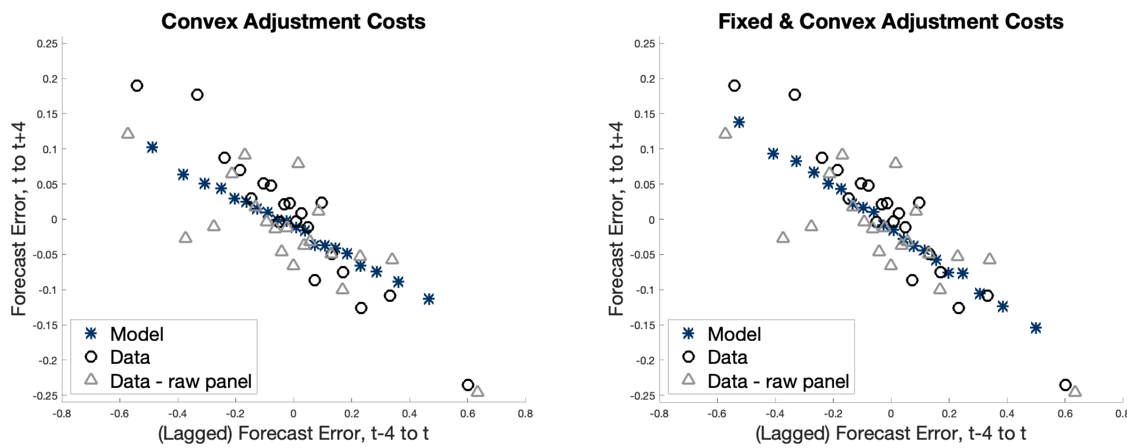
Notes: Figures 5a to 5c compute the mean forecast error, excess absolute forecast error, and the regression slope of forecast errors for sales growth in quarters t to $t+4$ on past sales growth from $t-1$ to t separately for each decile or quintile of firm-level sales distribution. Figures 5d and 5e compute the mean forecast error and excess absolute forecast error for each month. Figures 5f to 5h compute the mean forecast error, excess absolute forecast error, and slope coefficient of forecast errors against past sales for each sector. Figures 5i and 5j report the coefficients from a regression of forecast errors and excess absolute forececast errors on a constant (not reported), an indicator for whether a firm is publicly-traded, and an indicator for whether it has an insider CEOs. Insider CEO firms are those for which the CEO is a major shareholder or is part of a major shareholding family. Figure 5k shows binned scatter plots of forecast-minus-realized sales growth for quarters t to $t+4$ against lagged sales growth in $t-1$ to t, separately for samples of firms that are privately held versus publicly traded, and those with outside versus insider CEOs. Data are from the Survey of Business Uncertainty, with the sample including all forecast error observations concerning sales growth, looking four quarters ahead. Figures 5a to 5j report 95 percent confidence intervals or bands based on firm-clustered standard errors. The sample period includes all months between 10/2014 to 5/2019. A forecast error observation consists of a response in quarter t with a well-formed subjective probability distribution for sales growth, looking 4 quarters ahead, for which I also observe realized sales growth between quarters t and $t+4$.

Figure 6: **Assessing Model Fit: Untargeted Relationships**

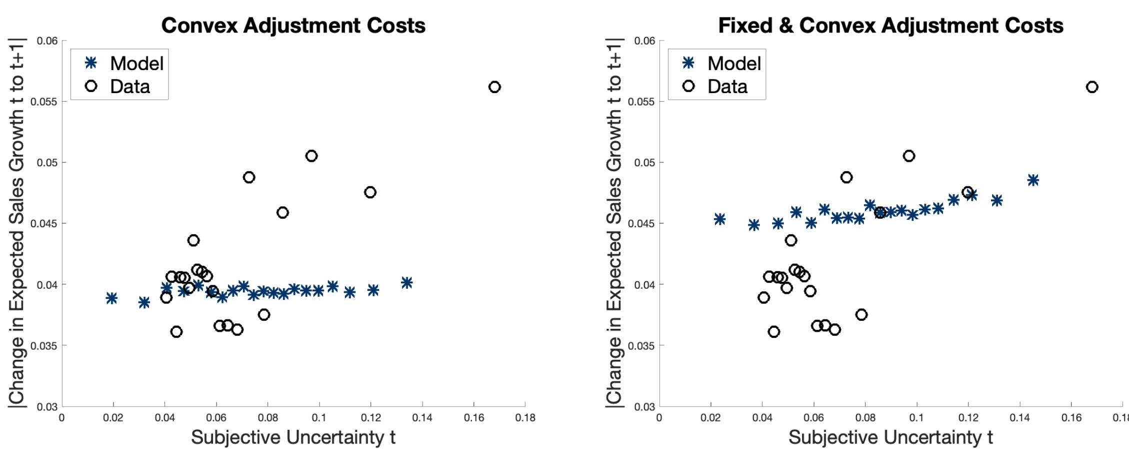
(a) **Hiring vs. Labor Productivity**



(b) **Forecast Error Autocorrelation**

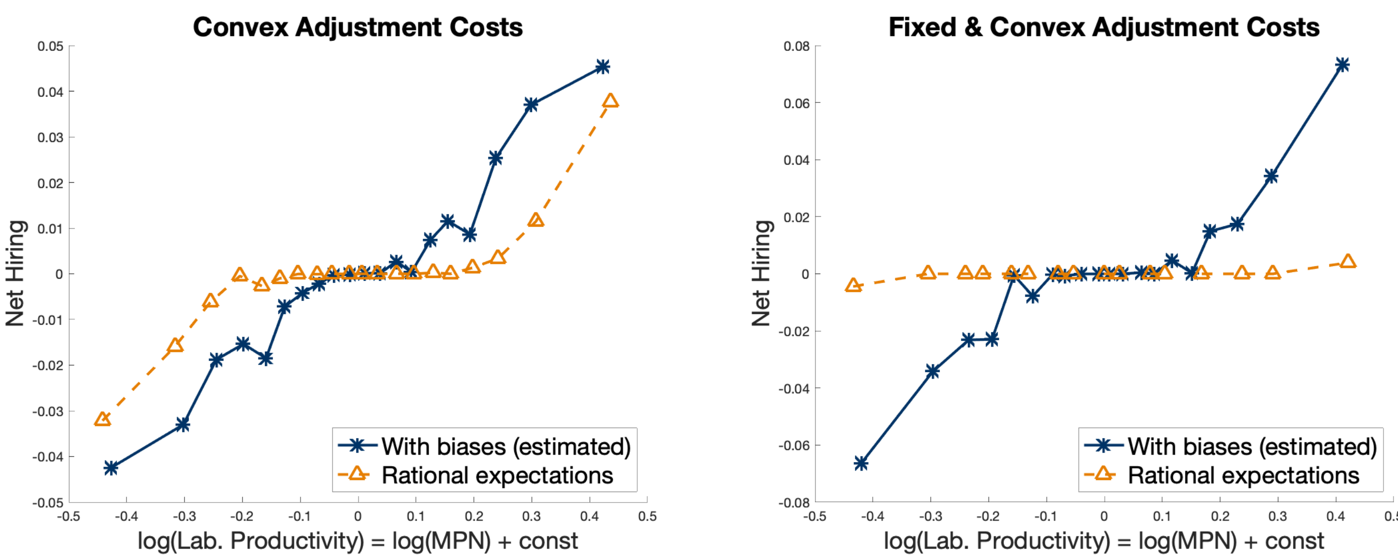


(c) **Updating Expectations vs. Uncertainty**



Notes: The three panels of Figure 6 show binned scatter plots of relationships in the data and the two key specifications of the model that are not directly targeted in the structural estimation. Figure 6a plots demeaned log(labor productivity) against net hiring. Figure 6b shows the autocorrelation of non-overlapping forecast errors. Figure 6c shows uncertainty in quarter t against the absolute change in expected sales growth (looking 4 quarters ahead) between t and $t+1$. To construct each figure in both the model and the data, I first sort the variable on the horizontal axis into 20 quantiles. Then, I compute the mean of both the variables on the vertical and horizontal within each quantile and plot them. Figure 6a shows two versions of the relationship in the model: with and without considering the sales and employment measurement error. All three sub-figures focus on the relationship in the data after removing firm and date fixed effects, to conform with the lack of persistent cross-firm heterogeity in the model. Figure 6b also shows the relationship in the raw panel data, to show it is similarly steep with and without including the firm and date fixed effects.

