The Micro and Macro
of Managerial Beliefs

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Abstract

This paper studies how biases in managerial beliefs affect firm performance and the macroeconomy. Using a new, confidential survey of US managers I establish three facts. (1) Managers are not over-optimistic: sales growth forecasts on average do not exceed realizations. (2) Managers are overconfident: 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 impact of managerial overconfidence and overextrapolation, I build and estimate a dynamic general equilibrium model with heterogeneous firms, whose managers may have biased beliefs. Overconfidence and overextrapolation lead managers to overreact to firm-level profitability shocks and thus overspend on adjustment costs, destroying 2.1 percent of the typical firm's value. Pervasive overreaction is also costly to the macroeconomy, lowering consumer welfare by 0.5 to 2.3 percent relative to an economy in which managers have rational expectations.

JEL Codes: E7, G4, D25 **Keywords:** Managers, beliefs, reallocation, optimism, overconfidence, overextrapolation

1   Introduction

Managerial decisions fundamentally involve uncertainty about future business prospects. Even practitioners like McKinsey's Bradley, Hirt, and Smit (2018) acknowledge that "Lack of certainty about the future is the very reason you need a strategy. Instead, embrace probability." The quality of managerial decisions, thus, depends crucially on the quality of managerial beliefs—on how well managers "embrace probability."

At a theoretical level, the benchmark case is one in which managers have rational expectations and "embrace probability" optimally. Under rational expectations, managers know the distribution of future outcomes. Absent other frictions, they use this knowledge to make decisions that maximize their firm's value. Moreover, firms use and allocate resources optimally in an economy populated by rational managers. Moving away from the rational expectations benchmark, managerial beliefs may be biased or systematically inconsistent with the firm's objective risks and prospects. Decisions based on such beliefs may thus destroy some the firm's value, and pervasive biases may lead to sub-optimal use and allocation of resources at the macro level. Thus, biases may also be costly in terms of aggregate welfare.

This paper asks how far managerial beliefs are from the rational expectations benchmark, and then quantifies how those beliefs impact firm value and macroeconomic outcomes. I build on prior work going back at least to Malmendier and Tate (2005) and Ben-David et al. (2013), who argued that at least some managers appear to be biased and showed how their decisions differed from those of more rational managers. My goal in this paper is to extend those seminal contributions by providing absolute (rather than relative) estimates of *how* and *by how much* corporate decisions and macroeconomic outcomes would differ if managers indeed had rational expectations. Obtaining these estimates introduces a new challenge: making quantitative sense of how managers form their beliefs and how those beliefs translate into decisions. This last point pushes the current frontiers of the economics literature. While economists have recently re-embraced data on firm, investor, and consumer expectations,[1] it remains largely an open question what sorts of quantitative models can jointly fit data on beliefs, decisions and actions.[2]

My paper tackles the above questions and challenges by developing survey-based measures

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[1]My paper is part of a new wave of empirical studies on beliefs and expectations. Manski (2004; 2018) reviews the history of using surveys to elicit expectations. While many earlier papers focus on consumer expectations (for example Dominitz and Manski (1997) and Dominitz (1998)) my paper is among several that focus on firm managers, including Gennaioli et al. (2016), Bloom et al. (2017), Bachmann et al. (2018), and Tanaka et al. (2018).

[2]Recent advances in this regard include Kaplan, Mitman, and Violante (2017) on the housing boom and bust; Fuster, Kaplan, and Zafar (2018) on hypothetical marginal propensities to consume; Maxted (2019) on the link between beliefs and risk premia; and Giglio, Maggiori, Stroebel, and Utkus (2019), who link retail investor beliefs to portfolio choices.

of the extent to which US managers have biased beliefs, and then uses them to estimate a dynamic general equilibrium model with heterogeneous firms. Using a new survey of US managers, I find that they believe firm performance is less volatile and more persistent than it is empirically; namely, managers are overconfident and overextrapolate. I then build and estimate a quantitative equilibrium model in which biased managers make dynamic hiring decisions subject to firm-specific uncertainty and adjustment costs. My estimated model fits an array of moments involving managerial beliefs and decisions, as well as firm outcomes. I thus show that canonical models of dynamic firm behavior can be extended to make sense of new data on beliefs. Based on counterfactuals from the estimated model, I argue that biased managers overreact to changes in their firm's profitability and overspend on adjustment costs, thus destroying some of their firm's value. At the macro level, pervasive overreaction is also costly because it destroys resources and pushes the economy away from its welfare-maximizing, rational-expectations equilibrium.

To measure whether managers are biased, I obtain data on managerial beliefs and realized outcomes from the Atlanta Fed/Chicago-Booth/Stanford Survey of Business Uncertainty (henceforth, SBU) developed by Altig et al. (2019). The SBU surveys high-level managers in the US, typically CEOs or CFOs, and elicits subjective probability distributions about future own-firm sales and employment growth. Responses are confidential and collected by a Federal Reserve Bank, so there are few obvious motives for respondents to misreport their beliefs. In the SBU data, I measure managers' subjective expectations (i.e. their forecasts) as well as their subjective uncertainty about sales and employment growth over the next year. I then test whether manager expectations and uncertainty are empirically consistent with outcomes, documenting three key facts.

First, managers do not appear to be *over-optimistic*. Forecast minus realized sales growth is on average negative and barely statistically significant at conventional levels.[3]

Second, managers responding to the SBU are *overconfident* or overprecise; that is, they underestimate the volatility of future sales growth.[4] I establish this second fact by showing that managers overestimate their forecasts' accuracy. While their subjective distributions would imply an average absolute forecast error of about 4 percentage points, in reality, the average absolute forecast error is close to 18 percentage points—more than four times as large.

Third, managers *overextrapolate* from current conditions. If a manager's firm experiences high sales growth in a quarter when she responds to the SBU, her forecast for sales growth

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[3]See Bachmann and Elstner (2015) for a similar finding among German manufacturing firms, as well as Boutros et al. (2019) for a similar result from the Duke CFO Survey.

[4]Ben-David, Graham, and Harvey (2013) similarly show that US managers underestimate the volatility of S&P 500 returns.

over the next four quarters tends to exceed the firm's actual performance. If, instead, the firm experiences shrinking sales, the manager tends to underestimate. For each additional percentage point of sales growth at the time of the forecast, managers on average overestimate future performance by an additional 0.2 percentage points. This behavior suggests managers overestimate the extent to which current business conditions will persist over the next year, overextrapolating from how things look at the time of the forecast.[5]

To understand how these features of managerial beliefs impact individual firms and the macro-economy, I build a dynamic general equilibrium model with heterogeneous firms, whose managers may be biased. Managers may misperceive the long-run mean, persistence, and volatility of their firm's profitability, with each of these biases corresponding to one of the three facts I document in the SBU data.[6] They make forward-looking hiring decisions under uncertainty, forecasting the firm's future profitability using their own subjective beliefs process. These hiring decisions are subject to adjustment costs that help the model account for the joint dynamics of firm-level sales and employment in the SBU data. Theoretically, adjustment costs also make managerial mistakes more costly, since resources spent on unnecessary adjustments are lost.

I estimate the model targeting three broad features of the SBU data: (1) the extent of managerial optimism, overconfidence, 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 majority of the targeted moments. One key contribution of this paper is precisely demonstrating that a canonical model of dynamic managerial optimization, extended to accommodate a managerial beliefs process, can match a range of empirical patterns about manager beliefs and decisions.

Using the estimated model, I quantify the costs of managerial biases and point to the mechanisms underlying those costs. At the micro level, switching to a manager who has rational expectations increases the net present value of the typical firm's cash flows by 2.1 percent. At the macro level, I find that consumer welfare is higher by 0.5 to 2.3 percent in an economy where managers have rational expectations.[7]

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[5]Overextrapolation is a common finding in the forecasting and psychology literatures. See La Porta (1996) and Bordalo, Gennaioli, Ma, and Shleifer (2018a) for similar results about professional analysts, as well as Rozsypal and Schlafmann (2017) for a similar finding for US households.

[6]While I opt for a reduced-form specification for the managerial beliefs process, my specification is broadly consistent with the more micro-founded diagnostic expectations framework used, for example, in Bordalo, Gennaioli, and Shleifer (2018b)

[7]For comparison, recent estimates of the welfare cost of business cycles range from about 0.1 to 1.5 percent in Krusell et al. (2009), while estimates of the welfare gains from trade liberalization range from 1 to 8 percent in Melitz and Redding (2015).

Managerial overconfidence and overextrapolation reduce firm value and consumer welfare because they lead managers to overreact to shocks, and thus overspend on adjustment costs. Since overconfident and overextrapolative managers perceive profitability shocks to be persistent and stable, they overreact relative to rational managers who appreciate that shocks are transitory and volatile. Overreaction means managers overspend on adjustment costs, which wastes otherwise valuable resources and thus reduces firm value and welfare. Additionally, equilibrium prices and allocations in an economy with pervasive overreaction differ from those in the welfare-maximizing, rational expectations equilibrium. How much managerial biases impact welfare depends partly on how far equilibrium prices and allocation are from those in the first-best equilibrium.

Based on the insight that overreaction is at the heart of why biases in managerial beliefs are costly, I demonstrate that a firing tax can reduce the extent of managerial overreaction and increase consumer welfare. Thus, I show that policy-makers can potentially alleviate some of the burden of managerial biases without changing how people think, which may be difficult or even impossible. This result also highlights that understanding how economic agents form their beliefs and make decisions is crucial to assessing the impact of government policies and other features of the economic environment. In many rational expectations models, a firing tax would be unambiguously welfare damaging, but in my paper it enhances welfare once we recognize that managerial beliefs lead to overreaction.

I find little evidence that managerial overconfidence and overextrapolation arise as a result of agency conflicts that are more acute for some firms than others. Managers of publicly-traded and privately-held firms exhibit similar degrees of overconfidence and overextrapolation. The same is true whether the CEO is a major shareholder or part of a major shareholding family (an "insider CEO") versus an outsider. Managerial biases are thus similarly costly for private and public firms, and actually less costly for firms with insider rather than outside CEOs. This analysis shows that biases are a robust feature of managerial beliefs, impacting corporate behavior broadly rather than narrowly. Regardless of the ultimate source of managerial biases, it appears that boards and shareholders find it difficult to identify, fire, and avoid hiring biased managers.

My paper makes four key contributions. First, I document new evidence about the extent to which US managers are overoptimistic, overconfident, and overextrapolate. Although my empirical findings are consistent with earlier work,[8] I contribute new, quantitative measures

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[8]Malmendier and Tate (2005) identify biased managers based on stock option exercise, and Ben-David, Graham, and Harvey (2013) use survey data to show that CFOs are overconfident about future S&P 500 returns. Gennaioli, Ma, and Shleifer (2016) argue that managers overextrapolate, as do Bordalo et al. (2018a) and Bordalo et al. (2017) for professional forecasters. Bachmann and Elstner (2015) find little evidence of managerial over-optimism about future sales growth, as do Boutros, Ben-David, Graham, Harvey, and Payne

of managerial over-optimism, overconfidence, and overextrapolation stemming from state-of-the-art data on beliefs.

Second, I extend a canonical heterogeneous firm model to accommodate biases in managerial beliefs and show that the model fits a wide array of new data moments, including several that relate beliefs to decisions and outcomes.[9] My paper thus builds on earlier work with behavioral models of firms, but which typically did not have the data to estimate or calibrate such models.[10]

Third, I provide new estimates of the real costs of overconfidence and overextrapolation at the micro and macro levels, highlighting how beliefs and reallocation frictions jointly determine these costs. This aspect of my paper sets me apart from related work, including Bachmann and Elstner (2015) and Ma, Sraer, and Thesmar (2018), who find smaller costs using frictionless models.[11] My paper thus contributes to a long literature in finance on managerial (mis)behavior, its determinants and impacts.[12]

Fourth, I demonstrate that the right policy instruments may alleviate the burden of managerial overconfidence. The fact that the right policy in my context—a firing tax—runs contrary to conventional wisdom further highlights the need to understand how beliefs relate to decisions quantitatively, and thus how government policies and other frictions shape that relationship.

One clear implication of my results is that overconfidence and overextrapolation could serve as an amplification mechanism for aggregate shocks, on account of the overreactions they induce. Quantifying the extent of such amplification goes beyond the scope of this paper, but is consistent with related work about beliefs' role in business and credit cycles.[13]

(2019). A separate literature in finance has documented biases among portfolio investors and mutual fund managers, for example Odean (1998),Barber and Odean (1999), Puetz and Ruenzi (2011), and Bailey et al. (2011).

[9]My approach contrasts with Alti and Tetlock (2014), who use asset-pricing anomalies rather than survey evidence on beliefs to structurally estimate the extent of overextrapolation and overconfidence among managers and investors. I also go beyond Giglio et al. (2019), who document a series of facts about beliefs and portfolio decisions, but stop short of estimating a model that captures those facts.

[10]For example, Fuster et al. (2010) study overextrapolation in the context of aggregate fluctuations; Hackbarth (2008) studies the impact of overconfidence on capital structure; Kim (2018) explores CEO compensation and portfolio choice; and Benigno and Karantounias (2019) consider the impact of overconfidence on information acquisition.

[11]Due to its focus on reallocation, my my paper relates to recent work on on the role of reallocation in the economy, including Decker et al. (2018) and Hsieh and Klenow (2017), as well as Asker et al. (2014) and David and Venkateswaran (2017).

[12]See Stein (2003) for a survey of the literature. Bertrand and Schoar (2003) show that CEOs impact firm performance, Bebchuk et al. (2008) studies corporate governance, Taylor (2010) studies CEO entrenchment, and Nikolov and Whited (2014) explore CEO incentives and cash-holding. My paper also relates to the literature on CEOs' personalities and style, including Kaplan et al. (2012) and Kaplan and Sorensen (2017), which show that execution ability and resoluteness are desirable CEO qualities that may be consistent with overconfidence and overextrapolation.

[13]In a closely related paper, Bordalo, Gennaioli, Shleifer, and Terry (2019) consider the impact of overex-

It is no coincidence that an emerging behavioral literature within macroeconomics focuses much of its attention on beliefs and their role in shaping consumer and firm behavior.[14] While my results are specific to my modeling assumptions and empirical sample, my key insight that beliefs data are crucial to modeling how economic agents make decisions applies more broadly.

The rest of the paper is structured as follows: Section 2 documents my empirical results about managerial beliefs using the Atlanta Fed/Chicago-Booth/Stanford Survey of Business Uncertainty. Section 3 develops a general equilibrium model in which biased managers run heterogeneous firms subject to idiosyncratic risk. Section 4 describes how I solve and estimate the model by targeting beliefs, decisions, and outcomes. Section 5 quantifies how biases in managerial beliefs impact the value of individual firms and the aggregate economy. Section 6 concludes.

