The Micro and Macro of Managerial Beliefs

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[Job Market Paper]

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Appendix here

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Abstract

I study how biases in managerial beliefs affect firm performance and the macro-economy. Using confidential survey data to test whether US managers have biased beliefs, I establish three facts. (1) Managers are neither over-optimistic nor pessimistic: their forecasts for future sales growth are correct on average. (2) Managers are overconfident: they underestimate future sales growth volatility. (3) Managers overextrapolate: their forecasts are too optimistic or pessimistic depending on whether the firm is growing or shrinking at the time of the forecast. To quantify the micro and macro implications of these facts, I build and estimate a general equilibrium model in which managers of heterogeneous firms may have biased beliefs and make dynamic hiring decisions subject to adjustment costs. Biased managers in the model overreact to changes in their firm's profitability because they believe it is persistent and stable. The model thus implies that a typical firm's value would increase by 1.9 percent if it hired a rational manager. At the macro level, pervasive overreaction results in too many resources spent on reallocation. Welfare would be higher by 1 percent in an economy with rational managers.

1 Introduction

Optimal management of a firm subject to uncertainty generally requires its manager to have correct beliefs about the firm's future business conditions. Intuitively, a manager who has biased beliefs may make mistakes that destroy some of the firm's value. Moreover, if biases are a pervasive feature of managerial beliefs, the sum of individual managers' mistakes may hurt the macroeconomy. While it is easy to make this string of arguments, there is little empirical and – especially – quantitative evidence on how biases in managerial beliefs affect outcomes at the micro and macro levels.

This paper develops new empirical measures of the extent to which US managers have biased beliefs and provides some of the first estimates of how biases impact the value of individual firms and the macro-economy. I use data from a confidential survey of US managers to test for biases in their beliefs about their own firm's future sales growth. Based on these empirical findings, I build and estimate a general equilibrium model in which biased managers make dynamic hiring decisions subject to uncertainty and adjustment costs. Using my estimated model I infer how counterfactual, unbiased managers would behave under the same environment and thus quantify how firm performance and macroeconomic outcomes would differ if managers were rational. My counterfactual experiments show biased managers overreact to changes in their firm's business conditions and overspend on adjustment costs, leading them to destroy 1.9 percent of the typical firm's value and collectively reduce aggregate welfare by about 1 percent of aggregate consumption.

I test for biases in US managers' beliefs using the Survey of Business Uncertainty (SBU), which is fielded by the Federal Reserve Bank of Atlanta (see Altig et al. (2018) for details). The SBU has been in the field monthly since October 2014, collecting data on manager beliefs about future outcomes at their own firm, in particular sales growth over the four quarters following the survey. Respondents are high-level managers like CFOs and CEOs, or others involved in decision-making. SBU responses are confidential and collected by a Federal Reserve Bank, so there are no obvious motives for respondents to misreport their beliefs in the survey. Furthermore, the SBU is especially well-suited to measuring the extent of biases in managerial beliefs because it asks respondents for five possible sales growth scenarios looking over the next four quarters (i.e. a lowest, low, middle, high, and highest scenario), and then asks them to assign a probability to each scenario. Since I observe these five-point approximations of managers' subjective distributions, I can measure both their subjective expectations (i.e. their forecasts) and their subjective uncertainty about future sales growth. This format contrasts with many other surveys that ask only for point estimates.

How biased do managers appear in the SBU data? To answer this question I document three facts. First, managers appear neither systematically optimistic nor pessimistic: pooling across firms and survey dates, I estimate the average forecast minus realized sales growth to be indistinguishable from zero.[1] Second, managers responding to the SBU are *overconfident*; that is, they underestimate the volatility of future sales growth and overestimate their forecasts' accuracy. While managers' subjective distributions would imply an average absolute forecast error of about 4 percentage points,

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[1]See Bachmann and Elstner (2015) for a similar finding among German manufacturing firms.

in reality the mean absolute forecast error is close to 18 percentage points, more than four times as large. This discrepancy points to a significant deviation from rational expectations. Third, managers *overextrapolate* from current conditions. If the manager's firm experiences high sales growth in a quarter when she responds to the SBU, her forecast tends to overestimate the firm's actual performance over the subsequent four quarters. If, instead, the firm experiences shrinking sales, the manager tends to underestimate. This pattern is consistent with managers overstating the degree to which the current state of affairs – positive or negative – will continue to persist into the future, a common finding in the forecasting and psychology literatures.[2] Quantitatively, for each additional percentage point of sales growth at the time of the forecast the manager overestimates future performance by an additional 0.2 percent. Again, this is a significant departure from rational expectations.