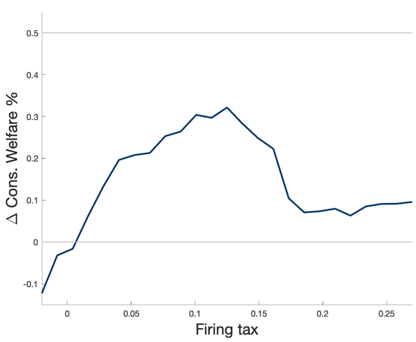
Figure 7: **Biases Encourage Overreaction and Excessive Reallocation**



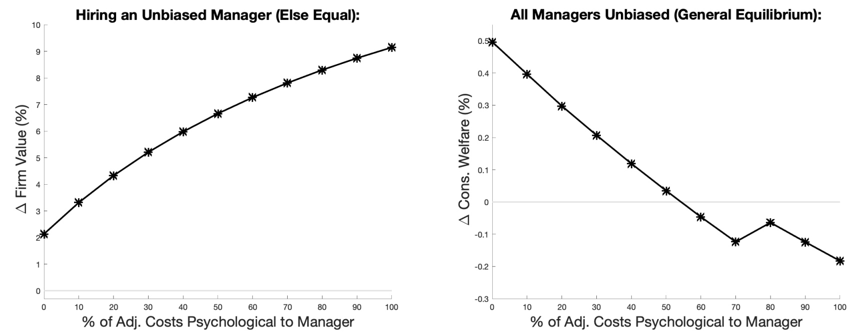
Notes: Each of the above figures shows bin-scatter plots of log(labor productivity) on the horizontal axis and net hiring on the vertical axis: (1) in the estimated model equilibrium with biases, and (2) in a counterfactual equilibrium in which all managers have rational expectations. The figure on the left uses the specification with convex adjustment costs only, and the one on the right uses the specification with both fixed and convex adjustment costs. To focus on the actual choices made by managers in the model, both figures depict the relationship ignoring measurement error in sales and employment. To construct each figure, I sort the stationary distribution of each economy into 20 quantiles by log(labor productivity) ratio and plot the mean labor productivity in each quantile on the horizontal axis against the mean net hiring rate in each quantile on the vertical axis.

Figure 8: **Model Robustness and Extensions**

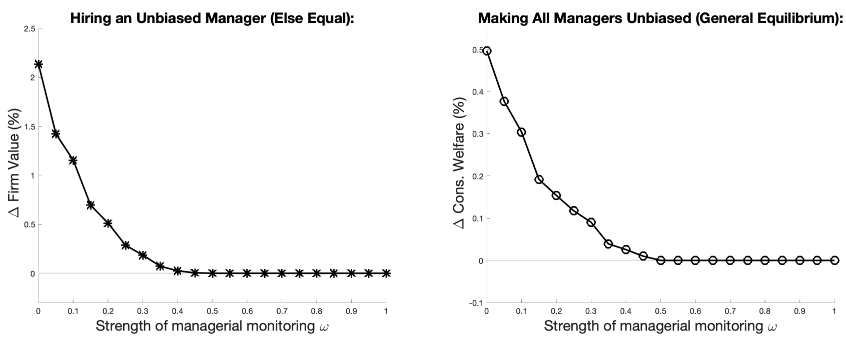
(a) **Taxing Layoffs**



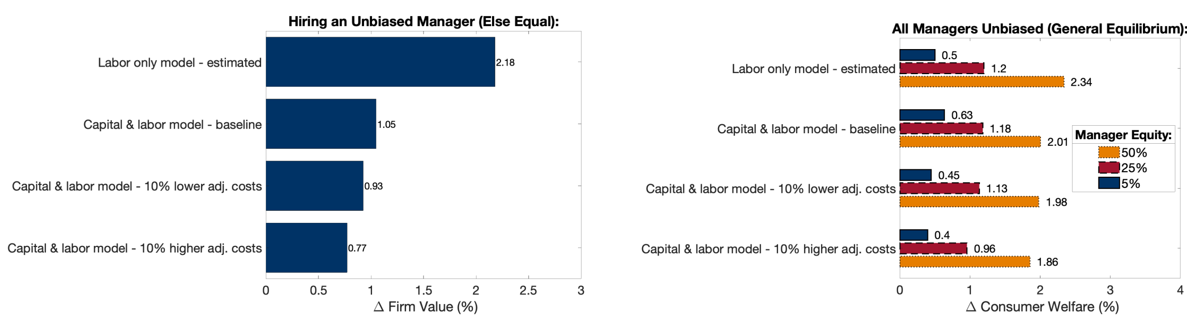
(b) **Agency: Managers Who Prefer a"Quiet Life"**



(c) **Monitoring and the Threat of Managerial Dismissal**



(d) **A Model with Capital and Labor**



Notes: Figure 8a shows how consumer welfare in an economy with biased managers depends on a tax on layoffs outlined in 6.1. Figure 8b shows the firm-value impact of hiring a manager with rational expectations (left) and the welfare impact of moving to an economy in which all managers have rational expectations (right) as a function of the share ψ of adjustments costs that are purely psychological to the manager. See Section 6.2 for details. Figure 8c shows the firm-value impact of hiring a manager with rational expectations (left) and the welfare impact of moving to an economy in which all managers have rational expectations (right), now as a function of how strongly rational shareholders monitor and dismiss managers who deviate from the shareholders' desired policy. See Section 6.3. Figure 8d shows the firm-value impact of hiring a manager with rational expectations (left) and the welfare impact of moving to an economy in which all managers have rational expectations (right) in the baseline labor-only model estimated in the paper as well as in three calibrations of an extended model with capital and labor. See Section 6.4 and Appendix C.3 for details.

Table 1: **Managerial Forecasts and Uncertainty Predict Planned, Current Hiring**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	**Planned Hiring, Next 12 Months**		**Hiring Uncertainty, Next 12 Months**		**Net Employment Growth, Quarter t**	
Forecast Sales Growth, Quarter t to $t+4$	0.408***	0.292***			0.157***	0.120**
	(0.047)	(0.057)			(0.045)	(0.053)
Sales Growth Uncertainty, Quarter t to $t+4$	-0.170***	-0.165***	0.612***	0.182***	-0.003	-0.221***
	(0.063)	(0.055)	(0.152)	(0.070)	(0.072)	(0.084)
Firm FE		Y		Y		Y
Date FE		Y		Y		Y
Observations	5,009	4,777	5,015	4,783	3,930	3,805
R-squared	0.125	0.481	0.192	0.842	0.005	0.152
Within R-squared		0.0652		0.0615		0.00627
Firms	883	651	883	651	643	518

Notes: This table regresses hiring plans and hiring uncertainty for the next 12 months (i.e., employment growth expectations and uncertainty) and current hiring (i.e., net employment growth in quarter t) on year-ahead sales growth forecasts and uncertainty. Columns (1), (3), and (5) estimate the relationship in the raw panel data, and columns (2), (4), and (6) focus on the within-firm relationship by including firm and date (survey wave) fixed effects. All columns report firm-clustered standard errors. Data are from the SBU covering all survey waves between 10/2014 and 5/2019. *** p<0.01, ** p<0.05, * p<0.1