2 Managerial Beliefs in the Survey of Business Uncertainty

In this section I use data from the Atlanta Fed/Chicago-Booth/Stanford Survey of Business Uncertainty to document three key facts about managerial beliefs regarding their own firms' future sales growth. Specifically:

1. Managers are not over-optimistic. Only those at the smallest firms appear to be pessimistic.

2. Managers are overconfident. 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, I document that managerial beliefs as reported in the Survey of Business Uncertainty are consistent with future sales and employment outcomes at the firm, with managerial hiring plans, as well as the firm's current employment growth (i.e. net hiring). This additional set of facts, which I collectively refer to as Fact 0, support my analysis of managerial

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trapolation in a business cycle model with credit cycles. That paper in turn builds on the credit cycle models in Bordalo, Gennaioli, and Shleifer (2018b), among others.

[14]Jurado (2016) studies distorted beliefs in a DSGE framework. Carroll et al. (2018) argue that sticky expectations help explain aggregate consumption behavior. Rozsypal and Schlafmann (2017) study overextrapolation among US households. Molavi (2018) explores macroeconomic equilibria without rational expectations. More broadly, Gabaix (2016) develops a theory of behavioral agents for macro models, and Acemoglu and Jensen (2018) analyze equilibrium dynamics in behavioral economies.

optimism, overconfidence, and overextrapolation in this section, and discipline managerial behavior in the quantitative model I consider later on in the paper.

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), which is fielded by the Federal Reserve Bank of Atlanta on a monthly basis. Here I provide an overview of the SBU data, but interested readers should refer to Altig et al. (2019) for full details about the survey's development and methodology.

The SBU surveys high-level firm managers of US firms monthly via email. Figure A.1 shows the most common job title in the SBU is "CFO (or other finance)", which accounts for nearly 70 percent of panel members, followed by "CEO" and "Owner" with just under 20 and 10 percent each. Responses are confidential and collected by a Federal Reserve Bank, so managers have no obvious incentive to skew their responses in one direction or another.

The SBU asks managers to report their firm's *current* and *past* performance, and then asks them to provide *five-point, subjective probability distributions* about future own-firm outcomes, looking one year ahead. Figure 1 shows the SBU's questionnaire for sales growth. After reporting their firm's current sales and its sales growth over the past 12 months, respondents provide five potential outcomes for the firm's sales growth over the next four quarters—a lowest, low, middle, high, and highest scenario. Then, they assign a probability to each of those five scenarios.[15] When providing the five support points and probabilities in the SBU, respondents are free to enter any potential forecast and probability for each of the scenarios, giving them 9 degrees of freedom to specify their distributions. This flexibility means that the survey can accommodate much heterogeneity in firm-level prospects, both across firms and within firms across time. The survey also asks a similar set of questions about the firm's level of employment twelve months into the future, shown in Appendix Figure A.2.

To study managerial beliefs, I follow the approach in Altig et al. (2019) by computing subjective moments of managers' five-point subjective distributions. I measure each manager's forecast as the subjective mean, namely by taking the inner product of the vector of potential outcomes and the vector of probabilities. Analogously, I measure subjective uncertainty by computing the subjective mean absolute deviation of the distribution. See the Online Appendix for more details on how I construct these subjective moments from the raw

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[15]Currently, the SBU requires the probability vector to add up to 100 percent. In previous waves, when the survey reminded managers but did not force them to provide probabilities adding up to 100, over 90 percent of all responses had probability vectors adding to 100 percent.

SBU data.[16] My analysis below tests for biases in managerial beliefs by comparing managers' ex-ante subjective first and second moments against analogous, ex-post moments from the survey data, exploiting the fact that the SBU tracks firm-level sales and employment over time.

Appendix Table A.1 reports summary statistics pertaining to my sample of SBU responses. The SBU has been fielded since October 2014, and I use data from all survey waves up to and including May 2019. Altig et al. (2019) report that in the first half of 2018, about 40 percent of emails sent 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, thereby maintaining consistent sample sizes across months.

The sample of firms in the SBU is broadly representative of the US business sector in employment-weighted terms. The survey over-samples 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 also carry more weight in the macro-economy; and partly due to higher response rates among larger firms. In the Online Appendix, I reproduce figures from Altig et al. (2019) showing the share of employment by firm size, sector, age, and region in the SBU in comparison to the universe of firms in US Census data. The typical SBU respondent is larger than the typical firm in the Census' Longitudinal Business Database, but also smaller than the publicly-traded firms which are the focus of other papers about managerial beliefs and behavior, including Ben-David et al. (2013), Malmendier and Tate (2005), Ma, Sraer, and Thesmar (2018), and Bordalo et al. (2019).

2.2 Fact 0: Managerial Beliefs Predict Outcomes, Hiring Plans, and Current Hiring

Before asking whether managerial beliefs appear to be rational, I document a series of basic facts about sales and employment growth beliefs as expressed in the SBU, which I collectively refer to as "Fact 0" of the paper. I show that managerial forecasts have high predictive power for outcomes, that beliefs about sales and employment growth appear to be consistent with each other, and sales forecasts are predictive of the firm's current employment growth (i.e. the firm's current net hiring decision). My results in this section are consistent with Giglio,

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[16]Using moments of manager's subjective distributions eschews a common critique (e.g. Cochrane (2017)) of survey-based studies of beliefs and expectations; namely, that point "expectations" or "best guesses" elicited in surveys may not correspond to the first moment of respondents' subjective probability distributions.

Maggiori, Stroebel, and Utkus (2019), who study the beliefs of retail investors.

To start, Figure 2a shows that managerial sales growth forecasts for the next four quarters are highly predictive of actual sales growth. Managerial hiring plans—i.e. managerial forecasts for the firm's employment growth over the next 12 months—in turn predict the firm's actual employment growth over the same horizon, as we can see in Figure 2b. Altig et al. (2019) also report the latter result directly, and allude to the result on sales. I report them again here to support my analysis of the SBU data.

Table 1 further explores the predictive power of managerial forecasts. The table shows managerial forecasts predict future sales and employment growth even after controlling for an array of other firm-level variables, including the firm's most recent quarterly sales and employment growth, its current capital expenditures, current employment, and a full set of industry, region, and firm age fixed effects. In columns (1) and (4) I regress actual sales and employment growth in the four quarters following a survey wave on all of these potential explanatory variables. In columns (2) and (5) I additionally include the manager's forecast. In both cases the coefficient on the forecast is positive, significant and statistically indistinct from unity. The overall r-squared and within–r-squared additionally jump by some 7 percentage points in both cases. Finally, in columns (3) and (6) I verify that the forecast's predictive power does not hinge on the inclusion of the other controls. The coefficient is positive and significant in both columns. Looking at the r-squared, we can see each respective forecast alone accounts for about 15% of the variance of sales or employment growth outcomes.

Managerial forecasts may predict outcomes, but do they also predict managerial choices? I explore this question in Figures 3 and 4. In Figure 3a, we can see that sales growth forecasts are highly predictive of managers' hiring plans. When managers forecast higher sales growth for the next year, they also forecast that the firm will have more employees in the future. In turn, uncertainty about future sales growth negatively predicts hiring plans (controlling for the sales growth forecast), as we can see in Figure 3b, and it positively predicts uncertainty about the firm's future employment growth, as Figure 3c shows. Subjective second moments, thus, are also informative for respondents' hiring plans, looking ahead over the next year.

In Figure 4, I show that beliefs have predictive power over the firm's current hiring (i.e. it's employment growth since the previous quarter). Figure 4a shows that current hiring is positively correlated with managerial sales forecasts for the next year. When managers expect the firm's sales to grow, they on average are expanding the firm's workforce already. In Figure 4b, however, I do not find a strong relationship between hiring and uncertainty, perhaps because uncertainty is only a second order concern for the firm's current employment decision.

In the Online Appendix I replicate the graphical results from this section, focusing on within firm variation. Namely, I show that beliefs predict outcomes, hiring plans, and current hiring even after including firm and date fixed effects. In those exercises, I additionally find a negative link between subjective uncertainty about future sales and current hiring.

The results in Figures 2 through 4 as well as Table 1—collectively, the paper's "Fact 0"— support the fundamental assumptions that I maintain for the rest of the paper. My analysis below assumes that managerial beliefs as reported in the survey are the beliefs managers use to make forward-looking decisions, to which Fact 0 lends credence. Additionally, the results from Fact 0 are empirical benchmarks that link beliefs with firm behavior and outcomes. Thus, when I estimate the quantitative model from Section 3, I discipline managerial behavior by targeting moments from Fact 0.

2.3 Fact 1: Managers are Not Over-Optimistic

Having established the basic properties of managerial beliefs in Fact 0, I turn my attention to whether managerial forecasts appear consistent with realized outcomes.

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 error (equal to forecast minus realized) pooling observations from all firms and survey waves. Looking at the top row of the table, columns (1) and (2) show that 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, implying it is statistically different from zero with ninety-five percent confidence. From this evidence alone, we might conclude that managers are mildly pessimistic, but the statistical significance 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, as we can see from the second row of Table 2. In the bottom panel of the table I also find that the employment-weighted mean forecast error is much closer to zero than the unweighted mean and not significant even with just firm-clustered standard errors. Altogether, it is hard to argue that managers are systematically pessimistic.

Figure 5 shows that managers also appear neither optimistic nor pessimistic when looking across firm sizes, survey waves, sectors, or firms with different forms of ownership and governance. In particular, Figure 5a shows that firms in the the bottom ten percent by sales on average give forecasts that fall short of realizations with 95 percent statistical significance. None of the mean forecast errors are statistically different from zero for the top nine deciles,

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however, and an F-test of the null hypothesis that all ten mean forecast errors is zero fails to reject with a p-value of 0.69. Again, these results suggests that managers are neither systematic optimists nor pessimists.

In Figure 5d I ask whether managers of publicly-traded firms or firms whose CEO is a major shareholder or is part of the family of major shareholders (an "insider CEO") make more optimistic or pessimistic forecasts. This question speaks to whether managerial biases are associated with the type of relationship between shareholders and management, including how strong or weak governance is.[17] Regressing managerial forecast errors on indicators for whether the firm is publicly-traded or has an insider CEO, I find no significant association between ownership and managerial optimism or pessimism.

2.4   Fact 2: Managers are Overconfident

Managers responding to the SBU are overconfident: they underestimate their firm's sales growth volatility and therefore overestimate the accuracy of their forecasts.[18]

Figure 6 illustrates the discrepancy in empirical versus subjective managerial forecast accuracy by superimposing two histograms. The blue bars show the empirical distribution of forecast minus realized sales growth in the SBU data. The red bars (with the dotted outline) show the distribution of forecast minus realized sales growth that would arise if sales growth realizations were drawn from each managers' five-point subjective probability distribution, independently across managers. 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.

Under the null hypothesis that managers have rational beliefs and shocks to sales growth are independent across firms, the empirical and subjective distributions of forecast errors should be identical. What we can see in Figure 6 is a sounding rejection of that hypothesis. The subjective distribution of forecast errors is much less dispersed, indicating that managers' actual forecast errors are much larger than what they expect ex-ante. In particular, managers understate the probability of being off by 10 to 20 percentage points, which are not tail outcomes under the empirical distribution. Thus, managerial overconfidence is not driven by a few extreme realizations or "Black Swans" that managers ignore ex-ante. Given that my data come from a low-volatility period for the US economy, covering late-2014 to mid-2019, it is not likely that the discrepancy is due to common shocks across firms.

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[17]I obtain information on firm ownership from a special question the SBU asked as part of the February and March 2019 survey waves. (See Appendix Figure A.3 for a screenshot of these questions.)

[18]Overconfidence is sometimes also termed "overprecision" due to its implications for managerial forecast precision. Other papers also use the term "overconfidence" to mean "excessive optimism" or a combination of optimism and overprecision, for example Malmendier and Tate (2005).

Table 3 quantifies the degree of overconfidence by comparing the mean absolute forecast error (equal to the absolute distance between forecast and realized sales growth) arising empirically against mean managerial uncertainty, (i.e. the mean absolute deviation across managers' subjective distributions). These two variables are analogous, so their means should be similar under the null that managers know the distribution of potential outcomes, and shocks are independent across firms. While managers' subjective distributions would imply a mean absolute forecast error of 0.035, the empirical mean absolute forecast error is 0.183 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 with both firm-clustered standard errors and two-way firm and date clustered errors. The magnitude of this excess error quantifies the degree of managerial overconfidence.

Although managers are overconfident, their subjective uncertainty strongly predicts future sales growth volatility. Figure 9 shows a bin-scatter plot (with the blue dots) of managers' subjective uncertainty on the horizontal axis against their absolute forecast errors on the vertical axis. The relationship slopes upward, meaning higher ex-ante uncertainty is associated with higher ex-post volatility.[19] Figure 7a also shows the bin-scatter plot (with the orange triangles) we would expect to see if sales growth realizations were drawn according managers' subjective distributions. In this case, expected absolute errors are equal to subjective uncertainty by definition, so the relationship falls along the 45 degree line. The vertical gap between the two plots implies that managers underestimate the *level* of uncertainty by a roughly constant amount at all levels of subjective uncertainty, even though they can perceive and express differences in firm-level volatility. To my knowledge, this is the first paper to document this feature of managerial overconfidence.

The stylized fact that managers are overconfident about their forecasts' accuracy also holds when looking across time and across sectors, as well as firm sizes. In Figures 7b to 7d, I plot the mean excess absolute forecast error for each month between October 2014 and May 2019, for each sector, and for each decile of the firm size distribution. In all cases the mean excess error typically ranges from 0.10 to 0.20 and is statistically significant. Looking across the firm size distribution in Figure 7d, it appears that managers of the smallest firms (which are likely to be less productive and less well-managed) appear to be more overconfident than the rest, but otherwise I find little heterogeneity in the degree of overconfidence. Finally, in Figure 7e I show that managerial overconfidence is not significantly higher or lower for publicly-traded firms or firms with an insider CEO, who is a major shareholder or part of a family of major shareholders. Thus, managerial overconfidence is unlikely to stem from principal-agent conflicts that differ starkly across these subsamples of firms.

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[19]This is also one of the key results in Altig et al. (2019).

In the Online Appendix, I argue that my measure of managerial overconfidence is unlikely to be driven by either measurement error in sales biasing the mean absolute forecast error upward, or by the fact that managers express their beliefs using a five-point discrete distribution.

2.5 Fact 3: Managers Overextrapolate

Managers in the SBU overextrapolate. Their forecasts tend to overstate realizations when those forecasts are made during high-performing quarters, and vice versa. Figure 8 uses a binned scatter plot to trace the relationship between forecast minus realized sales growth growth for quarters t and $t+4$, against the firm's sales growth between quarters $t-1$ and t. We can see a strong positive relationship, indicating that managerial forecast errors are highly predictable from their firm's recent sales growth performance. This pattern is consistent with overextrapolation, whereby managers overestimate how much future business conditions will resemble today's.