To understand how biases impact individual firms and the macro-economy, I build a general equilibrium model with heterogeneous firms run by managers who may have biased beliefs. Managers in the model may misperceive the overall mean, persistence, and volatility of business conditions, with each of these three potential biases corresponding to one of the three facts I document in the SBU data. Managers in the model choose the firm's labor under uncertainty, forecasting future conditions under their own, possibly biased beliefs. These hiring decisions are subject to adjustment costs that force managers to trade off the perceived benefit of hiring or laying off workers against the cost of making those adjustments. Theoretically, the presence of adjustment costs means that hiring or laying off workers involves up-front costs that managers may later regret having paid, increasing the stakes in their decisions. Empirically, adjustment costs also help the model account for the joint dynamics of firm-level sales and employment, which are positively but not perfectly correlated in the data.

I quantify the implications of managerial mistakes by confronting my model against the SBU data, structurally estimating the parameters that empirically account for: (1) the extent of managerial optimist, overconfidence, and overextrapolation; and, (2) the joint behavior of sales and employment, the two key endogenous variables in my model that I also observe in the SBU. Intuitively, the statistics I use to test for managerial biases are informative of the extent of biases, conditional on the technology and environment in which their firms operate. Employment and sales growth fluctuations, in turn, are informative of the technology, uncertainty, and frictions managers face as they make forward-looking decisions given some beliefs. By matching moments related both to managerial biases and decisions I discipline the structural parameters that are crucial for inferring how managers would behave if they had different beliefs. To my knowledge, no other paper structurally estimates a micro-to-macro model by jointly targeting moments related to managerial probability assessments and moments related to endogenous outcomes like employment and sales.

Quantitatively, how and by how much do biases in managerial beliefs affect firm value and macroeconomic outcomes? I use my estimated model and consider two types of counterfactual

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[2]See La Porta (1996) and Bordalo et al. (2018) for similar results about professional analysts, as well as Rozsypal and Schlafmann (2017) for a similar finding for US households.

exercises. To study the impact of biases on firm value, I consider replacing a single firm's biased manager with an unbiased one *leaving all else equal*, including the firm's current labor force and the state of its current business conditions. For the typical firm, switching to an unbiased manager increases the net present value of the firm's cash flows by 1.9 percent. To consider the impact of biases on the macro-economy I consider a second counterfactual in which all firms are run by rational managers. I solve for the stationary general equilibrium of this second economy to accounts for differences in the equilibrium wage, labor, profits and consumption after changing all firms' dynamic behavior. I find consumer welfare in the efficient, unbiased economy is higher by 1.0 percent, while GDP is also 1.6 percent higher. 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).

What specifically do biased managers do to destroys firm value at the micro level and reduce welfare for the aggregate economy? Using my estimated model, I show biased managers overreact to changes in their firm's profitability and thus devote too many resources to adapting to changes in the firm's business conditions. When new business opportunities arise, biased managers believe these opportunities are persistent and stable when they are actually transitory and volatile. Thus, biased managers are especially eager to take-up new opportunities and especially willing to pay the costs associated with take-up. The opposite happens when business conditions deteriorate. These dynamics reduce firm value at the micro level since managers spend too many resources hiring and laying off workers.

At the macro level, biased managers reduce welfare because their overreactions result in excess reallocation. By contrast, rational managers respond cautiously to fluctuations in firm-level business conditions, reallocating fewer workers towards firms where the marginal product of labor is high. Firms in the unbiased economy are thus farther from their optimal scale on average than in the estimated economy with biases, and dispersion in the marginal revenue product of labor is actually higher by 6.6 percent.[3] It may seem counterintuitive to find this higher static "misallocation" in the economy with rational managers. The reason behind this result is that there are costs to hiring and firing workers, so more reallocation is not necessarily better. Given the amount of uncertainty and the magnitude of dynamic adjustment frictions, rational managers efficiently choose a slower pace of reallocation, increasing welfare relative to the economy with biased managers.