Table 2: **Managers are Not Overoptimistic**

	(1)	(2)	(3)
	Sales Growth		**Forecast Error**
	Forecast	Realized	Forecast - Realized
Unweighted Mean	0.040	0.054	-0.014
Firm-clustered SE	(0.003)	(0.007)	(0.006)
Firm-and-date clustered SE	(0.003)	(0.008)	(0.008)
Obs.	2,580	2,580	2,580
Firms	446	446	446
Employment-weighted Mean	0.039	0.047	-0.007
Firm-clustered SE	(0.003)	(0.012)	(0.012)
Obs.	2,526	2,526	2,526
Firms	437	437	437

Notes: This table shows the mean forecast and realized sales growth, as well as the mean forecast error (= forecast minus realized) for sales growth, looking four quarters ahead. The top panel reports unweighted means as well as firm- and two-way firm-and-date-clustered standard errors. The bottom table reports employment-weighted means and firm-clustered standard errors. Data are from the SBU and sample period includes all months between 10/2014 to 5/2019. A forecast error observation consists of a response in quarter t with a well-formed subjective probability distribution for sales growth, looking 4 quarters ahead, for which I also observe realized sales growth between quarters t and $t+4$.

Table 3: **Managers are Overprecise**

	(1)	(2)	(3)
	Absolute Forecast Error		**Excess Error**
	Empirical	Subjective	Empirical - Subjective
Unweighted Mean	0.183	0.035	0.148
Firm-clustered SE	(0.007)	(0.002)	(0.006)
Firm-and-date-clustered SE	(0.006)	(0.003)	(0.006)
Obs.	2,580	2,580	2,580
Firms	446	446	446
Employment-weighted Mean	0.143	0.023	0.120
Firm-clustered SE	(0.012)	(0.002)	(0.011)
Obs.	2,526	2,526	2,526
Firms	437	437	437

Notes: This table reports the means of empirical absolute forecast errors and subjective absolute forecast errors, as well as the difference between the two, the excess absolute forecast error. A respondent's subjective absolute forecast error is the subjective mean absolute deviation from her forecast. The top panel reports unweighted means as well as firm- and two-way firm-and-date-clustered standard errors. The bottom panel reports employment-weighted means and firm-clustered standard errors. Data are from the SBU and the sample period includes all months between 10/2014 to 5/2019. A forecast error observation consists of a response in quarter t with a well-formed subjective probability distribution for sales growth, looking 4 quarters ahead, for which I also observe realized sales growth between quarters t and $t + 4$.

Table 4: **Managers Overextrapolate**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	**Forecast - Realized Sales Growth, quarter t to $t + 4$**					
Sales Growth,	0.207***	0.173***	0.205***	0.220***	0.232***	0.212***
quarter $t - 1$ to t	(0.026)	(0.059)	(0.026)	(0.029)	(0.029)	(0.041)
Date FE			Y		Y	Y
Date x Sector FE				Y		
Firm FE					Y	Y
Employment-weighted		Y				Y
Observations		1,825	1,829	1,754	1,775	1,774
R-squared		0.043	0.085	0.251	0.359	0.461

Notes: This table regresses managers' forecast minus realized sales growth between quarter t and $t + 4$ on the firm's sales growth between quarters $t - 1$ and t. Robust standard errors in parentheses, clustered by firm. Data are from the SBU and sample period includes all months between 10/2014 to 5/2019. A forecast error observation consists of a response in quarter t with a well-formed subjective probability distribution for sales growth, looking 4 quarters ahead, for which I also observe realized sales growth between quarters t and $t + 4$. *** p<0.01, ** p<0.05, * p<0.1

Table 5: **Externally Calibrated Parameters**

Parameter	Value	Description	Target/Source
q	0.08	Quarterly separation rate	Shimer (2005)
μ	0	Mean $\log(z)$	Normalization
γ	2	Inverse EIS	Hall (2009)
η	2	Inverse Frisch elasticity of lab. supply	Chetty et al. (2011)
β	$0.96^{1/4}$	Household discount factor	Annual Interest Rate of 4%
χ	Several	Disutility of work	Steady-state labor $N^* = 1/3$
θ	0.05 - 0.50	Managers' share of equity	Nikolov and Whited (2014)

Notes: This table reports the values of externally-calibrated parameters and the target or source used to pick the values. I calibrate the household's disutility of work χ targeting a steady-state amount of labor N equal to one third in the baseline equilibrium in which managers are biased. Thus, the value of χ varies across specifications of the model, depending on the adjustment costs and my choice for the managerial equity share θ for a particular simulation. My baseline choice for managerial equity θ is 0.05 (5 percent) following Nikolov and Whited (2014), but also consider 0.25 and 0.50 in Table 9.

Table 6: **Estimated Parameters**

		Estimate (SE)		
		Adjustment costs specification		
Parameter	**Description**	**Convex only**	**Fixed only**	**Fixed & convex**
α	Revenue returns to scale	0.832 (0.007)	0.337 (0.001)	0.875 (0.003)
λ	Quadratic adjustment costs	30.3 (0.446)		14.6 (0.088)
F	Fixed adjustment costs		0.255 (0.007)	0.039 (0.0003)
ρ	True shock persistence	0.856 (0.002)	0.599 (0.003)	0.749 (0.002)
$\tilde{\rho}$	Subjective Shock persistence	0.911 (0.001)	0.916 (0.0001)	0.898 (0.0008)
σ	True shock volatility	0.114 (0.0002)	0.010 (0.0002)	0.137 (0.0002)
$\tilde{\sigma}$	Subjective shock volatility	0.044 (0.0001)	0.028 (0.0001)	0.049 (0.0001)
$\tilde{\mu}$	Subjective shock mean	-0.003 (5.25e-6)	-0.005 (6.07e-6)	-0.003 (2.25e-5)
σ_ξ	Sales, employment measurement error	0.096 (0.0001)	0.083 (0.0003)	0.091(0.0002)
σ_ν	Expectations, uncertainty measurement error	0.029 (0.0001)	0.033 (2.89e-5)	0.031 (4.85e-5)

Notes: This table shows parameter estimates and standard errors obtained by using minimum-distance estimation to estimate three specifications of my model with (1) only convex, (2) only fixed adjustment costs, and (3) hybrid (convex and fixed) adjustment costs. See Table 7 for the target moments in the data and their corresponding model moments in each specification. My estimation procedure uses the inverse firm-level clustered covariance matrix of SBU data moments as a weighting matrix and to construct standard errors via standard asymptotics. I perform the numerical optimization of the econometric objective using a simulated annealing algorithm.