In Table 4, I show that past sales' growth ability to predict future forecast errors is a robust feature of managerial beliefs. In column (1) I report the estimate from the cross sectional regression corresponding to Figure 8. Quantitatively, I find that 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 0.07, relative to a mean unconditional forecast error of -0.015. Column (2) reports results from an employment-weighted specification, resulting a slightly smaller slope coefficient. In column (3) I add date fixed effects, and in column (4) sector-by-date effects, to test whether the relationship holds for firms subject to the same macro or sector-specific shocks. In both cases the coefficient on recent sales growth barely differs from that in column (1). In columns (5) and (6) I use firm fixed effects and time dummies to control for persistent firm-level differences and the aggregate environment, weighting by employment in (6). Again, the estimated coefficient barely moves relative to the cross-sectional specification

Figure 9 shows that the degree of overextrapolation is similar for firms with different characteristics. First, I show that overextrapolation differs across small and large firms in Figure 9a by estimating the relationship between forecast errors on lagged sales growth once more, but now computing a separate coefficient for each quintile of the distribution of sales levels. I obtain similar coefficients across all five quintiles. In Figure 9b. I also fail to reject the null hypotheses that the slope between lagged sales growth and forecast errors is equal across subsamples of publicly-traded versus privately-held firms, or firms with and without insider CEOs. As with optimism and overconfidence, overextrapolation is not associated

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with a particular type of relationship between managers and shareholders.

In the Online Appendix, I argue my results on overextrapolation are unlikely to be driven by measurement error[20] and show additional evidence of overextrapolation from alternative specifications. In particular, sales growth forecasts are predictable based on managers' reports of the firm's sales growth in the past 12 months, and from lagged forecast errors.

3 A General Equilibrium of 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—in particular overconfidence and overextrapolation—impact managerial decisions and thus firm behavior and macro outcomes. The model builds on the standard setup based on Hopenhayn (1992) and Hopenhayn and Rogerson (1993), which I extend by giving managers their own subjective stochastic process for future firm-level shocks .

3.1 Technology and Environment

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

$$\hat{y}(z_t, n_t) \quad = \quad z_t n_t^{\alpha}$$

The returns to scale parameter, α, lies within the unit interval $(0, 1)$. I remain agnostic about the specific sources of decreasing returns, which may 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:

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

I refer to this stochastic process as the state of firm-level "profitability" or "business conditions", since z captures fluctuations in both the firm's demand and supply. Stationarity of the shock process capture mean reversion in sales levels I estimate in the SBU data. There is no aggregate risk.

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[20]In particular, transitory measurement error would mechanically generate a negative correlation between past sales growth from $t-1$ to t and subsequent sales growth from t to $t+4$.

Firms hire labor in a competitive market and pay the equilibrium wage w_t. Each firm's operating income in quarter t is it's 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. After observing her firm's current idiosyncratic shock z_t, each manager decides how many workers to hire or lay off to obtain labor n_{t+1} the following quarter, which follows:

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

The firm's workforce next quarter includes labor already working at the firm less exogenous separations (occurring at a rate q) plus net hiring or layoffs h_t. I assume managers choose n_{t+1} under uncertainty about next quarter's shock to profitability z_{t+1}. These dynamics capture real-world lags in searching, 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 cost of posting vacancies, extra hours spent by human resources searching and interviewing candidates, and the cost of training new hires. They also include costs associated with layoffs, like revenue lost as the firm rebalances duties across the remaining workers. Since my model abstracts from capital investment, these adjustment costs may also be interpreted as the underlying capital adjustment costs in a setup with both capital and labor where labor is frictionless and follows capital. I assume these adjustment costs are quadratic in the gross rate of hiring and scale with firm size:[21]

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

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 each firm's current idiosyncratic shock z_t, its current labor n_t, its manager's choice of labor for next quarter n_{t+1} and the equilibrium wage w_t

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

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[21]The adjustment costs literature has long debated what the right specification for adjustment costs is (e.g. see Cooper and Haltiwanger (2006) and Bloom (2009)). My quadratic specification follows standard practice involving firm-level data that aggregates several establishments, product lines, and divisions belonging to the same firm.

3.2 Managerial Beliefs

Recall that firm-level business conditions z_t follow a standard log-Normal autoregressive process, shown in Equation 1. Managers in the model observe their firms' current state z_t, but believe the stochastic process for this variable follows:

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

The parameters $\tilde{\mu}$, $\tilde{\rho}$, and $\tilde{\sigma}$ distort managers' sense of optimism, persistence, and uncertainty about future profitability relative to the objective process in Equation 1. If $\tilde{\mu} > \mu$, managers on average overestimate $\log(z_{t+1})$; that is, they are over-optimistic. If $\tilde{\rho} > \rho > 0$ they overestimate the persistence of firm-level profitability, meaning they overextrapolate. If $\tilde{\sigma} < \sigma$, managers are overconfident 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 optimistic or pessimistic, but they are overconfident and overextrapolate. Although I impose a reduced form managerial beliefs process, my specification resembles the psychologically-founded diagnostic expectations developed and used by Bordalo et al. (2018b), Bordalo et al. (2018a), and Bordalo et al. (2019).

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.[22][23] Managers are thus incentivized to optimize the net present value of their firms' cash flows, choosing the firm's labor under uncertainty about future profitability. The key feature of the model is that managers use their subjective beliefs process rather than the objective shock process when making those decisions, so they end up optimizing their *subjective* valuation of the firm.

   In quarter t, each manager observes her firm's current shock z_t, the firm's current labor n_t, the current market wage w_t, and the risk-free rate r_{t+1}. The manager then chooses the

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[22]How much of the firm's equity is held by managers is irrelevant for solving for their investment policies, finding the stationary distribution of firms state state, or estimating the main parameters of the model. However, general equilibrium outcomes depend on who ultimately owns the firms, so in Section **??** below I show how my general equilibrium counterfactuals differ with alternative choices for θ.

[23]In Section **??** I estimate the model separately for firms with insider versus outside CEOs as well as publicly-traded versus privately-held firms to see how my model captures differences in behavior across firms with differing agency frictions and governance.

next quarter's labor n_{t+1}, which may involve paying adjustment costs $AC(n_t, n_{t+1})$, to solve the following problem:

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

Here, 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 decision to adjust the firm's labor involves a trade off between spending on adjustment costs today, which reduces current cash flows $\pi(\cdot)$, and reacting to the firm's latest profitability shock, which increases the manager's expected valuation of the firm next quarter. The magnitude of adjustment costs are therefore critical to managerial decision-making, and to the link between managerial beliefs and decisions.[24]

3.4 Objective Firm Value

I denote the *objective* value of a firm with business conditions z_t and labor n_t by $V(z_t, n_t; \cdot)$—without the tilde superscript. $V(z_t, n_t; \cdot)$ represents the net present value of cash flows, forecasting future shocks with the *objective* stochastic process in 1 and taking as given the choices of the firm's manager.

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 solution to the managerial optimization problem in 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 with 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 $\tilde{V}(z_t, n_t; \cdot)$, but the two are identical when the managerial beliefs process coincides with the objective shock process—i.e. when managers have rational expectations. $V(z_t, n_t; \cdot)$ also generally falls below the firm's optimal value.

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[24]In a closely-related and contemporaneous paper Ma, Sraer, and Thesmar (2018) focus more on static misallocation and less on adjustment costs as potential reasons for why managerial biases might be costly.

One of my key contributions in this paper is to quantify how much more firm value could be generated by replacing the typical biased manager with another who is rational.[25]

3.5 Household

There is an infinitely-lived representative household who 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

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

where $\phi_t(z, n)$ is the measure of firms with profitability z and labor n in quarter t. Again, $\kappa(z, n; \cdot)$ is the hiring policy of a manager whose firm is in state (z, n) in quarter t. The household can also save and borrow using a zero-net-supply, risk-free bond B_{t+1}. Since there is no aggregate risk in the economy and the mutual fund is perfectly diversified against firm-level 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

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

so its optimality conditions are the usual inter-temporal Euler equation and intra-temporal labor-leisure tradeoff:

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[25]I view $V(z_t, n_t; \cdot)$ as a model quantity rather than an asset price. The model I present in this section is directed towards understanding and rationalizing employment dynamics rather than asset prices, and lacks well-developed equity markets. It's true that $V(z_t, n_t; \cdot)$ is the price that outsiders with correct or rational beliefs would be willing to pay for individual firms in the model, but I am hesitant to make predictions about asset-pricing without more evidence on outside investors' beliefs. Moreover, close to 90 percent of firms in the SBU are privately-held, so it seems reasonable to think about firm value as a quantity rather than a publicly-available market price. In closely-related work Alti and Tetlock (2014) argue that a model similar to mine can explain asset return anomalies if firms are run by managers aiming to maximize overconfident, overextrapolative investors' valuations of firms.

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

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

I deliberately keep the household and its optimization problem simple to focus my analysis on managerial decisions and firm outcomes. However, the household's optimality conditions pin down equilibrium prices and so affect my estimates of the aggregate costs of managerial overconfidence and overextrapolation. Changing the behavior of all managers changes equilibrium prices, which need to be consistent with the household's optimality conditions.

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 (2018), which extends the setup in Grandmont et al. (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 $\phi : \mathcal{Z} \times \mathcal{N} \to [0, 1]$ such that:

1. $\tilde{V}(z_t, n_t; w, r)$ solves each manager's optimization problem from equation 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 business conditions; namely:

$$\phi_{t+1}(z, n) = \phi_t(z, n) \quad \forall z, n, t$$

$$\phi(z', n') = \int_{\mathcal{Z}, N} \phi(z, n) \cdot Pr(z'|z) \cdot \mathbf{1}(n' = \kappa(z, n; w, r)) \mathrm{d}z \mathrm{d}n$$

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

$$N^S = \int_{\mathcal{Z}, \mathcal{N}} n \cdot \phi(z, n) \mathrm{d}z \mathrm{d}n$$

$$B = 0 \quad \text{in zero net supply by assumption}$$

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 for shocks, as given in equation 1. Once again,

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$n_{t+1} = \kappa(z_t, n_t; w_t, r_{t+1})$ is the employment chosen by a manager whose firm is currently in state (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, where instead we have deterministic sequence of prices $\{w_t, r_{t+1}\}_{t=0}^{\infty}$, a time varying distribution of firms $\phi_t(z, n; w_t, r_{t+1})$, and managers' and household's optimality conditions as well as market clearing hold period-by-period, with both the managers and the household taking the price sequence as given.

My model abstracts from aggregate risk and instead focuses on how managerial beliefs about firm-specific shocks affect managerial decisions and (stationary) aggregate outcomes. While this abstraction makes the model quantitatively tractable, it means that managerial biases affect aggregate outcomes only to the extent that they change the allocation of resources across firms, the household's labor-leisure tradeoff and the amount of resources ultimately spent on consumption versus adjustment costs. To the extent that managers are also overconfident and extrapolate with respect to aggregate shocks, my quantitative analysis will likely *underestimate* the costs of managerial overconfidence and overextrapolation.

4   Model Solution and Estimation

To quantify the implications of managerial beliefs for firm behavior, firm value, and the macro-economy I estimate the model from Section 3 using SBU data. This section describes: (1) how I obtain solutions to 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 values for the model's key parameters.

4.1   Computing the Stationary General Equilibrium of the Model

Solving and simulating economic models in which agents have biased beliefs imposes relatively few constraints relative to standard rational-expectations modeling.[26] In practice, I simply need to use the manager's subjective to compute their dynamic hiring policy, acknowledging that the distribution of shocks follows the objective process.

Here, I sketch out the algorithm I use to compute the economy's stationary equilibrium. For full details see the Online Appendix. To begin, I use the household's inter-temporal

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[26]As explained in Jurado (2016), subjective beliefs are well defined if they agree with the objective process on the set of outcomes that may occur with positive probability, potentially disagreeing on what that positive probability is. Since both the subjective and objective processes in the model in equations 1 and 3 have infinite support and have Gaussian innovations, the model in Section 3 satisfies this requirement. Formally, this requires the subjective conditional variance $\tilde{\sigma}$ to be strictly greater than zero, although it could be arbitrarily small.

Euler equation 7 to pin down the steady-state risk-free rate: $r = 1/\beta - 1$. Then, I iterate through the following steps:

1. Given a guess for w, I numerically solve for managers' optimal subjective valuation of the business in 4 using value function iteration aided by Howard's improvement algorithm over a discretized (z, n) state space. For this step, I use the manager's subjective stochastic process from Equation 3 to forecast the firm's future profitability and continuation value.

2. I compute the stationary distribution $\phi(z, n; w)$ of firms that arises from (1) managers' policy functions $n_{t+1} = \kappa(z_t, n_t; w)$ obtained from step 1, and (2) the *objective* stochastic process for idiosyncratic profitability shocks from Equation 1. I compute $\phi(\cdot)$ numerically using a non-stochastic simulation algorithm based on the procedure outlined in Young (2010). This procedure is conceptually equivalent to simulating a long panel of firms, but eschews the need to draw random numbers and thereby avoids introducing simulation error to model-implied moments.

3. Using the stationary distribution $\phi(\cdot; w)$ I compute the household's implied consumption $C = wN^D + \Pi$, where $N^D = \int_{\mathcal{Z} \times \mathcal{N}} n \cdot \phi(z, n; w) \mathrm{d}z \mathrm{d}n$ is aggregate labor demand and Π 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 Exercise

I estimate the model from Section 3 via minimum-distance estimation, choosing model parameters to match an array of moments from the SBU's firm-level data.

Prior to estimation, I calibrate a number of parameters from prior literature or based on normalizations. Table 5 shows these calibrated parameters, most of which pertain only to the household's problem and so do not directly affect managerial behavior or firm-level output dynamics in the economy's stationary general equilibrium. The main exception is the household's discount factor β, which, again, maps directly to the risk-free.

On the firm side of the economy, I normalize the objective mean of the driving 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 (based on managerial equity holdings in publicly-traded companies

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from Nikolov and Whited, 2014) to as much as 50 percent. My choice for θ does not affect my estimates of the model's other parameters because it drops out of the managers' problem in 4, but it does affect my general equilibrium counterfactuals because it changes the household's capital income and thus its labor supply decision. My analysis of the macroeconomic costs of managerial biases thus considers the impact of θ.

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

$$\min_\theta \quad [m(\vartheta) - m(X)]'W[m(\vartheta) - m(X)]. \tag{9}$$

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

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

1. The extent of managerial optimism, overconfidence and overextrapolation (3 moments), which come directly from my analysis of Facts 1 through 3 from Section 2.

2. The relationships between managerial forecasts and uncertainty with outcomes, hiring plans and hiring decisions (12 moments). Collectively, these moments constitute Fact 0 from Section 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), which is informative of the persistence of firm-level shocks.

Table 6a shows the full list of targeted moments along with their values, and their counterparts from the estimated model. See the Online Appendix for more details on how I construct my model and data moments and the estimation procedure.

While there isn't a one-to-one mapping from models to parameters, certain moments are particularly informative for certain parameters. Here I provide a heuristic description of how

moments map to parameters based on comparative static exercises in which I obtain model moments for different parameter vectors. In the Online Appendix I also report the sensitivity of my estimated parameters to moments following Andrews, Gentzkow, and Shapiro (2017).