I also ask whether overextrapolation or overconfidence is quantitatively more consequential. While both biases contribute to managerial overreaction and excess reallocation, my results show that eliminating overextrapolation on its own would bring larger increases in firm value at the micro level and welfare at the macro level. Intuitively, overextrapolation distorts managers subjective expectations (i.e. their first moments) and thus has first order impact on their hiring decisions, while overconfidence distorts their subjective uncertainty (i.e. the second moment) and thus has second order impact. This finding suggests practitioners and policy-makers looking to alleviate the

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[3]Dispersion in the marginal product of labor or capital is a common metric for assessing the extent of misallocation in an economy, following Restuccia and Rogerson (2008), and Hsieh and Klenow (2009). This approach, however, assumes the environment is one in which firms optimize their inputs statically at each point in time.

impact of biases in managerial beliefs may wish to focus on curbing the degree of overextrapolation.

My analysis takes as given that biased managers operate the firms in my model. This simplicity allows me to quantify the micro- and macroeconomic costs of biased beliefs, of which there is scant evidence in the literature. Having said that, there are two important questions I do not address directly in my analysis: Why do firms hire and retain biased managers in the first place? How do my results relate to the broader literature on corporate governance and agency conflicts?

As for why firms hire biased managers, I see at least two possibilities. First, it may take years of forecast data to establish whether any *individual* manager is biased. Even rational managers should be correct on average, but not necessarily for each individual realization. Based on my estimates, 25 years' worth of quarterly forecasts are not enough to distinguish statistically between a manager who systematically over- or underestimates future sales growth by up to 5 percentage points. It is also not enough to reject the null that managers do not overextrapolate to the degree I uncover. Keeping in mind that the median CEO and CFO tenure is about 7 years, this issue of statistical power may be an important reason why firms cannot simply identify and fire biased managers. Instead, my analysis uses data on *hundreds* of managers from different firms, enabling me to draw conclusions about the average amount of bias. In a second possibility, biased individuals may be endogenously selected for managerial roles for example if managers have multiple trains including unobservable ability and bias. Thus, shareholders and directors may optimally promote managers based on past performance, favoring those who are particularly overconfident as well as those with higher managerial ability.

To consider how my findings relate to oversight and agency conflicts, I re-estimate my model on subsamples of firms with (1) strong versus weak governance; (2) recent M&A activity versus no recent acquisitions as a rough proxy for empire-building managers; (3) above versus below median firm size to proxy for whether they are likely to be owner-operated and thus in the owner's sole control. These exercises show consistently that firms with better oversight and firms where conflicts appear more severe behave in ways that are consistent with their managers being more biased. Exploring the quantitative relationship between biases and other forms of agency conflicts is a promising avenue for future work.

My paper has four key contributions. First, I document new evidence about the extent of biases in managerial beliefs using state-of-the-art survey data. Although my empirical findings are qualitatively consistent with earlier work, I contribute by measuring several biases in the same data and providing interpretable, quantitative measures of managerial biases. Second, I integrate this empirical evidence with a heterogeneous agent general equilibrium framework, paying close attention to how managerial beliefs and frictions to hiring and firing jointly account for firm-level sales and employment dynamics. Third, I larger impact of biased beliefs at the micro and macro levels relative to earlier work that found smaller real costs of biases, in particular for the macroeconomy. [4] Finally, I model several biases and investigate which are most costly for individual firms and for the aggregate economy.

[4]See, for example Bachmann and Elstner (2015) and Ma, Sraer, and Thesmar (2018).

Related Literature

My paper is part of a new wave of empirical studies focusing on the beliefs of economic agents, several of which also challenge the hypothesis that agents have full information and rational expectations. My core contribution in this regard is providing measures of the extent to which managers are overconfident and overextrapolate when making subjective probability assessments about their own firm's future performance. This work draws on a long literature that shows the validity of eliciting subjective probabilities via surveys. Manski (2004; 2018) provides an overview of the literature and points the promise of using this type of of data in empirical work. My paper is among several recent studies that focus on the beliefs of firm managers, whereas many earlier contributions studied household beliefs about future income.[5] Additionally, I provide new evidence that managers are biased with regards to their own firm's future performance, which has first order impact on their business decisions. Many earlier papers, by contrast, focused on challenging the full information rational expectations hypothesis among professional forecasters, or among managers making forecasts about the stock market as a whole, where the link between beliefs and decisions is less clear.[6]

Mine is not the first study to consider the impact of managerial biases on individual firms or the macro-economy. My contribution relative to this earlier work is connecting empirical evidence on beliefs and decisions, and endogenous outcomes with a heterogeneous-agent general equilibrium framework. By contrast, many of these earlier contributions make descriptive comparisons of managers who appear more biased versus more rational in the data.[7] Several papers use model with managerial biases to study how biases might impact firm behavior theoretically[8] and asset prices quantitatively[9], without looking directly at evidence on managerial beliefs.