Table 7: **Structural Estimation Results: Data and Model Moments**

		Adjustment costs specification					
		Convex only		Fixed only		Fixed & convex	
Moment	**Data**	**Model**	**T-stat**	**Model**	**T-stat**	**Model**	**T-stat**
Mean(Forecast Error$_{t,t+4}$)	-0.016	-0.011	0.72	-0.017	-0.17	-0.012	0.68
Mean(Excess Absolute Forecast Error$_{t,t+4}$)	0.15	0.13	**-2.74**	0.12	**-4.72**	0.14	-1.57
Cov(Forecast Error$_{t,t+4}$, Sales Growth$_{t-1,t}$)	0.014	0.011	-1.37	0.011	-1.43	0.013	-0.25
Cov(Sales Growth Forecast$_{t,t+4}$, Hiring Plans$_{t,t+4}$)	6.7e-4	4.8e-4	-0.85	0.6e-4	**-2.76**	5.4e-4	-0.60
Cov(Sales Growth Uncertainty$_{t,t+4}$,Hiring Uncertainty$_{t,t+4}$)	2.9e-4	1.4e-4	-1.03	0.3e-4	-1.75	1.9e-4	-0.71
Cov(Net Hiring$_t$, Sales Growth Forecast$_{t,t+4}$)	2.8e-4	0.9e-4	-1.13	1.8e-4	-0.56	2.2e-4	-0.36
Cov(Net Hiring$_t$, Sales Growth Uncertainty$_{t,t+4}$)	-3.7e-4	0.00e-4	1.16	0.0e-4	1.16	0.0e-4	1.18
Cov(Sales Growth Forecast$_{t,t+4}$, Realized Sales Growth$_{t,t+4}$)	1.7e-3	3.3e-3	**2.76**	3.9e-3	**3.78**	4.0e-3	**3.93**
Cov(Hiring Plans$_{t,t+4}$, Realized Employment Growth$_{t,t+4}$)	2.2e-3	2.5e-3	0.46	0.3e-3	**-2.77**	2.1e-3	-0.17
Cov(Sales Growth Uncertainty$_{t,t+4}$, Sales Abs. Forecast Error$_{t,t+4}$)	3.4e-4	0.5e-4	-1.76	0.4e-4	-1.80	1.6e-4	-1.08
Cov(Hiring Uncertainty$_{t,t+4}$, Hiring Abs. Forecast Error$_{t,t+4}$)	2.8e-4	3.5e-4	0.58	3.6e-4	0.64	4.3e-4	1.28
Var(Sales Growth Forecast$_{t,t+4}$)	3.6e-3	3.3e-3	-0.74	2.5e-3	**-2.96**	3.4e-3	-0.54
Var(Hiring Plans$_{t,t+4}$)	3.6e-3	3.6e-3	0.00	1.3e-3	**-5.11**	3.4e-3	-0.31
Var(Sales Growth Uncertainty$_{t,t+4}$)	1.5e-3	0.9e-3	-0.72	1.1e-3	-0.46	1.1e-3	-0.56
Var(Hiring Uncertainty$_{t,t+4}$)	1.1e-3	1.1e-3	-0.04	1.3e-3	0.41	1.3e-3	0.47
Var(Sales Growth$_{t-1,t}$)	0.059	0.032	**-6.75**	0.027	**-8.21**	0.037	**-5.61**
Var(Net Hiring$_t$)	0.018	0.019	0.87	0.015	-1.44	0.018	0.00
Cov(Net Hiring$_t$, Sales Growth$_{t-1,t}$)	2.1e-3	1.4e-3	-0.75	0.6e-3	-1.58	2.2e-3	0.11
Cov(Sales Growth$_{t,t+4}$,Sales Growth$_{t-1,t}$)	-0.014	-0.011	1.53	-0.012	0.69	-0.013	0.35
Econometric objective		94.0		204.7		87.1	

Notes: This table shows the target moments from the SBU data I use in the minimum-distance estimation of the model from Section 3 in the paper. The table also reports the corresponding model moments in the estimated solution of three model specifications with (1) convex only, (2) fixed only, and (3) hybrid (convex and fixed) adjustment costs, and the t-statistic for the null hypothesis that a pair of corresponding model and data moments are equal. T-statistics that imply a pair of moments are statistically significantly different with 95 percent confidence are in **bold**. The bottom line of the table reports the minimum value of the econometric objective obtained in each of the three minimum distance-estimations. I estimate all data moments using SBU data with a sample period covering 10/2014 to 5/2019. I compute target variances and covariances using only within-firm variation, namely, after purging variation explained by firm and date (calendar quarter) fixed effects. I compute model moments numerically from the stationary distribution of firms in the model. My estimation procedure uses the inverse firm-level clustered covariance matrix of SBU data moments as a weighting matrix. The numerical optimization of the econometric objective uses a simulated annealing algorithm.

Table 8: **Eliminating Managerial Biases Increases Firm Value**

Adjustment costs specification	**Counterfactual**	**Δ True Firm Value (%)**
Convex only	$\tilde{\sigma} = \sigma$ only	1.40
	$\tilde{\rho} = \rho$ only	0.81
	$\tilde{\rho} = \rho$, and $\tilde{\sigma} = \sigma$	1.96
	$\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, and $\tilde{\mu} = \mu$	2.13
Fixed & convex	$\tilde{\sigma} = \sigma$ only	0.87
	$\tilde{\rho} = \rho$ only	5.44
	$\tilde{\rho} = \rho$, and $\tilde{\sigma} = \sigma$	6.61
	$\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, and $\tilde{\mu} = \mu$	6.83

Notes: This table shows the average change in value a firm would obtain if it hired manager who uses the beliefs process specified in each row, relative to a manager who uses the beliefs process estimated in each specification of the model. At each point in the (z, n) state space of the model, I compute the objective value generated by the biased manager in my estimated model as well as the objective value generated by a counterfactual manager whose beliefs corresponds to the specified counterfactual. Then, I compute the average percent gain in firm value under the stationary distribution of firms in each specification of the estimated model.

Table 9: **Managerial Biases and Aggregate Outcomes**

(a) **Welfare and GDP are Higher Without Biases**

Adjustment costs specification	**Managerial equity share θ**	Δ Consumer Welfare %	ΔY %
Convex only	0.05	0.50	1.07
	0.25	1.20	0.83
	0.50	2.34	0.31
Fixed & convex	0.05	1.10	0.90
	0.25	1.59	0.90
	0.50	2.23	0.02

(b) **Biases Encourage Excessive Reallocation**

Adjustment costs specification	**Economy**	Empl. vol. $\sigma(\log n)$	Measured empl. vol. $\sqrt{\sigma^2(\log n)+\sigma_\xi^2}$	100 $\times$Realloc.	$\sigma(\log(MPN))$	$AC/Y \times 100$
Convex only	With Biases	0.222	0.242	1.41	0.207	23.7
	No Biases	0.148	0.176	0.57	0.215	22.5
	Δ	**-33.4%**	**-27.0%**	**-59.6%**	**3.45%**	**-1.20 p.p**
Fixed & convex	With Biases	0.195	0.216	1.51	0.201	12.3
	No Biases	0.035	0.098	.042	0.208	10.0
	Δ	**-82.2%**	**-54.8%**	**-97.2%**	**3.46%**	**-2.23 p.p.**

(c) **Effects of Overconfidence vs. Overextrapolation vs. Pessimism**

Adjustment costs specification	**Counterfactual**	Δ C. Welfare %	$\Delta\sigma(\log(MPN))$ %
Convex only	$\tilde{\sigma}=\sigma$ only	0.28	0.72
	$\tilde{\rho}=\rho$ only	0.22	3.59
	$\tilde{\rho}=\rho$ and $\tilde{\sigma}=\sigma$	0.39	3.56
	$\tilde{\rho}=\rho$, $\tilde{\sigma}=\sigma$, and $\tilde{\mu}=\mu$	0.50	3.45
Fixed & convex	$\tilde{\sigma}=\sigma$ only	0.32	0.52
	$\tilde{\rho}=\rho$ only	0.94	3.48
	$\tilde{\rho}=\rho$ and $\tilde{\sigma}=\sigma$	1.06	3.41
	$\tilde{\rho}=\rho$, $\tilde{\sigma}=\sigma$, and $\tilde{\mu}=\mu$	1.10	3.46

Notes: The top table shows the difference in the household's consumption-equivalent welfare and aggregate output (GDP) in the long-run equilibrium of an economy in which managers have rational expectations relative to the long-run equilibrium of my baseline economy with biased managers. The second table computes steady-state values of employment volatility, the rate of reallocation (defined as the amount of job creation and destruction in the economy as in Davis and Haltiwanger (1992)), dispersion in the marginal product of labor, and aggregate adjustment costs paid as a share of GDP in both economies. The bottom table shows the difference in consumption-equivalent welfare and dispersion in the marginal product of labor between an economy in which managers use a beliefs process as specified in each row and my baseline economy with biased managers. The middle and bottom tables focus on a calibration of the economy with managerial equity θ equal to 5 percent.