The moments in group (1) regarding optimism, overconfidence, and overextrapolation identify the gap between parameters in the objective and subjective stochastic processes, namely the gap between $\tilde{\mu}$ and μ, $\tilde{\sigma}$ and σ, and $\tilde{\rho}$ and ρ. Among the the moments in group (3), the variance of quarterly sales growth is particularly informative for the true standard deviation of firm-level shocks, σ. In turn, the (negative) covariance between sales growth in quarters $t-1$ and t with sales growth over quarters t to $t+4$ helps identify the true persistence of shocks, ρ, while the covariance of employment and sales growth helps pin down the magnitude of adjustment costs, λ. The moments from group (2) mostly discipline the link between managerial beliefs and decisions, but the covariance between sales growth forecasts and hiring plans (i.e. employment growth forecasts) is particularly informative about the revenue elasticity of labor α and the adjustment cost parameter λ.

As part of my estimation, I acknowledge that the SBU may have nontrivial measurement error, since it is a self-reported survey and it collects only discrete approximations of managers' subjective distributions. Thus, I assume that quarterly sales and employment *levels* have multiplicative lognormal i.i.d error $\xi \sim \log \mathcal{N}(0, \sigma_\xi^2)$, so sales and employment *growth* are measured with i.i.d. error distributed $\mathcal{N}(0, 2\sigma_\xi^2)$. Similarly, I assume managerial forecasts and subjective uncertainty about future sales and employment *growth* are measured with i.i.d error $\nu \sim \mathcal{N}(0, \sigma_\nu^2)$. Both forms of measurement error may materially affect model moments $m(\vartheta)$. Appendix A provides full details on how measurement error affects model moments.

I estimate the variances of both types of measurement error along with the economic parameters already included ϑ, accomplishing several goals. First, allowing for measurement error in model moments provides added flexibility for the model to fit the data. Second, measurement error in sales growth inflates the moments that measure the extent of overconfidence and overextrapolation in the data, so failing to acknowledge the presence of measurement error would bias my estimates towards finding stronger overconfidence and overextrapolation. Finally, the novelty of the SBU data makes the magnitude of its measurement error interesting in its own right. Because my specification for measurement error is parsimonious, the estimation is overidentified by 10 degrees of freedom even after including σ_ξ^2 and σ_ν^2 in ϑ. This parsimony also creates restrictions that identify σ_ξ^2 and σ_ν^2, as each parameter affects several model moments.

I use a simulated annealing algorithm to undertake the numerical minimization problem in 9, with the aim of finding a global rather than a local minimum for my econometric

objective. 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 et al. (2017) show that using the efficient weighting matrix has desirable small-sample properties in minimum-distance estimation exercises of dynamic models of firms.

4.3   Estimation Results

Table 6 shows the results from my structural estimation of the model.

4.3.1   Assessing the model's fit

Sub-table 6a displays the value of the 19 targeted moments in the data and the model. The right column of the table also shows the t-statistic for the null hypothesis that the model and data moments are identical. Although the model is overidentified by 10 degrees of freedom, it fits a majority of the targeted moments, with only 4 being statistically different across the model and the data. This result is one of my paper's key contributions, namely showing that a dynamic model of managerial decision-making with a managerial beliefs process can match a broad set of empirical features of manager beliefs, decisions, and firm outcomes.

Looking at the three forecast error moments that discipline the extent of managerial biases, however, managers appear somewhat more rational in the model than they do in the SBU data. All three are smaller in absolute value in the model than in the data. (They would all be zero if managers had rational expectations). The excess absolute forecast error moment—which measures the degree of overconfidence—is even statistically different across the model and the data, although arguably not economically significant. In any case, having managers that are somewhat more rational in the model makes my analysis of the costs of managerial biases conservative.

The model also understates the variance of sales growth, likely because there is more measurement error in reported sales than in employment in the SBU, and I imposed a common error variance for sales and employment. However, the model is able to match other features of firm level sales and employment dynamics, including the variance of measured employment growth, the covariance of net hiring in quarter t with sales growth between $t-1$ and t, and the covariance of sales growth over quarter t to $t+4$ with sales growth in quarters $t-1$ to t.

Figure shows that the model fits a key non-targeted relationship, namely that describing how labor productivity relates to the firm's current hiring decision. This relationship is a two-dimensional representation of the model's policy function, essentially the "empirical policy function" proposed in Bazdresch, Kahn, and Whited (2017) as a natural benchmark

for estimation and evaluation of dynamic models. Each point in the figure depicts one of twenty quantiles of labor productivity, plotting the mean for each quantile on the horizontal axis against the mean net hiring rate for firms in that quantile on the horizontal axis. The black circles show the empirical relationship, while the blue asterisks show the relationship in the model's stationary distribution. The two relationships align, meaning the model fits this key non-targeted empirical benchmark.

4.3.2 Estimates of the economic parameters

Sub-table 6b shows my parameter estimates and their standard errors . My estimate of the revenue-elasticity of capital, α, is 0.83, which is within the typical range of estimated returns to scale for revenue production functions in macroeconomics. My estimate for the the quadratic adjustment cost parameter λ is about 30, but this number is difficult to interpret since adjustment costs estimates are model and context dependent. Moving to my estimates of the objective stochastic process, I find the standard deviation of the shocks to business conditions is 0.13, a typical value for a quarterly model with adjustment costs. Similarly, the autocorrelation of the persistent shocks, ρ, is 0.85, is reasonable for quarterly shocks to firm-level profitability.

4.3.3 The magnitude of pessimism, overconfidence, and overextrapolation

My estimates of the subjective stochastic process confirm my interpretation of the evidence from Section 2, specifically that managers are neither overoptimistic nor pessimistic, but they are overconfident and overextrapolate.

Consistent with Fact 1 from Section 2, managers in the estimated model are mildly pessimistic, as evidenced by an estimate of $\tilde{\mu}$ equal to -0.003. Quantitatively, this value of $\tilde{\mu}$ implies that managers underestimate the mean innovation to $\log(z_t)$ by 2.5 percent of its (true) standard deviation σ.

Managers are, by contrast, meaningfully overconfident and overextrapolative. They believe the volatility of shocks to business conditions $\tilde{\sigma}$ equals 0.044, about 38 percent as large as the true volatility σ, equal to 0.113. Managers also believe the autocorrelation of $\log(z)$, $\tilde{\rho}$, is 0.91, higher than the true autocorrelation ρ, which is 0.85. Quantitatively, these estimates imply that managers believe the half-life of innovations to $\log(z)$ is about 7.4 quarters, 67 percent higher than the true half life of about 4.4 quarters.

5 Micro and Macro Costs of Biases in Managerial Beliefs

To quantify how managerial beliefs—particularly, overconfidence and overextrapolation—impact the value of individual firms and aggregate economic outcomes, I conduct two different types of counterfactual exercises:

1. I ask how much firm value would increase for the typical firm in my estimated economy if it hired a rational manager, holding all else constant. In particular, I fix the firm's current profitability z_t, its labor force n_t, and general equilibrium prices.

2. I solve for the aggregate steady state of an economy with rational managers and compare aggregate outcomes between this efficient, unbiased economy and my estimated economy with biased managers.

My quantitative results in this section are based on the parameter estimates and calibration choices described in Section 4, but in the Online Appendix I show that my results are robust to changing some of the key technological parameters of the model.

5.1 Managerial Beliefs and Firm Value

Table 7 shows how the value of the typical firm would change if we replaced its biased manager with another who knows some of the true parameters of the firm-level shock process in equation 1, holding all else equal.

To compute each line in Table 7, I first compute objective firm value under a biased manager at each point in the (z, n) state space of the model, $V(z, n; w, r)$. Then, I compute firm value under a counterfactual unbiased manager $V^c(z, n; wr)$. Obtaining $V(\cdot)$ and $V^c(\cdot)$ entails solving for the biased and unbiased managers' policy functions $\kappa(\cdot)$ and $\kappa^c(\cdot)$ and then iterating on these policies to find a solution to functional equation in 5. Finally, I compute how much larger $V^c(\cdot)$ is over $V(\cdot)$ in percentage terms at each point in the (z, n) state space and average those percentage gains using the stationary distribution of firms in the economy.

The bottom line of Table 7 considers the benchmark case, in which a manager with rational beliefs (i.e. for whom $\tilde{\mu} = \mu$, $\tilde{\sigma} = \sigma$, and $\tilde{\rho} = \rho$) takes over running the firm and generates 2.1 percent higher value for the typical firm going forward. Looking at the second line from the bottom, essentially all of that gain in value could be realized by replacing a biased manager with another who fails to overextrapolate and isn't overconfident ($\tilde{\rho} = \rho$ and $\tilde{\sigma} = \sigma$) but slightly understates the mean innovation to $\log(z_t)$ ($\tilde{\mu} = -0.003 < \mu = 0$). This result is consistent with my conclusion in Section 2 that managers are not systematically

optimistic or pessimistic, so on the margin their mild pessimism is less costly than their overconfidence and overextrapolation.

The top two rows of Table 7 show how much firm value would increase by replacing the typical manager with another who either appreciates the true risk in innovations to fundamentals ($\tilde{\sigma} = \sigma$) *or* appreciates the true degree of mean reversion in fundamentals ($\tilde{\rho} = \rho$). In such cases, firm value would increase by 1.4 percent and 0.8 percent, respectively, accounting for about two-thirds and one-third of the potential gains in firm value from hiring a rational manager. The relative magnitude of these firm value gains may seem counterintuitive, since overextrapolation distorts managers' subjective first moments and thus should have first-order impact on their policies, while overconfidence distorts their second moments. My estimates of managerial overconfidence, however, are arguably more severe than those of managerial extrapolation: $\tilde{\sigma}$ is about 60 percent smaller than σ, but $\tilde{\rho}$ is only 7 percent larger than ρ.

It is not easy to judge whether my estimates of the cost of managerial biases are particularly large or small. I would argue that my results are conservative in light of the substantial deviations from rational expectations I estimate from the SBU data. Managers in my model, after all, cannot make catastrophic, irreversible decisions, and long-run firm profitability is invariant to managerial actions ($\mu = 0$). Concretely, they cannot choose to develop new product lines or divisions that make or break the firm's future, and similarly cannot overburden the firm with debt or push it towards bankruptcy. Future work may seek to explore whether biases in managerial beliefs may lead to costlier mistakes. Having said that, my estimates of the firm-value cost of biases are of a similar order of magnitude as estimates in prior literature of managerial misbehavior or entrenchment. Terry (2016) quantifies the firm value cost of managerial short-termism at about 1 percent of firm value. Taylor (2010) estimates the cost of CEO entrenchment at 3 percent and Wu (2017) argues that managerial dividend smoothing leads to a 2 percent loss in firm value.

5.1.1 Heterogeneity across subsamples

How much heterogeneity is there in the magnitude of managerial biases and, accordingly, in how much firm value biased managers destroy? In particular, how do firms fare differently when managers are subject to stronger or weaker oversight? If managerial biases arise from agency conflicts, for example if major shareholders appoint a relative or a friend as CEOs regardless of her suitability for the role, we might see different degrees of bias and firm value losses across different sorts of firms.

To address these questions, Table 8 displays parameter estimates and quantifies the firm value loss due to biases for six subsamples of the SBU data. Specifically, I repeat

the estimation separately for large (above median employment) versus small (below median employment) firms, for firms that are publicly-traded versus privately held, as well as firms with insider CEOs who are major shareholders or part of a major shareholding family, versus firms with outside CEOs. Since I have information on firm size for essentially all observations in the full SBU sample, we can think of the the small versus large split as a partition in terms of firm size. Instead, the public/private and inside/outside CEO estimations restrict attention to those firms that answered the special questions about ownership in the February or March 2019 surveys.[27]

Looking at Table 8, firm value losses due to beliefs range from 0.64 to 4.74 percent of firm value across the several subsamples, similar to my baseline estimate of 2.13 percent for the full sample. Differences in the parameter estimates can also point to the sources of heterogeneity across samples. For example, small firms exhibit more overextrapolation than large firms (i.e. a larger gap between $\tilde{\rho}$ and ρ); accordingly, I find managers of small firms destroy more value than those at large firms. Publicly-traded versus privately held firms, by contrast, exhibit similar degrees of overconfidence (in terms of the $\tilde{\sigma}/\sigma$ ratio) and overextrapolation, and they destroy similar amounts of firm value— between 4 and 5 percent. Finally, firms with insider versus outside CEOs also appear similar, but those with insider CEOs have smaller returns to scale ($\alpha = 0.55$ rather than 0.75), which may reflect a more limited managerial span of control, but also means managerial mistakes are less costly.

Altogether, this exercise suggests that firms with very different governance structures (especially those where major shareholders have strong relationships with management) all seem to have biased managers and who destroy some firm value. It is therefore difficult to argue that biases reflect agency conflicts that are characteristic of certain types of firms, while they are absent from firms with stronger governance and more sophisticated, professional managers.

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 a long-run, aggregate outcome in a counterfactual economy with unbiased managers (for whom $\tilde{\mu} = \mu$, $\tilde{\sigma} = \sigma$, and $\tilde{\rho} = \rho$) and the same outcome in an economy with managers who are overconfident and overextrapolate, according to my estimation results.

Consumer welfare, GDP, and labor productivity are higher in economies with rational managers, but how much higher depends on the share of firm equity held by managers (θ). In

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[27]See Appendix Figure A.3 for a screenshot of the ownership questions.

Table 9 I report results for $\theta = 0.05$ at the low end, consistent with the share of managerial equity in publicly-traded firms in Nikolov and Whited, 2014; for $\theta = 0.50$ at the high end, based on the fact that some 60 percent of SBU firms have CEOs who are major shareholders or part of a major shareholding family; and for a middle-of-the-road value of $\theta = 0.25$. Without data on the typical share of firm equity held by management in my sample, it is hard to say what the correct value of θ is, but I believe it is unlikely it would be lower than the 5 percent share estimated among publicly-traded firms, or higher than a controlling share (50%). Given that lower values of θ lead to more conservative results, I use 5 percent as my baseline choice below.

Aggregate consumer welfare is larger in the unbiased economy by 0.50 to 2.34 percent in consumption equivalent terms. GDP (gross output less adjustment costs) is also higher by 0.3 to 1.1 percent, while labor productivity is higher by 0.07 to 0.26 percent. For comparison, recent estimates of the cost of business cycles amount to about 1 percent in consumption equivalent terms (Krusell, Mukoyama, Şahin, and Smith Jr, 2009)) after considering the impact of long-term unemployment. In Terry (2016) the welfare cost of managerial short-termism is 0.44 percent of consumption.