Relative to previous work that does integrate empirical evidence on beliefs with behavioral models of firm behavior, I find larger costs of biased beliefs, especially at the macro level. These results contrast for example with Bachmann and Elstner (2015), who study optimism and pessimism among German manufacturers, and a recent paper by Ma, Sraer, and Thesmar (2018), who use publicly-traded firms' sales guidance as a proxy for managerial beliefs. Relative to both these

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[5]See for example Gennaioli et al. (2016) on the relationship of survey expectations and investment, and Bachmann et al. (2018),Bloom et al. (2017), and Tanaka et al. (2018) who study how beliefs reflect firms' business environment, how beliefs respond to shock realizations, and whether making accurate forecasts correlates with firm performance, including .

[6]Coibion and Gorodnichenko (2012; 2015) find that consensus forecast behavior is consistent with the existence of information frictions. Baker et al. (2018) study how forecasters update their beliefs and attention in response to unexpected shocks like natural disasters. Bordalo et al. (2017) and Bordalo et al. (2018) argue that professional forecasters have overextrapolative beliefs about listed firms and the macro-economy. Ben-David et al. (2013) and Boutros et al. (2018) argue that managers are overconfident about the S&P 500 and learn to a limited degree about past mistakes. Gennaioli et al. (2016) argue like I do that managers of listed firms overextrapolate based on current aggregate and firm-specific conditions.

[7]This literature includes seminal contributions by Malmendier and Tate (2005) and Ben-David et al. (2013), who identify managers who appear more biased than others and show empirically that the two groups behave differently.

[8]For example, Fuster et al. (2010) study the impact of incorrect beliefs using a model of investment dynamics with overextrapolation, focusing on its qualitative implications for the business cycle, asset prices, and volatility. Hackbarth (2008) similarly analyzes theoretically how beliefs biases may impact capital structure decisions.

[9]Alti and Tetlock (2014), structurally estimate the degree of overextrapolation and overconfidence based on asset-pricing anomalies rather than survey evidence on beliefs. They argue that biases generate empirical asset-pricing patterns that do not arise in rational-expectations models and largely abstract from the real implications of biases.

papers, I show adjustment frictions help account empirically for firm-level sales and employment dynamics and find them to be a key component of why biased managers destroy firm value and reduce aggregate welfare in my model. Additionally, I test for and model several biases simultaneously, and I assess which biases appear to be more costly.

More broadly, I contribute to a long literature in corporate finance focusing on the impact of business executives on their organizations and managerial style, especially when there are agency frictions or biases in beliefs.[10] My paper is also part of an emerging literature in macroeconomics attempting to consider how behavioral biases – in particular with regards to beliefs– impact the macroeconomy and aggregate dynamics.[11] In a similar sense, I contribute to the broad literature investigating the macroeconomic impact of microeconomic distortions to firm-level activity, including work by Restuccia and Rogerson (2008) and Hsieh and Klenow (2009) on misallocation.[12] One of my key contributions shows that managerial biases can reduce measures of static misallocation by encouraging excess, costly reallocation of resources across firms, a result that resembles the core finding in Asker et al. (2014). My paper thus relates to recent debates on the role of reallocation, including Decker et al. (2018) and Hsieh and Klenow (2017). Finally, my paper follows the long tradition of modeling firm behavior and managerial decision-making within a dynamic framework subject to adjustment costs and other frictions.[13]

The rest of the paper is structured as follows: Section 2 introduces the Survey of Business Uncertainty, my data source on managerial beliefs, and documents that managers are neither over-optimistic nor pessimistic but they are overconfident and overextrapolate. Section 3 describes my general equilibrium model of firm-level employment dynamics in which biased managers run heterogeneous firms subject to idiosyncratic risk. Section 4 discusses how I solve and estimate the model. Section 5 quantifies how biases impact the value of individual firms and the aggregate economy. Section 6 tests the robustness of my quantitative results and reports results from some extensions. Section 7 concludes.

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[10]See Stein (2003) for a comprehensive survey, Bertrand and Schoar (2003) for a study on the impact of CEOs on firm performance, Bebchuk et al. (2008) on corporate governance, Taylor (2010) on CEO entrenchment and Nikolov and Whited (2014) on CEO incentives and cash-holding. Goel and Thakor (2008) and Bolton et al. (2012) study theoretically why biased individuals may end up in managerial positions. My also relates to the literature on CEOs' personalities and style, including Kaplan et al. (2012) and Kaplan and Sorensen (2017), which show that CEO quality is multidimensional, and that execution ability and resoluteness are desirable qualities in CEOs that resemble how overconfident and overextrapolative managers behave in my framework.