Table 10: **Subsample Heterogeneity**

		Sample					
Parameter		**Small**	**Large**	**Publicly traded**	**Privately held**	**Inside CEO**	**Outside CEO**
Revenue returns to scale	α	0.749 (0.017)	0.791 (0.008)	0.895 (0.035)	0.876 (0.012)	0.587 (0.015)	0.751 (0.006)
Quadratic adjustment costs	λ	30.4 (0.755)	24.0 (1.20)	20.0 (4.80)	30.3 (2.26)	16.0 (0.256)	28.1 (0.336)
True shock persistence	ρ	0.761 (0.002)	0.862 (0.002)	0.857 (0.010)	0.841 (0.005)	0.885 (0.002)	0.738 (0.005)
Subjective shock persistence	$\tilde{\rho}$	0.922 (0.002)	0.911 (0.001)	0.925 (0.004)	0.905 (0.004)	0.923 (0.002)	0.935 (0.0008)
True shock volatility	σ	0.150 (0.001)	0.095 (0.0003)	0.025 (0.0004)	0.115 (0.0006)	0.108 (0.0006)	0.077 (0.0008)
Subjective shock volatility	$\tilde{\sigma}$	0.062 (0.0006)	0.039 (0.0002)	0.009 (0.0001)	0.045 (0.0004)	0.048 (0.0004)	0.024 (0.002)
Subjective shock mean	$\tilde{\mu}$	-0.003 (1.31e-5)	-1.19e-5 (3.93e-7)	-0.005 (1.46e-5)	-0.004 (6.98e-6)	-0.0050 (2.03e-5)	-0.006 (1.47e-5)
Sales, employment meas. err.	σ_{ξ}	0.103 (0.0005)	0.083 (0.0001)	0.041 (0.0003)	0.106 (0.0002)	0.112 (0.0001)	0.049 (0.0008)
Expectations, uncertainty meas. err.	σ_{ν}	0.035 (0.0001)	0.017 (0.0001)	0.005 (0.0002)	0.028 (0.0001)	0.031 (0.0001)	0.004 (0.0007)
		Counterfactual: $\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, and $\tilde{\mu} = \mu$					
Δ True Firm Value (%)		3.02	0.64	4.74	4.24	0.35	3.11

Notes: This table reports parameter estimates, standard errors, and the average increase in firm value that would arise from replacing a biased manager with another who has rational expectations for the following subsamples of the SBU: (1) small firms, with below median employment; (2) large firms, with above-median employment; (3) publicly traded, firms; (4) privately held firms; (5) firms with an insider CEO, who is a a major shareholder or a member of a major shareholding family; and (6) firms with an outside CEO (i.e., without an insider CEO). Data on whether firms are publicly-traded or not and on whether the CEO is an insider come from special questions that were part of the February and March 2019 SBU survey waves (see Appendix Figure A.4 for a screenshot of the relevant questions).

A Appendix Tables and Figures

Table A.1: **SBU Summary Statistics**

Variable	(1) **N**	(2) **mean**	(3) **sd**	(4) **p25**	(5) **p50**	(6) **p75**
Expected Employment Growth, Next 12 Months	6,442	0.009	0.081	-0.011	0.007	0.034
Uncertainty about Employment Growth, Next 12 Months	6,445	0.057	0.064	0.022	0.038	0.065
Expected Sales Growth, Next 4 Quarters	6,541	0.041	0.081	0.011	0.036	0.068
Uncertainty about Sales Growth, Next 4 Quarters	6,542	0.045	0.049	0.016	0.028	0.053
Realized Employment Growth, Next 12 Months	3,249	0.025	0.166	-0.043	0.014	0.087
Realized Sales Growth, Next Four Quarters	2,633	0.053	0.261	-0.057	0.050	0.178
Forecast Error for Sales Growth, Next 4 Quarters	2,580	-0.014	0.253	-0.140	-0.013	0.099
Sales, Current Quarter	6,729	36.3	108.9	2.75	7.5	21.7
Current Employment	7,720	410.20	1005.65	61	142	300
Sales Growth, Past Quarter	4,520	0.012	0.362	-0.095	0.000	0.113
Employment Growth (i.e. Net Hiring), Past Quarter	4,494	0.005	0.144	-0.029	0.000	0.038
Reported Employment Growth, Past 12 Months	6,801	0.021	0.123	-0.018	0.018	0.069
Publicly-traded	8,025	0.112	0.315	0	0	0
Inside CEO	7.957	0.580	0.494	0	1	1

Notes: This table shows summary statistics for key variables from the Survey of Business Uncertainty, pooling responses from all managers and survey waves between 10/2014 and 5/2019. Expectations and uncertainty are the mean and mean absolute deviation of managers' subjective distribution as reported in the SBU. Forecast errors are the manager's expectation, less the actual sales growth measured over the next four quarters. I compute all growth rates by normalizing the change by the average of the starting and ending values. All variables are winsorized at the 1st and 99th percentiles.

Table A.2: **Managerial Forecasts Have Predictive Power**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	**Realized Sales Growth, t to $t+4$**			**Actual Hiring, t to $t+4$**		
Sales Growth Forecast, t to $t+4$		0.873***	0.716***			
		(0.144)	(0.242)			
Forecast (Planned) Hiring, t to $t+4$					0.865***	0.764***
					(0.177)	(0.095)
Sales Growth, $t-1$ to t	0.002	-0.007		0.041**	0.023*	
	(0.015)	(0.014)		(0.017)	(0.013)	
Net Hiring, t	0.044	0.045		-0.103*	-0.071*	
	(0.049)	(0.042)		(0.055)	(0.037)	
log(Cap. Expenditures), t	-0.066***	-0.050***		0.001	0.000	
	(0.022)	(0.017)		(0.017)	(0.014)	
log(Employees), t	-0.019**	-0.016**		0.001	-0.005	
	(0.008)	(0.007)		(0.006)	(0.005)	
Industry FE (14)	Y	Y		Y	Y	
Region FE (9)	Y	Y		Y	Y	
Age FE (22)	Y	Y		Y	Y	
Observations	951	951	1,906	813	813	2,190
Within R-squared	0.042	0.145		0.0197	0.214	
R-squared	0.327	0.400	0.166	0.151	0.319	0.167

Notes: Columns (1) to (3) regress actual sales growth between quarters t and t+4 on information available in the quarter of the forecast. Columns (4) to (6) do the same for actual net hiring between t and t+4. I respectively include the respondent's forecast for sales growth or net hiring to show it has significant predictive power and its inclusion increases the marginal R-squared . I weight regressions by measures of accuracy for realized sales growth and actual hiring. Standard errors are in parentheses, clustered by firm. Data are from the SBU covering 10/2014 to 5/2019 collapsed to quarterly frequency. *** p<0.01, ** p<0.05, * p<0.1

Table A.3: **Optimism, Overprecision, and Overextrapolation and Survey Experience**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Phenomenon:	**Optimism/Pessimism**			**Overprecision**			**Overextrapolation**		
Dependent Variable	**Forecast - Realized Sales Growth qtr. t to $t+4$**			**Excess Abs. Forecast Error qtr. t to $t+4$**			**Forecast - Realized Sales Growth qtr. t to $t+4$**		
No. of prev. responses		-0.001	-0.001		0.000	0.000		-0.000	0.004
		(0.001)	(0.005)		(0.001)	(0.003)		(0.001)	(0.006)
Past sales growth							0.207***	0.190***	0.145**
							(0.026)	(0.048)	(0.058)
Past sales growth × No. of prev. responses								0.001	0.006*
								(0.003)	(0.003)
Constant	-0.014**			0.148***			-0.024***		
	(0.006)			(0.006)			(0.008)		
Date FE		Y	Y		Y	Y		Y	Y
Firm FE			Y			Y			Y
Observations	2,580	2,580	2,484	2,580	2,580	2,484	1,829	1,829	1,775
Firms	446	446	350	446	446	350	329	329	275
R-squared	-0.000	0.022	0.246	-0.000	0.020	0.366	0.061	0.085	0.362
Within R-squared			1.24e-05			9.15e-07			0.0978