Why are welfare, GDP, and productivity higher in economies with unbiased managers? I argue that overextrapolation and overconfidence lead managers in the model to overreact to shocks. We can see this behavior in Figure 11, which, again, represents the joint distribution of labor productivity (essentially, the marginal product of labor) and current net hiring in the baseline economy with biases and the counterfactual economy with rational managers. The upward sloping relationship in both economies shows that managers hire workers when the firm's marginal product of labor is high, and lay off workers when it is low. They key difference between the two economies is this relationship is steeper for the economy with biased managers. When overextrapolative managers observe an innovation to firm-level profitability $\log(z_t)$, they overestimate how persistent it is, which leads them to overestimate how many workers they should hire or lay off. Overconfident managers who observe the same innovation also feel quite certain about the firm's future marginal product of labor, so they are more willing to pay the costs associated with adjusting the firm's labor force.

Overconfidence and overextrapolation are costly to the aggregate economy because pervasive overreaction to shocks results in excessive, costly reallocation. Indeed, Table 9b shows that the rate of reallocation[28] in an economy with rational managers is 60 percent lower than in the baseline economy with biased managers. This drop in reallocation means firms in the unbiased economy are on average farther from their optimal scale. Dispersion in the

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[28]I measure the rate of reallocation as the employment-weighted average of absolute firm-level employment growth, scaled by aggregate labor, following Davis and Haltiwanger (1992).

marginal product of labor (i.e. static misallocation) is thus higher by about 3.5% in the unbiased economy. Based on these statistics alone, it appears that biased managers are better at allocating scarce labor across firms and should therefore generate higher welfare. Reallocation is costly, however, and biased managers overestimate its benefits relative to its costs, thus spending too many resources on reallocation. An economy with rational managers thus spends 1.2 fewer percentage points of GDP on reallocation. Reducing unnecessary (and costly) reallocation enables the rational economy to deliver higher consumer welfare. This logic applies equally regardless of how much firm equity biased managers hold. Indeed, Table 9b fixes managerial equity θ at 5 percent, but the results are virtually identical for other values of θ.

In Table 9c I explore how aggregate welfare and reallocation differ across counterfactual economies in which managers are not overconfident ($\tilde{\sigma} = \sigma$), do not overextrapolate ($\tilde{\rho} = \rho$) or both together, fixing managerial equity at 5 percent. Each entry in the table reports differences in outcomes relative to the economy with biased managers. For ease of comparison, the bottom line replicates the results from Table 9a, in which managers are fully rational. We can see that eliminating either overconfidence or overextrapolation (or both) improves consumer welfare and results in less reallocation, higher dispersion in the marginal product of labor, and fewer resources spent on adjustment costs. As with the firm-value cost of biases, eliminating both overconfidence and overextrapolation while keeping managers' mild pessimism (the case with $\tilde{\rho} = \rho$ and $\tilde{\sigma} = \sigma$ only) delivers welfare and efficiency gains that are almost as large as what we would obtain from eliminating all biases. Moreover, Table 9c shows that there is an optimal degree of reallocation. Doing too much of it, or too little (as in the $\tilde{\rho} = \rho$ and combined $\tilde{\rho} = \rho$ and $\tilde{\sigma} = \sigma$ counterfactuals) leads to lower welfare than in the unbiased economy.

While pervasive overreaction and excessive reallocation are the underlying reason why managerial biases are costly for the macroeconomy, the share of managerial equity θ also determines how overreaction translates into consumer welfare differences via general equilibrium effects. Table 9d shows that equilibrium wages are higher when managers have rational expectations; particularly when managers hold a larger share of firm equity θ. Thus, the economy with biased managers is farther away from the first-best, rational expectations equilibrium for higher values of θ, meaning differences in consumer welfare across the biased and rational economies increase with θ. The latter result also means the capitalist managers are worse off in equilibrium in economies where they have rational expectations, as we can see from the drop in firm profits in Table 9d. To alleviate this tension, the final column of Table 9d reports the weighted average change in consumption-equivalent welfare for consumers and managers collectively, weighting by each group's share of consumption in biased equilibrium.

In all cases, consumers' gains more than compensate for managers' losses, so eliminating managerial biases improves overall welfare based on this broader criterion.

5.2.1 Policy implications

My headline result that managerial overconfidence and overextrapolation are costly because they encourage excessive hiring and firing begs the question: what can policy-makers do to mitigate the costs of managerial biases? In particular, can we improve outcomes when managers are biased without changing how they form their beliefs, which may be difficult or even impossible?

In Figure 12 I show that taxing layoffs and rebating the revenue to consumers can discourage managers from overreacting and improve consumer welfare. Introducing such a tax τ_f modifies firm cash flows and the representative household's budget constraint as follows:

$$
\begin{aligned}
\pi(z_t, n_t, n_{t+1}; w_t) &= z_t n_t^\alpha - w_t n_t \cdot (1 + \tau_f \mathbf{1}(n_{t+1} < n_t)) - AC(n_t, n_{t+1}) \\
C_t + B_{t+1} &= w_t N_t + (1 + r_t) B_t + \Pi_t + T_t.
\end{aligned}
$$

Imposing a balanced government, the household's transfer is:

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

To obtain the welfare effect of the tax, I solve for the model's stationary equilibrium for a range of taxes τ_f and compare consumer welfare in equilibria with the tax against welfare in my estimated model, fixing the managerial equity share θ at 5 percent. Figure 12 plots the change in welfare due to the tax as well as the potential welfare gains from moving to an economy with rational managers, at 0.5 percent of consumption.

Taxing firms when they lay off workers discourages managers from overreacting to profitability shocks, which leads to fewer resources wasted on reallocation. Consumer welfare rises by up to about 0.3 percent of consumption, or about 60 percent of the welfare costs of managerial overextrapolation and overconfidence. Subsidizing hiring and firing, by contrast, exacerbates the costs of managerial biases and lowers consumer welfare, as we can see for the region that has negative τ_f taxes. These results stand in contrast with canonical wisdom that discouraging resource reallocation is detrimental to welfare and productivity.[29]

This exercise teaches us two broad lessons from about the relationship between policy and managerial beliefs. First, even if we cannot change the nature of beliefs, there may

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[29]For example see the arguments by Decker et al. (2018) on the potential role of reallocation frictions for US productivity growth slowdown.

exist policies that mitigate the macroeconomic costs of managerial overreaction. Second, the impact of public policies can depend on the nature managerial beliefs, thus making beliefs relevant for policy debates.[30] Admittedly, my model lacks many features of reality that could make taxing layoffs problematic in practice. Lack of a firm lifecycle and entry-exit dynamics, for example, could make taxing layoffs very costly in terms of aggregate productivity by suppressing entrepreneurship. At the other extreme, it could be that managerial overconfidence and overextrapolation are welfare improving if there are strong regulatory frictions to reallocation, for example if my estimated adjustment costs are less technological and more due to inefficient government bureaucracy. My goal here is not to make particular policy recommendations, but rather to argue that understanding how and why biases impact firm behavior is key to thinking about the impact of policies that nudge them to behave differently.

6 Conclusion

This paper uses a new survey of US managers to study how their beliefs affect firm behavior, performance, and macroeconomic outcomes. I find that while managers are not overoptimistic, they believe firm performance is less volatile and more persistent than it is empirically; namely, managers are overconfident and overextrapolate. Guided by these empirical facts, I build and estimate a dynamic general equilibrium model with heterogeneous firms to quantify the impact of managerial overconfidence and overextrapolation. My estimated model matches a wide array of moments related to managerial beliefs, decisions, and firm outcomes and reveals that biased managers overreact to changes in profitability. Overreaction lowers firm value by 2.1 percent at the micro level and lowers consumer welfare by 0.5 to 2.3 percent because it leads managers to spend too many resources adjusting to volatile, transitory shifts in profitability.

My finding that managerial beliefs lead to overreaction has broader implications for behavioral macroeconomics. In particular, overconfidence and overextrapolation may serve an important role in amplifying aggregate shocks. This intuition is already present in recent papers like Bordalo, Gennaioli, and Shleifer (2018b) and Bordalo, Gennaioli, Shleifer, and Terry (2019), but there is ample room for a new generation of macro models to consider how overreaction shapes macro and financial fluctuations.

Additionally, my paper highlights the need to understand how firms end up hiring and

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[30]In the Online Appendix I expand on the latter point by showing that the welfare cost of taxation is higher when managers are overconfident and overextrapolate, and similarly that managerial overreaction is more costly when there are distortionary taxes.

retaining biased managers. While my paper cannot do justice to this question, by measuring and quantifying the implications of prevailing biases it makes some headway. My estimates show that biases impact firms broadly. They are not a feature of individual sectors, firms of a certain size, or firms with a particular form of governance. Thus my results suggest boards of directors and shareholders may find it difficult to identify biased managers. They may even actively promote and select managers who exhibit decisiveness and confidence.[31] Whatever the case, my paper points to avenues for answering these and other questions about managerial selection and behavior.

References

ACEMOGLU, D. AND M. K. JENSEN (2018): "Equilibrium Analysis in the Behavioral Neoclassical Growth Model," .

ALTI, A. AND P. C. TETLOCK (2014): "Biased beliefs, asset prices, and investment: A structural approach," *The Journal of Finance*, 69, 325–361.

ALTIG, D., J. M. BARRERO, N. BLOOM, S. J. DAVIS, B. H. MEYER, AND N. PARKER (2019): "Surveying Business Uncertainty," Tech. rep.

ANDREWS, I., M. GENTZKOW, AND J. M. SHAPIRO (2017): "Measuring the sensitivity of parameter estimates to estimation moments," *The Quarterly Journal of Economics*, 132, 1553–1592.

ASKER, J., A. COLLARD-WEXLER, AND J. DE LOECKER (2014): "Dynamic inputs and resource (mis) allocation," *Journal of Political Economy*, 122, 1013–1063.

BACHMANN, R., K. CARSTENSEN, S. LAUTENBACHER, AND M. SCHNEIDER (2018): "Uncertainty and Change: Survey Evidence of Firmsâ Subjective Beliefs," .

BACHMANN, R. AND S. ELSTNER (2015): "Firm optimism and pessimism," *European Economic Review*, 79, 297–325.

BAILEY, W., A. KUMAR, AND D. NG (2011): "Behavioral biases of mutual fund investors," *Journal of Financial Economics*, 102, 1–27.

BARBER, B. AND T. ODEAN (1999): "Do investors trade too much?" *American Economic Review*, 89, 1279–1298.

BAZDRESCH, S., R. J. KAHN, AND T. M. WHITED (2017): "Estimating and testing dynamic corporate finance models," *The Review of Financial Studies*, 31, 322–361.

BEBCHUK, L., A. COHEN, AND A. FERRELL (2008): "What matters in corporate governance?" *The Review of financial studies*, 22, 783–827.

BEN-DAVID, I., J. R. GRAHAM, AND C. R. HARVEY (2013): "MANAGERIAL MISCALIBRATION," *The Quarterly Journal of Economics*, 1547, 1584.

BENIGNO, P. AND A. G. KARANTOUNIAS (2019): "Overconfidence, subjective perception and pricing behavior," *Journal of Economic Behavior & Organization*, 164, 107–132.

BERTRAND, M. AND A. SCHOAR (2003): "Managing with style: The effect of managers on firm policies," *The Quarterly Journal of Economics*, 118, 1169–1208.

BLOOM, N. (2009): "The impact of uncertainty shocks," *Econometrica*, 77, 623–685.

BLOOM, N., S. DAVIS, L. FOSTER, B. LUCKING, S. OHLMACHER, AND I. SAPORTA EKSTEN (2017): "Business-Level Expectations and Uncertainty," .

BORDALO, P., N. GENNAIOLI, Y. MA, AND A. SHLEIFER (2018a): "Overreaction in macroeconomic expectations," Tech. rep., Working Paper.

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[31]For example, see Goel and Thakor (2008) for a formal model in which such tournament incentives optimally result in hiring overconfident managers. Kaplan, Klebanov, and Sorensen (2012) and Kaplan and Sorensen (2017) also show empirically that decisiveness appears to be a desirable trait in CEOs.

BORDALO, P., N. GENNAIOLI, R. L. PORTA, AND A. SHLEIFER (2017): "Diagnostic expectations and stock returns," Tech. rep., National Bureau of Economic Research.

BORDALO, P., N. GENNAIOLI, AND A. SHLEIFER (2018b): "Diagnostic expectations and credit cycles," *The Journal of Finance*, 73, 199–227.

BORDALO, P., N. GENNAIOLI, A. SHLEIFER, AND S. J. TERRY (2019): "Real Credit Cycles," .

BOUTROS, M., I. BEN-DAVID, J. R. GRAHAM, C. R. HARVEY, AND J. W. PAYNE (2019): "The Persistence of Miscalibration," *Available at SSRN 3462107*.

BRADLEY, C., M. HIRT, AND S. SMIT (2018): "How to confront uncertainty in your strategy," Tech. rep., McKinsey & Company.

CARROLL, C. D., E. CRAWLEY, J. SLACALEK, K. TOKUOKA, AND M. N. WHITE (2018): "Sticky expectations and consumption dynamics," Tech. rep., National Bureau of Economic Research.

CHETTY, R., A. GUREN, D. MANOLI, AND A. WEBER (2011): "Are micro and macro labor supply elasticities consistent? A review of evidence on the intensive and extensive margins," *American Economic Review*, 101, 471–75.

COCHRANE, J. H. (2017): "Macro-finance," *Review of Finance*, 21, 945–985.

COOPER, R. W. AND J. C. HALTIWANGER (2006): "On the nature of capital adjustment costs," *The Review of Economic Studies*, 73, 611–633.

DAVID, J. M. AND V. VENKATESWARAN (2017): "Capital Misallocation: Frictions or Distortions?" Working Paper 23129, National Bureau of Economic Research.

DAVIS, S. J. AND J. HALTIWANGER (1992): "Gross job creation, gross job destruction, and employment reallocation," *The Quarterly Journal of Economics*, 107, 819–863.

DECKER, R. A., J. C. HALTIWANGER, R. S. JARMIN, AND J. MIRANDA (2018): "Changing business dynamism and productivity: Shocks vs. responsiveness," Tech. rep., National Bureau of Economic Research.

DOMINITZ, J. (1998): "Earnings expectations, revisions, and realizations," *Review of Economics and statistics*, 80, 374–388.

DOMINITZ, J. AND C. F. MANSKI (1997): "Using expectations data to study subjective income expectations," *Journal of the American statistical Association*, 92, 855–867.

FUSTER, A., B. HEBERT, AND D. LAIBSON (2010): "Investment dynamics with natural expectations," *International journal of central banking/Bank of Canada*, 8, 243.

FUSTER, A., G. KAPLAN, AND B. ZAFAR (2018): "What would you do with 500?*spendingresponsestogains, losses, newsandloans*," Tech. rep., National Bureau of Economic Research.

GABAIX, X. (2016): "Behavioral Macroeconomics Via Sparse Dynamic Programming," Tech. rep., National Bureau of Economic Research.

GENNAIOLI, N., Y. MA, AND A. SHLEIFER (2016): "Expectations and investment," *NBER Macroeconomics Annual*, 30, 379–431.