[11]Jurado (2016) shows that distorted beliefs help explain fluctuations in consumption and stock prices. Carroll et al. (2018) show that sticky expectations about aggregates help explain aggregate consumption behavior. Rozsypal and Schlafmann (2017) study the macro implications of overextrapolation in US households' beliefs about their future income. Theoretical contributions include those by Gabaix (2016) on a general framework for modeling behavioral agents in macro models, and Acemoglu and Jensen (2018), who show that equilibrium analysis in behavioral economies can be tractable.

[12]More recent papers have attempted to uncover specific distortions that impact aggregate outcomes, for example David et al. (2016) on information and financial markets, and Terry (2016) on short-termism.

[13]This literature includes, among many others Bernanke (1983), Hopenhayn (1992),Hopenhayn and Rogerson (1993),Abel and Eberly (1997), Pindyck (1988), Hennessy and Whited (2005), Cooper and Haltiwanger (2006), Khan and Thomas (2008), Bloom (2009), and Winberry (2015).

2 Managerial Beliefs Biases in the Survey of Business Uncertainty

In this section I use data from the Survey of Business Uncertainty to document three facts about managers' subjective beliefs regarding their own firms' sales growth, looking four quarters ahead. Specifically:

1. Managers are neither over-optimistic nor pessimistic

2. Managers are overconfident (i.e. they overestimate the precision of their forecasts)

3. Managers overextrapolate from current conditions

Broadly speaking these three facts characterize biases in managers' subjective first and second moments, so theoretically they have first and second order impact on managers' dynamic policy functions. Although managers' beliefs may be biased in other ways, first and and second moments seem a reasonable place to start.

My analysis throughout this section exploits the fact that the SBU is a panel that allows me to track firms' performance across time and compare realized performance against the managers' ex-ante beliefs. I acknowledge that even under the null hypothesis that managers have ex-ante correct beliefs, individual realizations are outcomes of a stochastic process and may thus differ from the ex-ante subjective forecast. The three facts I document in this section uncover *systematic* discrepancies between beliefs and realizations after applying the law of large numbers to average out the random component in individual realizations.

A natural question regarding my findings in this Section concerns why market forces fail to identify and throw out biased managers, or why managers fail to learn about their own beliefs biases? In Appendix A.10 I argue that it is not obvious the market or managers' themselves could gather the data necessary to make such assessments. That said, my main goal in this Section is to document the extent of biases I can identify in the SBU data in order to quantify the implications of managerial biases, regardless of the underlying reasons why those biases arise.

2.1 The Survey of Business Uncertainty

My data on managers' subjective beliefs comes from the *Survey of Business Uncertainty* (SBU), run by the Federal Reserve Bank of Atlanta and developed in conjunction with researchers at Stanford University and the University of Chicago's Booth School of Business[14]. The SBU surveys high-level firm managers on a monthly basis via email. Figure 1 shows the most common job title in the SBU is CFO (or other finance) for nearly 70 percent of panel members, followed by CEO and owner with just under 20 and 10 percent each. Survey questions then ask these managers to provide subjective probability distributions about their own firms' real outcomes, looking ahead over the next year. Interested readers should see Appendix A for full details on how I define and measure the variables

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[14]This paper and Altig et al. (2018) are the first ever analyzing the SBU data.

that I use to analyze managers' subjective beliefs, and may also refer to Altig et al. (2018) for more details about the survey's development and methodology.

The SBU's sampling frame comes from Dun & Bradstreet and includes firms from the entire private business sector of the US and from all regions of the country. In Appendix A.1, I reproduce figures from Altig et al. (2018) showing that the SBU is broadly representative of the US economy in employment weighted terms. The survey over-samples larger and older firms, as well as firms in cyclical, highly capital-intensive sectors (esp. durables manufacturing). The typical SBU respondent is thus larger than the typical firm in the Census Bureau's Longitudinal Business Database, but also smaller than the publicly-traded firms which are the focus of other papers about managers' subjective beliefs like Ben-David et al. (2013), Malmendier and Tate (2005), and Ma et al. (2018). Specifically, the mean and median employment of respondents as of June 2018 is 152 and 632. Readers may refer to A for more summary statistics on SBU respondents and the sample of forecast errors I analyze in this section. I view the fact that respondents are typically older firms as a feature rather than a bug – at least for the work that I undertake in this paper. In much of what follows I measure how biased managers' beliefs are and abstract from learning. Because firms in the SBU are older, assuming that firms have formed beliefs about the environment they operate in seems more reasonable for my sample than, say, for a sample consisting of highly-innovative startups.