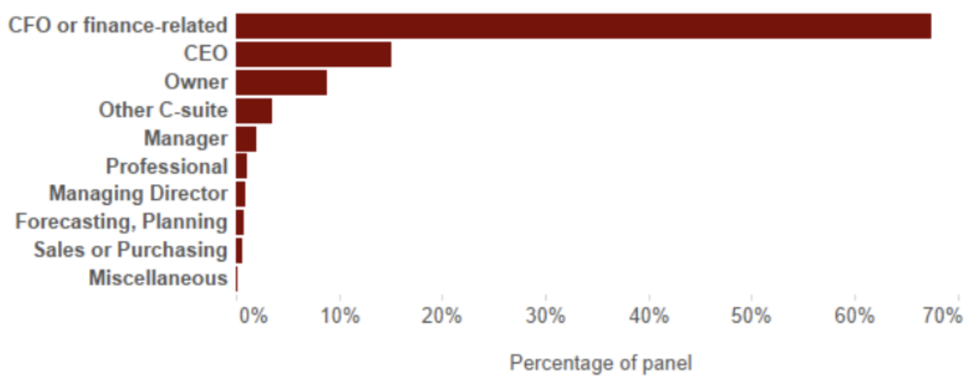
Notes: Columns (1) regresses the forecast-minus-realized sales growth covering quarters t to $t+4$ for firm i in a given month on a constant. Column (2) adds the number of previous responses made by the firm prior to the current survey month and date (i.e., survey wave) fixed effects. Column (3) adds firm fixed effects, dropping singleton observations. Columns (4) to (6) repeat the exercise from (1) to (3) but now using the excess absolute forecast error (i.e., the difference between the firm's actual absolute forecast error for sales growth from quarter t to $t+4$ and its subjective absolute forecast error or subjective uncertainty). Column (7) regresses forecast-minus-realized sales growth covering quarters t to $t+4$ on the firm's past sales growth from quarter $t-1$ to t. Column (8) adds date (i.e,. survey wave) fixed effects, the number of previous survey responses and, the interaction between past sales growth and the number of previous survey responses. Column (9) adds firm fixed effects. In all columns, the number of previous responses is censored at 30. Firm-clustered robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.4: **Change in Labor Market Equilibrium from Eliminating Managerial Biases**

Adjustment costs specification	**Managerial equity share** θ	Δ Consumer Welfare %	ΔY %	ΔN %	Δ Wage %
Convex only	0.05	0.50	1.07	1.00	4.86
	0.25	1.20	0.82	0.70	4.94
	0.50	2.34	0.30	0.04	5.26
Fixed & convex	0.05	1.10	0.90	-0.11	3.78
	0.25	1.59	0.90	-0.11	3.78
	0.50	2.23	0.02	-1.12	3.79

Notes: This table expands on Table 9a by reporting additional statistics about the economy-wide labor market equilibrium in counterfactual economies in which managers have rational expectations, relative to the baseline economy in which managers are biased.

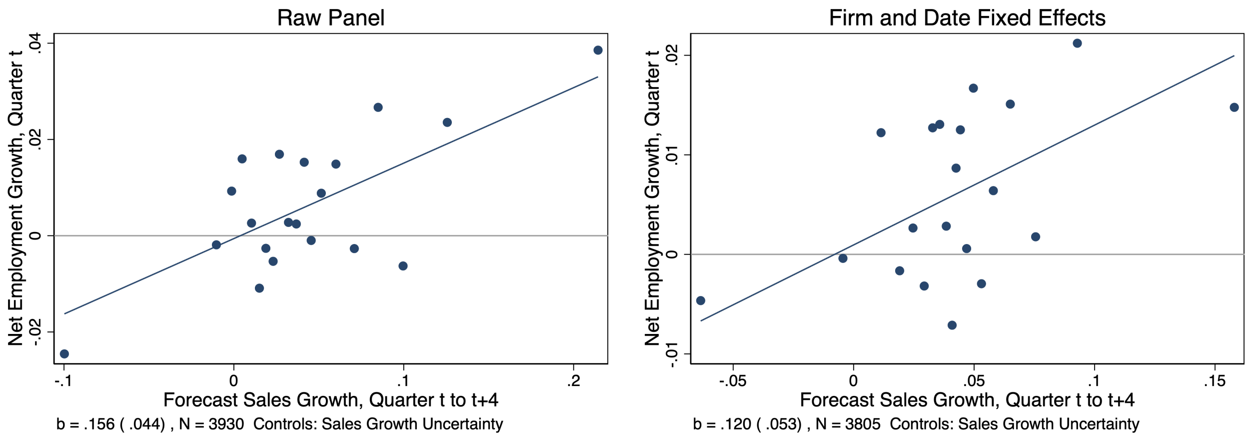
Figure A.1: **SBU Respondents are Primarily CFOs and CEOs**



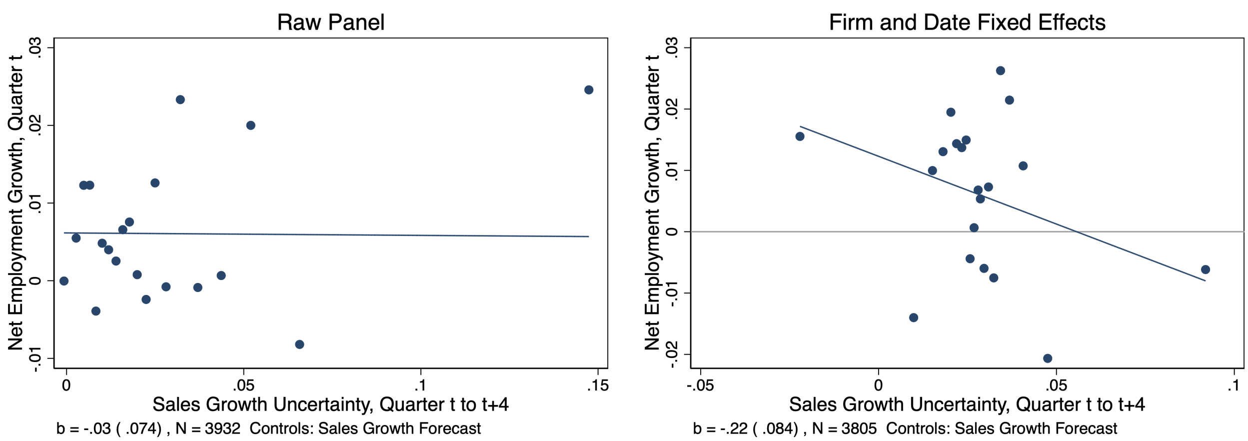
Notes: This figure shows the share of SBU panel memebers whose job title falls into each of the following categories as of July 2018.