GIGLIO, S., M. MAGGIORI, J. STROEBEL, AND S. UTKUS (2019): "Five facts about beliefs and portfolios," Tech. rep., National Bureau of Economic Research.

GOEL, A. M. AND A. V. THAKOR (2008): "Overconfidence, CEO selection, and corporate governance," *The Journal of Finance*, 63, 2737–2784.

GRANDMONT, J. M. ET AL. (1977): "Temporary general equilibrium theory," *Econometrica*, 45, 535–572.

HACKBARTH, D. (2008): "Managerial traits and capital structure decisions," *Journal of Financial and Quantitative Analysis*, 43, 843–881.

HALL, R. E. (2009): "Reconciling cyclical movements in the marginal value of time and the marginal product of labor," *Journal of political Economy*, 117, 281–323.

HOPENHAYN, H. AND R. ROGERSON (1993): "Job turnover and policy evaluation: A general equilibrium analysis," *Journal of political Economy*, 101, 915–938.

HOPENHAYN, H. A. (1992): "Entry, exit, and firm dynamics in long run equilibrium," *Econometrica: Journal of the Econometric Society*, 1127–1150.

HSIEH, C.-T. AND P. J. KLENOW (2017): "The Reallocation Myth," *Fostering a Dynamic Global Economy*.

JURADO, K. (2016): "Advance Information and Distorted Beliefs in Macroeconomic and Financial Fluctuations," *Unpublished*.

KAPLAN, G., K. MITMAN, AND G. L. VIOLANTE (2017): "The housing boom and bust: Model meets evidence," Tech. rep., National Bureau of Economic Research.

Kaplan, S. N., M. M. Klebanov, and M. Sorensen (2012): "Which CEO characteristics and abilities matter?" *The Journal of Finance*, 67, 973–1007.

Kaplan, S. N. and M. Sorensen (2017): "Are CEOs different? Characteristics of top managers," Tech. rep., National Bureau of Economic Research.

Kim, H.-S. (2018): "Effects of CEO miscalibration on compensation and hedging," *Finance Research Letters*.

Krusell, P., T. Mukoyama, A. Şahin, and A. A. Smith Jr (2009): "Revisiting the welfare effects of eliminating business cycles," *Review of Economic Dynamics*, 12, 393–404.

La Porta, R. (1996): "Expectations and the cross-section of stock returns," *The Journal of Finance*, 51, 1715–1742.

Lucas, R. E. (1978): "On the size distribution of business firms," *The Bell Journal of Economics*, 508–523.

Ma, Y., D. A. Sraer, and D. Thesmar (2018): "The Aggregate Cost of Systematic Forecast Errors," .

Malmendier, U. and G. Tate (2005): "CEO overconfidence and corporate investment," *The journal of finance*, 60, 2661–2700.

Manski, C. F. (2004): "Measuring expectations," *Econometrica*, 72, 1329–1376.

——— (2018): "Survey measurement of probabilistic macroeconomic expectations: progress and promise," *NBER Macroeconomics Annual*, 32, 411–471.

Maxted, P. D. (2019): "A Macro-Finance Model with Sentiment," Tech. rep.

Melitz, M. J. and S. J. Redding (2015): "New trade models, new welfare implications," *American Economic Review*, 105, 1105–46.

Molavi, P. (2018): "Macroeconomics with Learning and Misspecification: A General Theory and Applications," .

Nikolov, B. and T. M. Whited (2014): "Agency conflicts and cash: Estimates from a dynamic model," *The Journal of Finance*, 69, 1883–1921.

Odean, T. (1998): "Volume, volatility, price, and profit when all traders are above average," *The Journal of Finance*, 53, 1887–1934.

Puetz, A. and S. Ruenzi (2011): "Overconfidence among professional investors: Evidence from mutual fund managers," *Journal of Business Finance & Accounting*, 38, 684–712.

Rozsypal, F. and K. Schlafmann (2017): "Overpersistence bias in individual income expectations and its aggregate implications," .

Shimer, R. (2005): "The cyclical behavior of equilibrium unemployment and vacancies," *American economic review*, 95, 25–49.

Stein, J. C. (2003): "Agency, information and corporate investment," in *Handbook of the Economics of Finance*, Elsevier, vol. 1, 111–165.

Tanaka, M., N. Bloom, J. M. David, and M. Koga (2018): "Firm Performance and Macro Forecast Accuracy," Tech. rep., National Bureau of Economic Research.

Taylor, L. A. (2010): "Why are CEOs rarely fired? Evidence from structural estimation," *The Journal of Finance*, 65, 2051–2087.

Terry, S. J. (2016): "The Macro Impact of Short-Termism," .

Woodford, M. (2013): "Macroeconomic analysis without the rational expectations hypothesis," *Annu. Rev. Econ.*, 5, 303–346.

Wu, Y. (2017): "What's behind smooth dividends? Evidence from structural estimation," *The Review of Financial Studies*, 31, 3979–4016.

Young, E. R. (2010): "Solving the incomplete markets model with aggregate uncertainty using the Krusell–Smith algorithm and non-stochastic simulations," *Journal of Economic Dynamics and Control*, 34, 36–41.

Figure 1: **Sales Questions in the *Survey of Business Uncertainty***

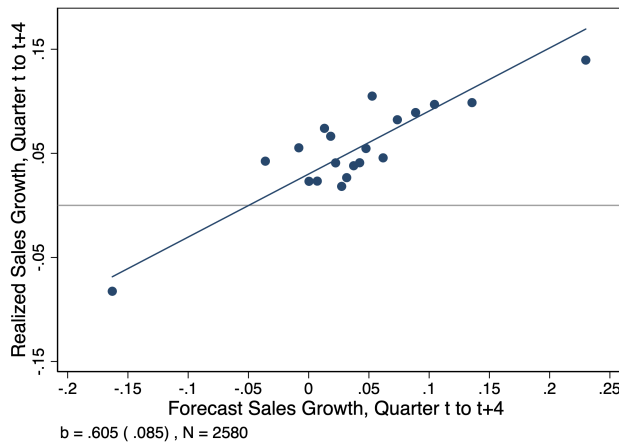**Notes:** Sales growth questions in the Survey of Business Uncertainty as they have appeared since September 2016. In months prior to September 2016, the SBU asked for sales growth beliefs in levels rather than growth rates. See the Online appendix for those earlier questions. The rates of sales growth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

Figure 2: **Sales and Employment Growth Forecasts Predict Outcomes**

(a) **Sales Growth Forecast Predict Sales Growth**   (b) **Hiring Plans Predict Actual Hiring**
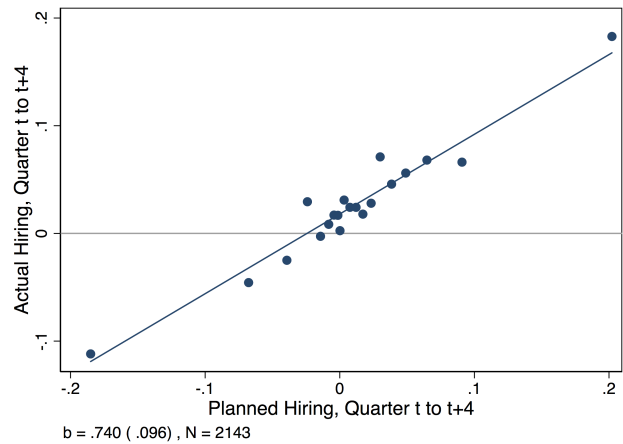
Notes: The top figure shows bin-scatter plots of managerial sales growth forecasts for the next four quarters on the horizontal axis against realized sales growth over those four quarters. The bottom figure shows managerial hiring plans (forecasts for employment growth) for the next 12 months against actual employment growth. The reported estimates and standard errors refer to the underlying population 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.
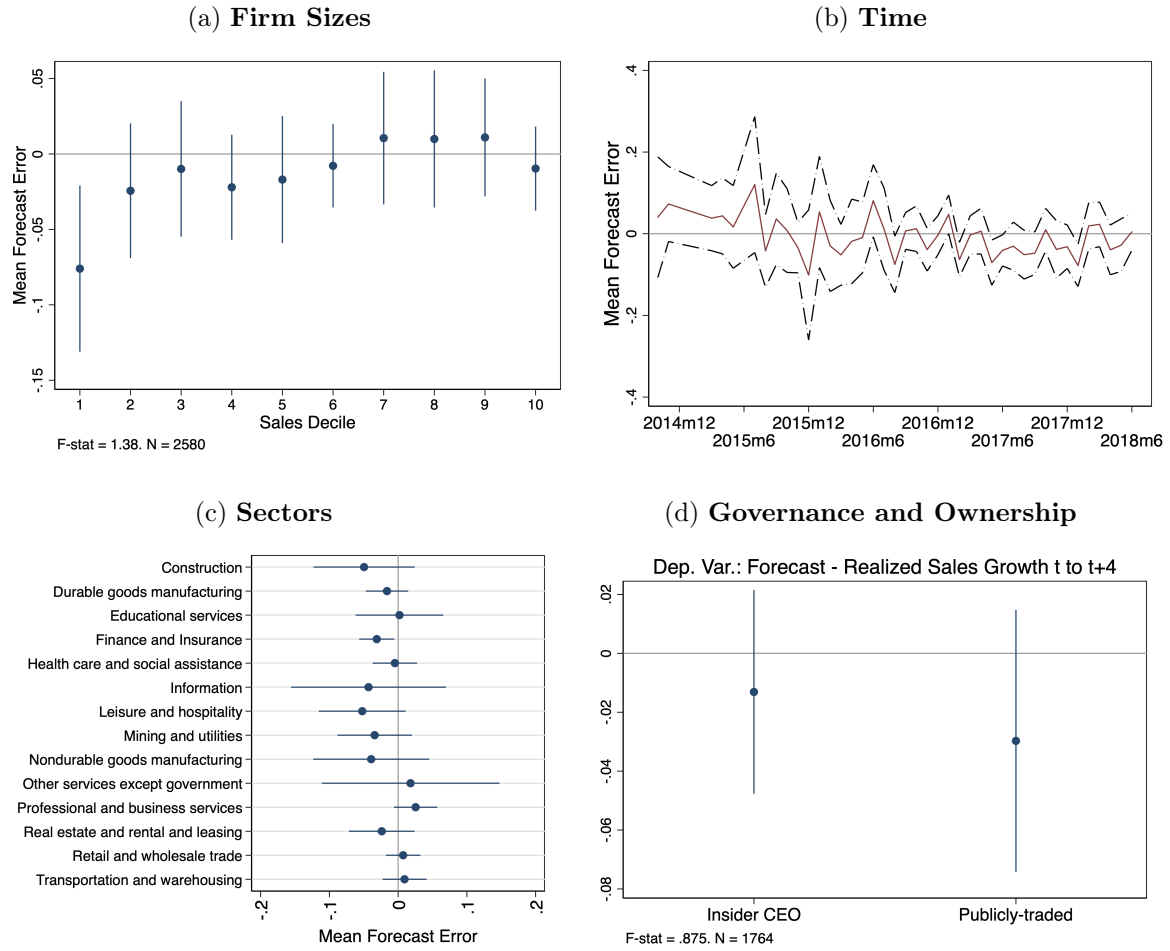
Figure 3: **Sales Growth Forecasts and Uncertainty Predict Planned Hiring**

(a) **Forecasts Predict Hiring Plans**

b = .421 (.053) , N = 5009

(b) **Uncertainty Predicts Hiring Plans**

b = -.17 (.062) , N = 5009

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

b = .611 (.152) , N = 5015
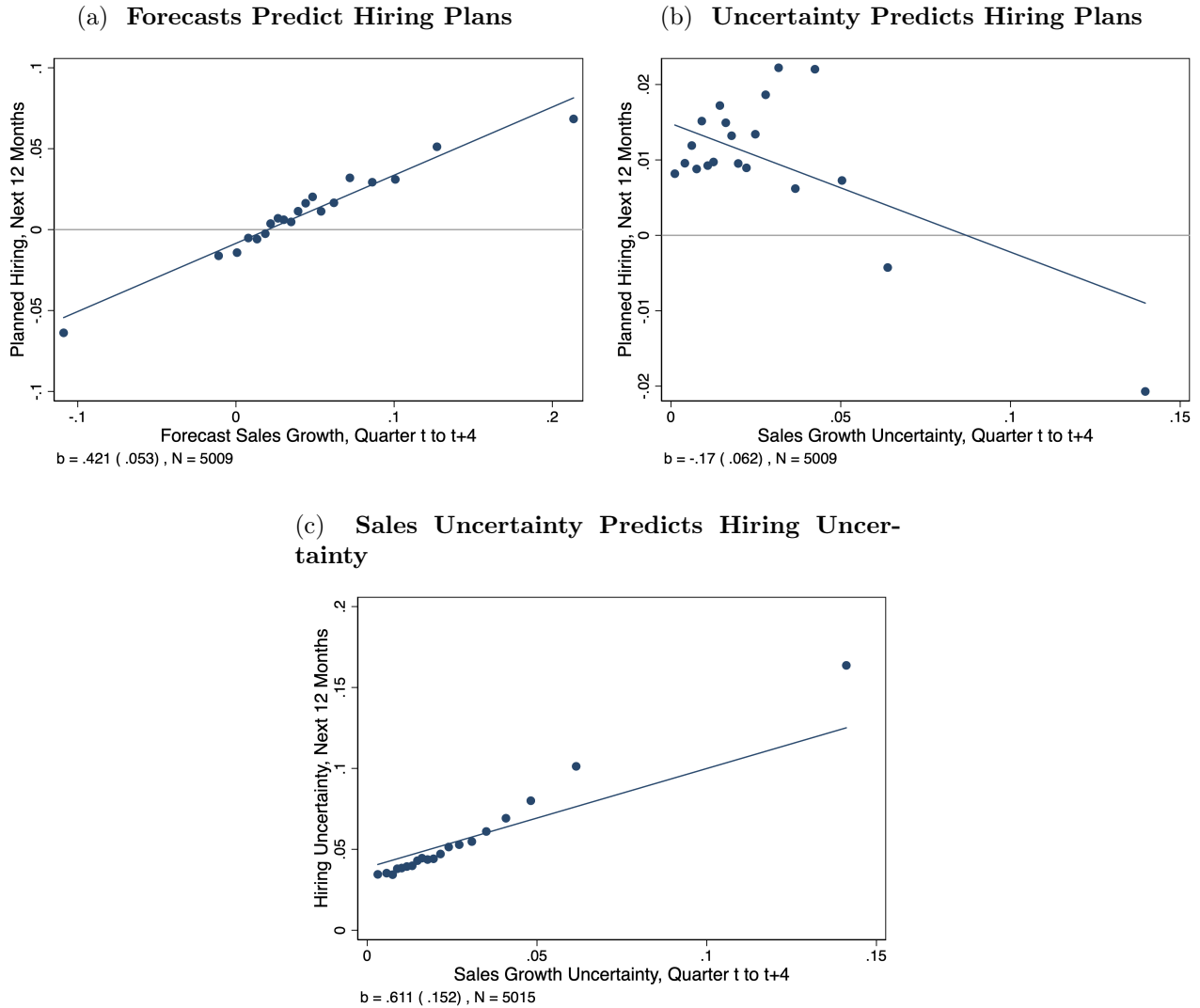
Notes: The top left figure shows a bin-scatter plot of planned hiring over the next 12 months (i.e. the managers' expectation for the firm's employment growth) on the vertical axis, conditional on her forecast for the firm's sales growth over the next four quarters. The top right figure shows a bin-scatter plot of planned hiring again on the vertical axis, now against the manager's subjective uncertainty (subjective mean absolute deviation) for sales growth over the next four quarters. The bottom figure shows a bin-scatter plot 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. The reported estimates and standard errors refer to the underlying population 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 Current Hiring**

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

b = .157 (.040) , N = 3930

b = -.03 (.074) , N = 3932
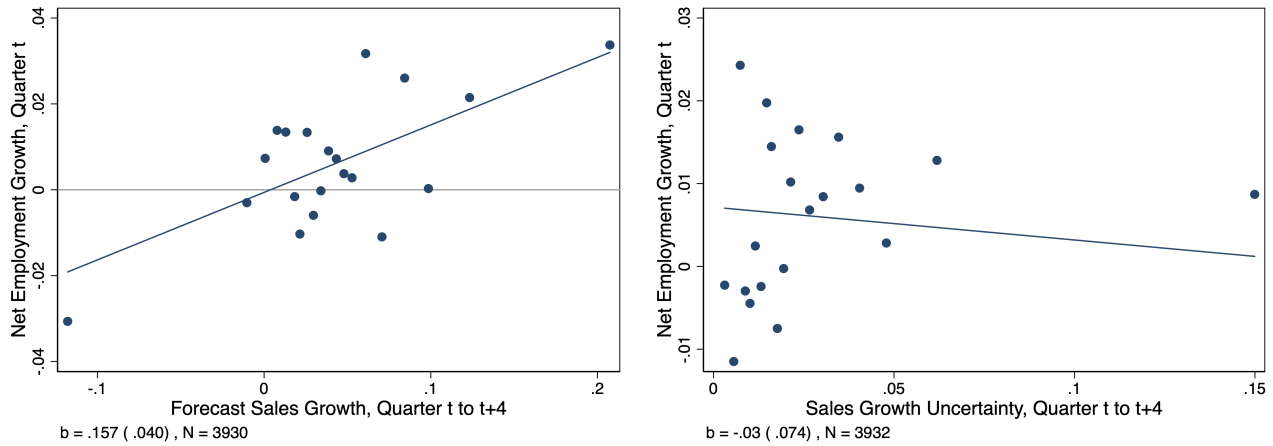
Notes: The top figure shows a bin-scatter plot of managerial sales growth forecasts for the next four quarters on the horizontal axis against the firm's current net hiring (the firm's employment growth relative to the previous quarter) on the vertical axis. The bottom figure shows a bin-scatter plot of managerial sales growth uncertainty over the next four quarters again against current net hiring. The reported estimates and standard errors refer to the underlying population 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.

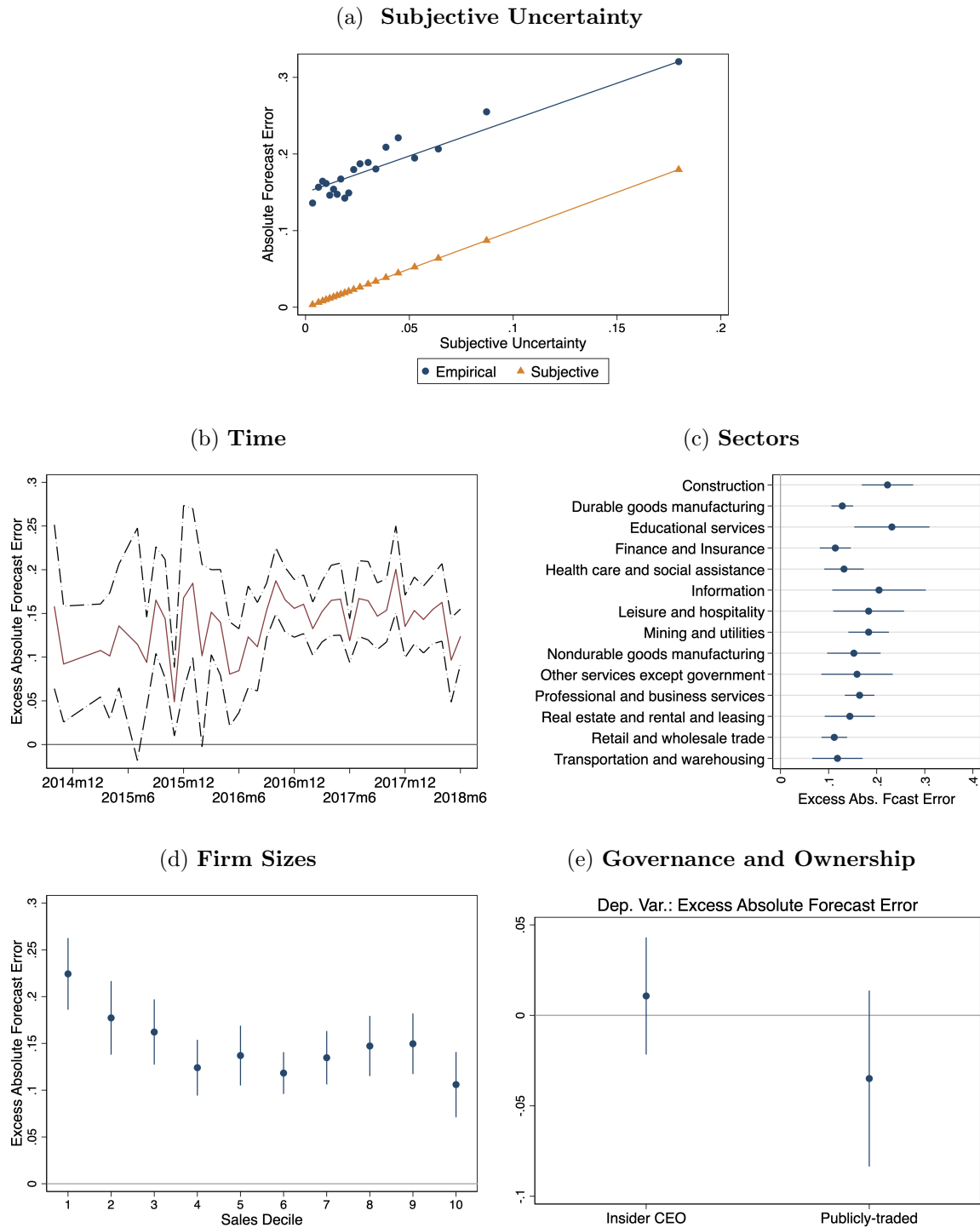Figure 5: **Heterogeneity in Optimism and Pessimism by:**

(a) **Firm Sizes**

F-stat = 1.38. N = 2580

(b) **Time**

(c) **Sectors**

(d) **Governance and Ownership**

F-stat = .875. N = 1764

Notes: This figure shows *(top left)* the mean forecast error for each decile of firm-level sales , *(top right)* for each month, *(bottom left)* each sector, and *(bottom right)* whether forecast errors are higher or lower for publicly-traded firms or firms with insider CEOs. Insider CEO firms are those for which the CEO is a major shareholder or is part of a major shareholding family. The broken lines in the top left figure are 95 percent confidence intervals. Data are from the Survey of Business Uncertainty, with the sample including all forecast error observations concerning sales growth, looking four quarters ahead. 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 $t+4$. $N = 2,580$.

Figure 6: **Managers are Overconfident**
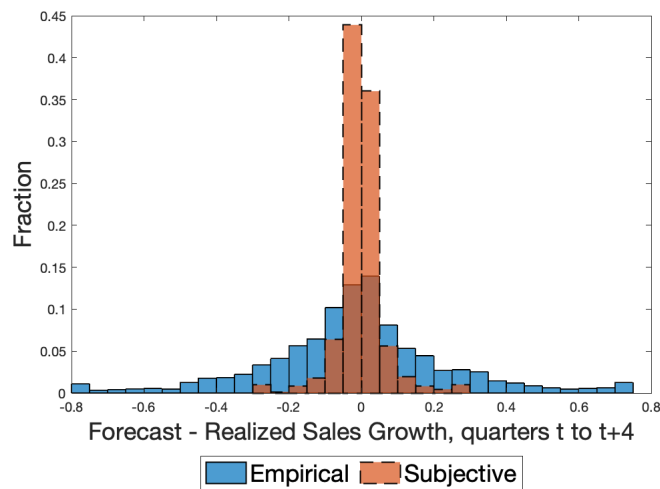
Notes: This figure plots the empirical distribution of forecast errors as well as the distribution of forecast errors that would arise if sales growth realizations were drawn from SBU respondents' subjective probability distributions. I scale each distribution so that the sum of the heights of the bars is equal to one, and fix the width of the bars to 0.05. 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 $t + 4$. $N = 2,580$.

Figure 7: **Heterogeneity in Overconfidence by:**

(a) **Subjective Uncertainty**

(b) **Time**

(c) **Sectors**

(d) **Firm Sizes**

(e) **Governance and Ownership**

Notes: This figure shows *(top)* bin-scatter plots of subjective and empirical absolute forecast errors against ex-ante subjective uncertainty. It also shows mean excess absolute forecast errors *(middle left)* by month, *(middle right)* by industry, and *(bottom left)* by decile of firm-level sales. Finally, it shows *(bottom right)* whether excess absolute forecast errors are on average higher or lower for publicly-traded firms or firms with insider CEOs. Firms have an insider CEO if he or she is a major shareholder or member of a family of major shareholders. The broken lines in the middle left figure are firm-clustered 95 percent confidence bands. A respondent's excess absolute forecast error is her absolute error less her ex-ante subjective mean absolute deviation t. Data are from the SBU and the sample period includes all monthly surveys 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 $t+4$. $N = 2,580$.

Figure 8: **Managers Overextrapolate from Current Conditions**

b = .207 (.026) , N = 1829
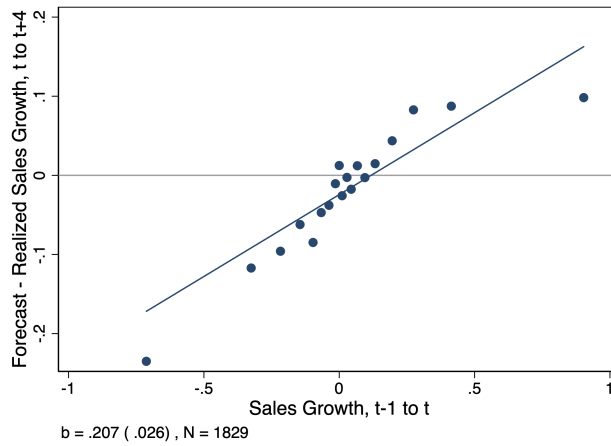
Notes: This figure shows a bin-scatter of realized forecast errors for sales growth between t and $t + 4$ on the vertical axis against realized sales growth between quarters $t - 1$ and t, just prior to the survey response. Data are from the SBU and sample period includes all months between 10/2014 to 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 $t + 4$. $N = 1,829$.

Figure 9: **Heterogeneity in Overextrapolation by:**

(a) **Firm Sizes**
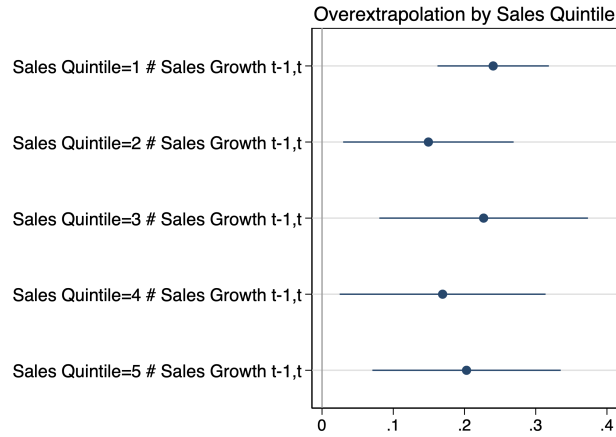

(b) **Governance and Ownership**
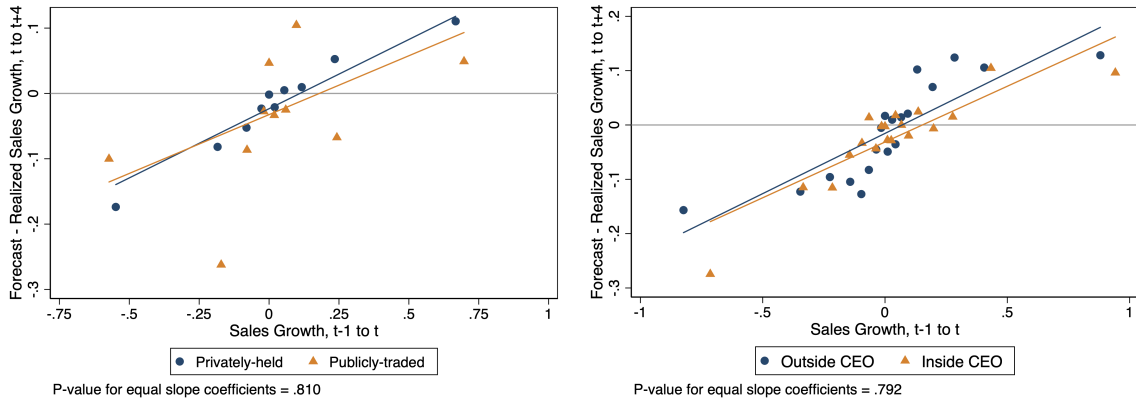
Notes: The top figure shows the coefficients from regressing forecast minus realized sales growth between quarter t and $t+4$ on the firm's lagged sales growth from $t-1$ to t separately for each of five quintiles of the distribution of sales level. The horizontal bars are 95 percent confidence intervals based on firm-clustered standard errors. The bottom figures show bin-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 inside CEOs. Data are from the SBU, with the sample covering all months between $10/2014$ to $5/2019$.