Figure A.2: **Sales Growth Forecasts and Uncertainty Predict Current Hiring**

(a) **Sales Growth Forecasts Predict Hiring Plans**

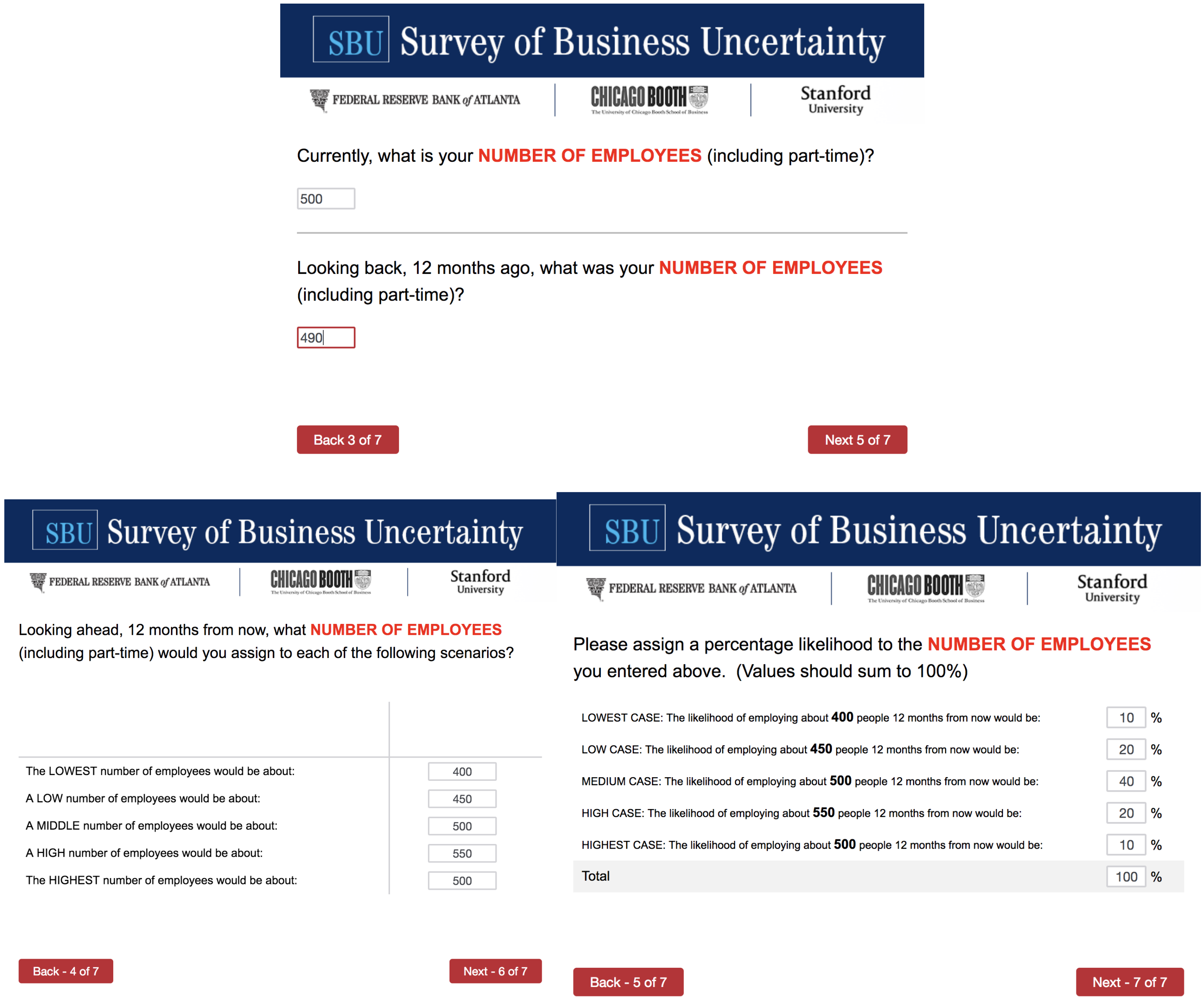


(b) **Sales Growth Forecasts Predict Hiring Plans**



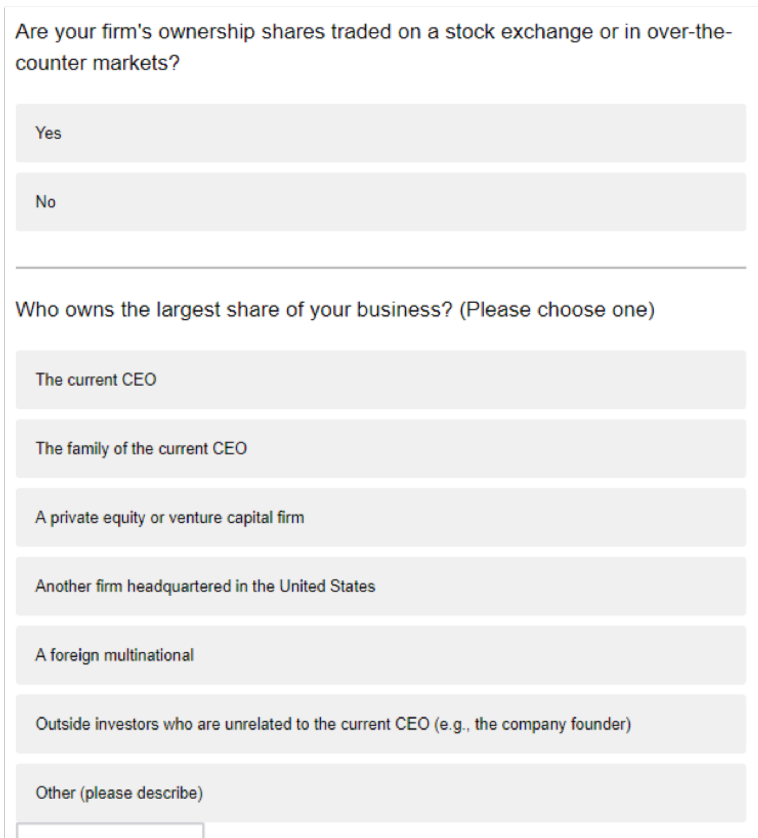
Notes: Figure A.2a shows binned scatter plots of managerial sales growth forecasts for the next four quarters on the horizontal axis against the firm's current net hiring (the firm's employment growth relative to the previous quarter) on the vertical axis. The left panel shows the relationship in the raw panel data, and the top right controls for firm and date fixed effects. Figure A.2b shows a binned scatter plot of managerial sales growth uncertainty over the next four quarters again against current net hiring. Again, the bottom left shows the relationship in the raw panel data, and the bottom right controls for firm and date fixed effects. The reported estimates and standard errors refer to the underlying regressions in the microdata. Data are from the SBU with the sample period covering 10/2014 to 5/2019. An observation corresponds to an individual firm's response to the SBU questionnaire in a given month.

Figure A.3: **SBU Questions About Employment**



Notes: This figure shows the questions about current employment and beliefs about future employment in the Survey of Business Uncertainty.

Figure A.4: **SBU Ownership Questions**



Are your firm's ownership shares traded on a stock exchange or in over-the-counter markets?

Yes

No

Who owns the largest share of your business? (Please choose one)

The current CEO

The family of the current CEO

A private equity or venture capital firm

Another firm headquartered in the United States

A foreign multinational

Outside investors who are unrelated to the current CEO (e.g., the company founder)

Other (please describe)

Notes: This figure shows the SBU's special questions on firm ownership fielded in February and March 2019. I classify a firm as publicly traded if it responds "yes" to the top question about whether its shares are traded on a stock exchange or in over-the-counter markets. I classify a firm as having an "insider CEO" if its response to the second question indicates that the current CEO or the family of the current CEO owns the largest share of the business. Additionally, I classify firms as having an "insider CEO" if the response to the bottom question is "Other" but the explanation indicates that the major shareholders are involved in the business, for example if a small number of partners who own equal shares of the business.