Figure 10: **Assessing Model Fit: Hiring versus Labor Productivity**
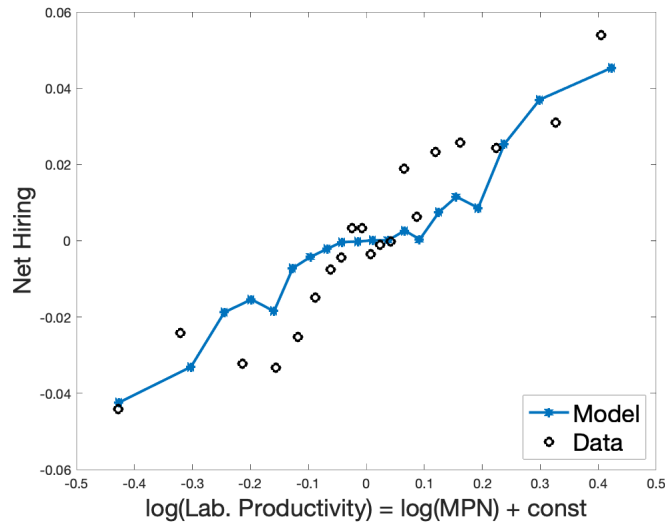
Notes: This figure shows the joint distribution of log(labor productivity) on the horizontal axis and net hiring on the vertical axis in the estimated model as well as in the SBU data. I sort the stationary distribution of the model economy and into 20 quantiles of log-labor productivity and plot the mean labor productivity in each quantile on the horizontal axis against the mean net hiring rate on the vertical axis. In the data, I also sort the empirical distribution of labor productivity into twenty quantiles and plot the mean for each quantile against the mean net hiring rate for the the observations in the quantile.

Figure 11: **Biases Encourage Overreaction, Excessive Reallocation**
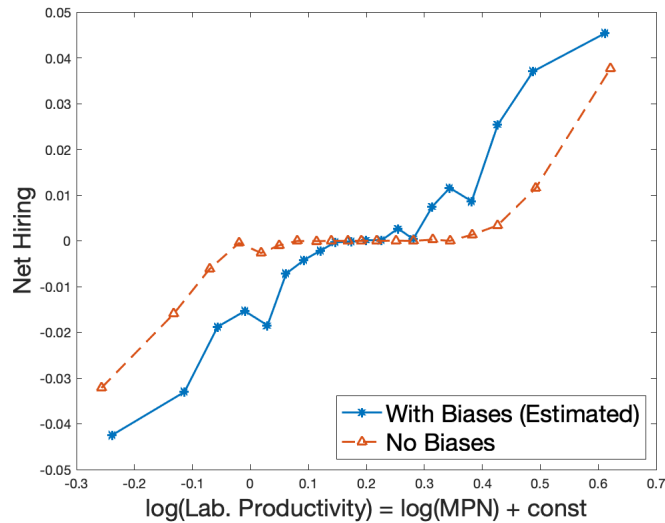
Notes: This figure shows the joint distribution of log(labor productivity) on the horizontal axis and net hiring on the vertical axis in my baseline economy with biases and a counterfactual economy in which all managers are unbiased. To construct the figure, I sort the stationary distribution of each 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 on the vertical axis.

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Figure 12: **Welfare Effects of a Tax on Hiring & Firing Expenditures**
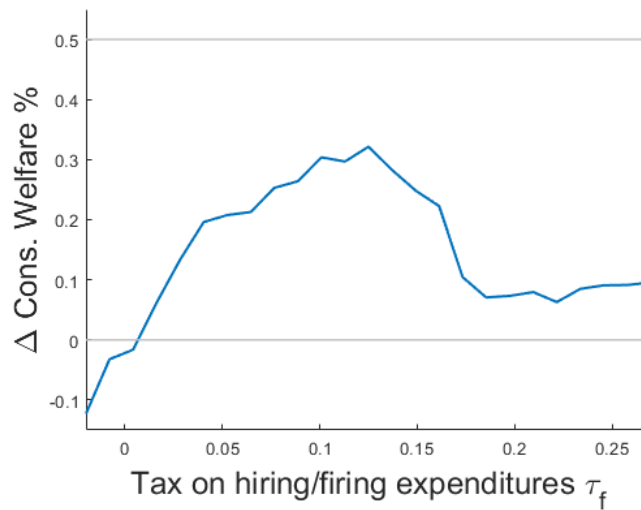
Notes: This figure shows the change in welfare across the steady state in an economy with a tax on hiring/firing expenditures relative to the baseline estimated economy. In both cases managers are biased. The curve shown uses a third-order polynomial to smooth out kinks due to numerical approximation of equilibrium.

Table 1: **Managerial Forecasts have Predictive Power**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	**Realized Sales**			**Actual Hiring, t**		
	Growth, t to t+4			**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 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 2: **Managers are Not Over-Optimistic**

	(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, across all forecast error observations in the SBU. The top panel computes the unweighted mean for each variable and two standard errors, clustering by firm and two-way clustering by firm and date. 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 Overconfident**

	(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 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**

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)
			Forecast - Realized Sales Growth, quarters t to $t+4$			
Sales Growth,	0.207***	0.173***	0.205***	0.220***	0.232***	0.212***
quarters $t-1$ 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 subjective probability distributions and realizations for firm-specific sales growth looking four quarters ahead of the date of the forecast from the *Survey of Business* Uncertainty. 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	29.7	Disutility of work	Steady-state labor $N^* = 1/3$
θ	0.05	Managers' share of equity	Nikolov and Whited (2014)

Table 6: **Structural Estimation Results**

(a) **Data and Model Moments**

Empirical fact/feature	Moment	Model	Data	T-stat
1	Mean(Forecast Error$_{t,t+4}$)	-0.011	-0.016	0.72
2	Mean(Excess Absolute Forecast Error$_{t,t+4}$)	0.130	0.148	-2.74
3	Cov(Forecast Error$_{t,t+4}$, Sales Growth$_{t-1,t}$)	0.011	0.014	-1.37
0	Cov(Sales Growth Forecast$_{t,t+4}$, Hiring Plans$_{t,t+4}$)	0.482e-3	0.671e-3	-0.85
0	Cov(Sales Growth Uncertainty$_{t,t+4}$, Hiring Uncertainty$_{t,t+4}$)	0.140e-3	0.289e-3	-1.03
0	Cov(Net Hiring$_t$, Sales Growth Forecast$_{t,t+4}$)	0.090e-3	0.287e-3	-1.13
0	Cov(Net Hiring$_t$, Sales Growth Uncertainty$_{t,t+4}$)	0.002e-3	-0.370e-3	1.16
0	Cov(Sales Growth Forecast$_{t,t+4}$, Realized Sales Growth$_{t,t+4}$)	0.331e-2	0.167e-2	2.76
0	Cov(Hiring Plans$_{t,t+4}$, Realized Employment Growth$_{t,t+4}$)	0.252e-2	0.221e-3	0.46
0	Cov(Sales Growth Uncertainty$_{t,t+4}$, Sales Abs. Forecast Error$_{t,t+4}$)	0.045e-3	0.336e-3	-1.76
0	Cov(Hiring Uncertainty$_{t,t+4}$, Hiring Abs. Forecast Error$_{t,t+4}$)	0.349e-3	0.279e-3	0.58
0	Var(Sales Growth Forecast$_{t,t+4}$)	0.329e-2	0.356e-2	-0.74
0	Var(Hiring Plans$_{t,t+4}$)	0.357e-2	0.357e-2	0
0	Var(Sales Growth Uncertainty$_{t,t+4}$)	0.094e-2	0.146e-2	-0.72
0	Var(Hiring Uncertainty$_{t,t+4}$)	0.113e-2	0.115e-2	-0.04
Dynamics	Var(Sales Growth$_{t-1,t}$)	0.032	0.059	-6.75
Dynamics	Var(Net Hiring$_t$)	0.019	0.018	0.87
Dynamics	Cov(Net Hiring$_t$, Sales Growth$_{t-1,t}$)	0.001	0.002	-0.75
Dynamics	Cov(Sales Growth$_{t,t+4}$, Sales Growth$_{t-1,t}$)	-0.011	-0.014	1.53

(b) **Estimated Parameters**

Parameter	Explanation	Estimate (SE)
α	Revenue returns to scale	0.832 (0.007)
λ	Quadratic adjustment costs	30.3 (0.446)
ρ	True shock persistence	0.856 (0.002)
$\tilde{\rho}$	Subjective Shock persistence	0.911 (0.001)
σ	True shock volatility	0.114 (0.0002)
$\tilde{\sigma}$	Subjective shock volatility	0.044 (0.0001)
$\tilde{\mu}$	Subjective shock mean	-0.003 (5.25e-6)
σ_ξ	Sales, employment measurement error	0.068 (6.39e-5)
σ_ν	Expectations, uncertainty measurement error	0.029 (0.0001)

Notes: This table shows the results from my structural estimation of the model from Section 3. Sub-table 6a *(top)* shows my target moments in the data and the corresponding model moments in the estimated solution. The third column of the table reports the t-statistic for the null hypothesis that each pair of model and data moments are equal. I estimate all data moments using SBU data with the sample period covering 10/2014 to 6/2018. I compute target variances and covariances using only within-firm variation, namely after purging variation explained by firm and date fixed effects. I compute model moments numerically from the stationary distribution of firms in the model. Sub-table 6b *(bottom)* shows the point estimates and standard errors of the parameters. My estimation procedure uses the inverse firm-level clustered covariance matrix of SBU data moments as a weighting matrix. I perform the numerical optimization of the econometric objective using a simulated annealing algorithm.

Table 7: **Eliminating Managerial Biases Increases Firm Value**

Counterfactual	Δ True Firm Value (%)
$\tilde{\sigma} = \sigma$ 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

Notes: This table shows how much firm value would increase by replacing a biased manager with another who has fewer or no subjective beliefs biases, holding all else constant. At each point in the (z, n) state space I compute the objective value generated by the biased managers in my estimated economy as well as the objective value generated by a counterfactual manager lacking pessimism ($\tilde{\mu} = \mu$), overconfidence ($\tilde{\sigma} = \sigma$), and/or overextrapolation ($\tilde{\rho} = \rho$). Then I compute the mean percent gain in firm value by averaging the gains across the state space under the stationary distribution of the economy with biases.

Table 8: **Heterogeneity Across Subsamples of Firms**

Parameter		Small	Large	Publicly-traded	Privately-held	Inside CEO	Outside CEO
				Sample			
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)	0.8854 (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 (1e-5)	-0.004 (6.98e-6)	-0.0050 (2.03e-5)	-0.006 (1.47e-5)
Sales, employment measurement error	σ_ξ	0.074 (0.0004)	0.059 (0.0001)	0.029 (0.0002)	0.075 (0.0001)	0.158 (0.0002)	0.035 (0.0006)
Expectations, uncertainty measurement error	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 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; (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.3 for a screenshot of the relevant questions).

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

(a) **Welfare, GDP, and Productivity are Higher in Economies with Rational Managers**

Managerial equity share θ	Δ Consumer Welfare %	ΔY %	$\Delta (Y/N)$ %
0.05	0.50	1.07	0.07
0.25	1.20	0.82	0.13
0.50	2.34	0.30	0.26

(b) **Biases Encourage Excessive Reallocation**

Managerial equity share θ	Economy	Reallocation Rate	$\sigma(\log(MPN))$	$AC/Y \times 100$
	With Biases	1.41	0.207	23.7
0.05	No Biases	0.57	0.214	22.5
	Δ	**-59.6%**	**3.45%**	**-1.20 p.p**

(c) **Effect of Overconfidence vs. Overextrapolation vs. Pessimism Managerial Equity Share $\theta = 0.05$**

Managerial equity share θ	Counterfactual	Δ C. Welfare %	Δ Realloc. %	$\Delta\sigma(\log(MPN))$ %	$\Delta AC/Y \times 100$
	$\tilde{\sigma} = \sigma$ only	0.28	-13.7	0.72	-0.25
	$\tilde{\rho} = \rho$ only	0.22	-59.0	3.59	-1.23
0.05	$\tilde{\rho} = \rho$ and $\tilde{\sigma} = \sigma$	0.39	-61.1	3.56	-1.26
	$\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, and $\tilde{\mu} = \mu$	0.50	-59.6	3.45	-1.20

(d) **Managerial Equity, General Equilibrium Effects, and Welfare**

Managerial equity share θ	Δ Consumer Welfare %	Δ Profits %	Δ Wage %	Δ Total Welfare %
0.05	0.50	-10.8	4.86	0.33
0.25	1.20	-11.0	4.94	0.31
0.50	2.34	-11.9	5.26	0.27

Notes: The top table shows the difference in the household's consumption-equivalent welfare, aggregate output (GDP), and labor productivity in the long-run equilibrium of an economy with unbiased managers relative to the long-run equilibrium of my baseline economy with biased managers. The second table compares steady-state values of the rate of reallocation (= aggregate net hiring as a fraction of total labor N), dispersion in the marginal product of labor, and aggregate adjustment costs paid as a share of aggregate output in my estimated economy with biases and managerial equity θ of 5 percent in comparison with an efficient economy with unbiased managers. The bottom table shows the difference in household consumption-equivalent welfare, reallocation, dispersion in the marginal product of labor, and adjustment costs as a share of GDP between an economy whose managers lack one or more of overconfidence ($\tilde{\sigma} = \sigma$), overextrapolation ($\tilde{\rho} = \rho$), or pessimism ($\tilde{\mu} = \mu$) relative to my baseline economy with biased managers. Finally, the bottom table compares the differences in consumer welfare, profits, wages, and total welfare across biased and unbiased economies with different managerial equity shares θ. Y is aggregate GDP, equal to gross output less adjustment costs.

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.

Figure A.1: **SBU Respondents are Primarily CFOs and CEOs**
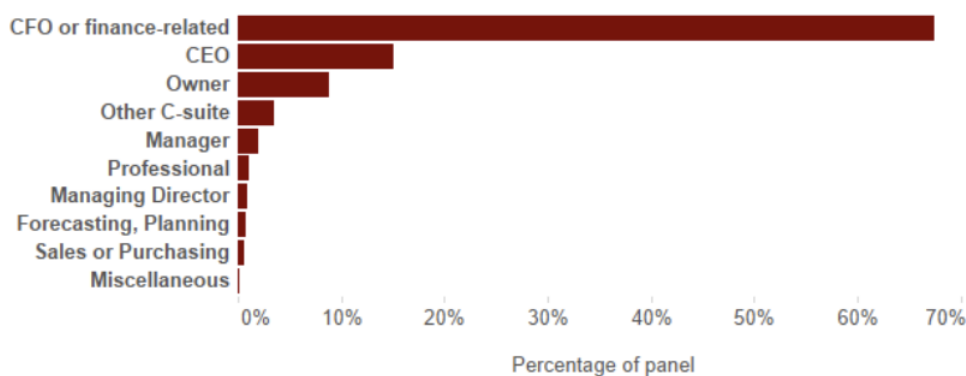
Notes: This figure shows the share of SBU panel memebers whose job title falls into each of the following categories as of July 2018.

Figure A.2: **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.3: **SBU Ownership Questions**

Notes: This figure shows the SBU Special Questions from January and February 2019 on firm ownership. I classify a firm as publicly traded if they respond "yes" to the top question about whether its shares are traded on a stock exchange or in over-the-counter markets. I classify firms as having an "insider CEO" if their response to the second question indicates that the current CEO or the family of the current CEO own 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 there is a small number of partners who own equal shares of the business.

A   Measurement Error and Model Moments

For estimation of the model in Section 4.2, I assume that there is measurement error in the level of sales and employment that is distributed i.i.d. $\mathcal{N}(0, \sigma_\xi^2)$. 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 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:

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

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