B Measurement Error and Model Moments

For estimation of the model in Section 4.2, I assume there is measurement error in the level of sales and employment that is distributed i.i.d. $\log \mathcal{N}(0, \sigma_\xi^2)$. Similarly, I assume managerial expectations and uncertainty about future sales and employment are measured with i.i.d. error distributed $\mathcal{N}(0, \sigma_\nu^2)$. Thus, the following model moments that I use in the structural estimation procedure are affected by the presence of measurement error:

- The measured variance of sales growth between $t-1$ and t is: $Var(\Delta y_t) + 2\sigma_\xi^2$.
- The measured variance of employment growth in t (i.e., net hiring in t) is: $Var(\Delta n_{t+1}) + 2\sigma_\xi^2$.
- The measured variances of sales growth forecasts for t to $t+4$ and hiring plans for t to $t+4$ become: $Var\left(\tilde{\mathbf{E}}[\Delta y_{t,t+4}]\right) + \sigma_\nu^2$ and $Var\left(\tilde{\mathbf{E}}[\Delta n_{t+1,t+5}]\right) + \sigma_\nu^2$.
- The measured variances of sales growth uncertainty for t to $t+4$ and hiring uncertainty for t to $t+4$ become: $Var\left(\widetilde{\mathbf{MAD}}[\Delta y_{t,t+4}]\right) + \sigma_\nu^2$ and $Var\left(\widetilde{\mathbf{MAD}}[\Delta n_{t+1,t+5}]\right) + \sigma_\nu^2$.
- The covariance between lagged sales growth from $t-1$ to t and sales growth from t to $t+4$ becomes $Cov(\Delta y_t, \Delta y_{t,t+4}) - \sigma_\xi^2$, and, similarly, the covariance between lagged sales and the subsequent forecast error becomes $Cov(\Delta y_t, \tilde{\mathbf{E}}[\Delta y_{t,t+4}] - \Delta y_{t,t+4}) + \sigma_\xi^2$.
- The mean excess absolute forecast error is amplified by the errors in measured sales and subjective uncertainty. Assuming realized sales growth between t and $t+4$, $\Delta y_{t,t+4}$, and the errors are approximately jointly normally distributed, I correct the mean excess absolute forecast error as follows:

  $$- \; Mean\left(\left|\tilde{\mathbf{E}}[\Delta y_{t,t+4}] - \Delta y_{t,t+4}\right| \cdot \sqrt{1 + \frac{2\sigma_\xi^2 + \sigma_\nu^2}{Var\left(\tilde{\mathbf{E}}[\Delta y_{t,t+4}] - \Delta y_{t,t+4}\right)}} - \widetilde{\mathbf{MAD}}[\Delta y_{t,t+4}]\right).$$

- Finally, the covariances between sales growth uncertainty and sales growth absolute forecast errors, as well as the covariance between hiring uncertainty and hiring absolute forecast errors are amplified by the error in measured sales and employment:

  $$- \; Cov\left(\widetilde{\mathbf{MAD}}[\Delta y_{t,t+4}], \left|\tilde{\mathbf{E}}[\Delta y_{t,t+4}] - \Delta y_{t,t+4}\right|\right) \cdot \sqrt{1 + \frac{2\sigma_\xi^2}{Var\left(\tilde{\mathbf{E}}[\Delta y_{t,t+4}] - \Delta y_{t,t+4}\right)}}$$

  $$- \; Cov\left(\widetilde{\mathbf{MAD}}[\Delta n_{t+1,t+5}], \left|\tilde{\mathbf{E}}[\Delta n_{t+1,t+5}] - \Delta n_{t+1,t+5}\right|\right) \cdot \sqrt{1 + \frac{2\sigma_\xi^2}{Var\left(\tilde{\mathbf{E}}[\Delta n_{t+1,t+5}] - \Delta n_{t+1,t+5}\right)}}.$$

C Model Robustness and Extensions Details

C.1 Taxing Layoffs: Government and Household Budget Constraints

When the government taxes firms that lay off workers (see Section 6.1 and specifically equation 11), it obtains tax revenue given by

$$T_t \;\; = \;\; = \tau_f \int_{\mathcal{Z}\times\mathcal{N}} w_t n_t \mathbf{1}(n_{t+1} < n)\phi(z,n)\mathrm{d}z\mathrm{d}n,$$

which aggregates over the two firm-level state variables (profitability z and labor n). The government levies the tax only on firms laying off workers on net (i.e., for which n_{t+1} is less than n_t) and the tax equals a rate τ_f of the wage bill.

I assume the government keeps a balanced budget, so it transfers all the tax revenue back to the representative household. The household budget constraint then becomes:

$$C_t + B_{t+1} \;\; = \;\; w_t N_t + (1+r_t)B_t + \Pi_t + T_t.$$

C.2 Monitoring and Managerial Dismissal: Details

I parameterize the probability that shareholders dismiss a manager who chooses an amount of labor n_{t+1} for next period, given the firm has current profitability z_t and labor n_t as follows:

$$\Omega(z_t, n_t, n_{t+1}; \omega) \;\; = \;\; \min\left\{\omega \cdot \left|\frac{\kappa^s(z_t, n_t; \cdot) - n_{t+1}}{\kappa^s(z_t, n_t; \cdot) + n_{t+1}}\right|, 1\right\}.$$

The function $\kappa^s(z_t, n_t; \cdot)$ is the shareholders' *desired* choice for labor next period. The term with the norm measures the distance between the manager's actual choice n_{t+1} and the shareholders' desired choice and is bounded between zero and one. In particular, this distance equals zero if the manager chooses the same amount of labor as the shareholders would like, and it equals one if $\kappa^s(z_t, n_t; \cdot) > 0$ and $n_{t+1} = 0$, or vice versa.

For example, if $\omega = 1$ the shareholders dismiss the manager for certain if she shuts down the firm when they would keep it running. They also dismiss the manager with positive probability unless she implements the desired policy.

C.3 Model with Capital and Labor: Details

Section 6.4 considers a two-factor model where capital and labor are both factors of production, extending the baseline setup from Section 3. Specifically, in this extended model firm sales are now

$$y_t = z_t \left(k_t^{\varsigma} l_t^{1-\varsigma} \right)^{\alpha},$$

the capital stock follows a standard law of motion,

$$k_{t+1} = k_t(1-\delta) + i_t,$$

and there are convex adjustment costs on both capital and labor:

$$AC(n_t, n_{t+1}, k_t, k_{t+1}) = \lambda_n n_t \left(\frac{n_{t+1} - (1-q)n_t}{n_t} \right)^2 + \lambda_k k_t \left(\frac{k_{t+1} - (1-\delta)k_t}{k_t} \right)^2.$$

Managerial beliefs are the same as in the baseline model (see equation 3) and managers still optimize their subjective valuation of the firm, now choosing both n_{t+1} and k_{t+1}.

The baseline calibration for the extended model with both capital and labor is based on my estimates of the model with convex adjustment costs only (see the first column of Table 6). Specifically, I take the parameters in the firm's objective profitability and in the managerial beliefs processes from those estimates, and likewise for the degree of decreasing returns to scale, α. I set the parameter that aggregates capital and labor under constant returns to scale, ς, equal to 0.35, consistent with a capital share of 35% in physical output before decreasing returns in sales (e.g., from monopolistic competition or limited managerial span of control) kick in.

The key remaining parameters to calibrate are λ_n and λ_k, which determine the magnitude of labor and capital adjustment costs, and the capital depreciation rate, δ. I set $\delta = 0.026$, consistent with a 10 percent annual depreciation rate. I set $\lambda_n = 17$ and $\lambda_k = 0.4$, which yield variances of employment growth and gross investment (i_t/k_t) of 0.024 and 1.8e-4. The former is similar to the variance of employment growth in my estimated model, and the latter is consistent with a standard deviation of quarterly investment of 0.013 in Michaels, Page, and Whited (2019), who estimate a quarterly model with capital and labor dynamics.