The SBU has been in the field each month since October 2014 with new data being added monthly. My analysis in this draft uses data up to June 2018. In the first half of 2018, the SBU had a monthly response rate of about 40 percent (40 percent of all emails sent out each month 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, therefore maintaining consistent sample sizes across months.

The Survey of Business Uncertainty differs from other well-known data sources about subjective beliefs because respondents are firm insiders answering *quantitative* questions about their *own firm*'s prospects under *confidentiality*[15]. This setting contrasts with the Philadelphia Federal Reserve Bank's Survey of Professional Forecasters (SPF), which asks professionals about the macro economy. The confidential nature of responses also distinguishes the SBU from the Institutional Brokers' Estimate System (I/B/E/S), which contains professional analysts' predictions about publicly-listed firms, and official forecasts ("guidance") issued *publicly* by management. The fact that the SBU asks quantitative questions also distinguishes it from more qualitative survey data on firm-specific expectations, [16].

The SBU is well-suited for studying managerial beliefs because elicits subjective probability dis-

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[15] For confidentiality reasons, as of early 2018 and throughout this project I have only had access to anonymized data from the SBU. Although I can link individual respondents (i.e. firms) across time using a dummy identifier, I have not match them to outside sources of data. In the medium run the authors of Altig et al. (2018) match up the SBU to the US Bureau of Census' Business Register and Longitudinal Business Database within Federal Research Data Centers.

[16] For example the IFO Business Survey questions used in Bachmann and Elstner (2015), and the quarterly NFIB survey of smaller US businesses are qualitative and thus less well-suited to quantifying managerial beliefs biases. Recent waves of the IFO Business Survey contain more quantitative data about firm's expectations and uncertainty, which are the focus of Bachmann et al. (2018).

tributions from its respondents. Figure 2 shows the SBU's questionnaire about sales growth, which is the focus of my study. For example, when answering questions about sales growth, respondents provide five potential outcomes for their own firm's sales growth over the next four quarters, corresponding to a lowest, low, middle, high, and highest scenario, and then assign a probability to each. Respondents are free to enter any potential forecast in each of the bins, typing that number directly into the survey rather than choosing it from a drop down menu or similar. The survey thus accommodates idiosyncratic heterogeneity in individual firms' prospects for sales growth looking a year ahead.

I exploit the fact that the SBU elicits five-point subjective probability distributions, constructing managers' forecasts for their firm's sales growth as the mean of their subjective probability distribution. Specifically, I compute each manager's forecast by taking the inner product of the vector of potential outcomes and the vector of probabilities. Similarly, I construct measures of subjective uncertainty by computing the mean absolute deviation and standard deviation of these subjective distributions. See Appendix A.2 for full details. Thus, I use the SBU to compute well-defined mathematical quantities pertaining to managers' beliefs. This procedure eschews a common critique regarding survey-based studies of beliefs and expectations that respondents' point "expectation" or "best guess" may not correspond to the formal statistical definition of "expectation" as the first moment of the respondent's subjective probability distribution.[17]

In addition to asking for managers' subjective distributions, the Survey of Business Uncertainty also elicits information about the firm's current conditions. Given my focus on sales growth and hiring, I focus on the dollar value of sales in the current quarter and the number of employees reported in the survey. Tracking the history of these current conditions allows me to compare managers' beliefs against actual performance and thus infer how accurate or how biased those beliefs are. Later, when I estimate my structural model I also target the joint dynamics of sales and employment to capture how SBU respondents make dynamic hiring decisions under their beliefs.

As in every survey-based study of subjective beliefs, the quality of respondents' answers is crucial. However, responses in the SBU appear to be of high quality. In nearly all cases the outcome scenarios are monotonic (lowest is less than low, which is less than middle, etc.), and similarly almost no responses assign 100 percent of the probability mass in a single scenario. Recent waves of the survey ensure managers cannot give a probability vector that does not add up to 100 percent, but in earlier waves over 90 percent of responses to questions about sales growth include probabilities that add up to 100 percent.

Additionally, beliefs about sales growth in the SBU are internally consistent with outcomes, medium run hiring plans, and current hiring. In Appendix A.4 I document that managers' sales growth forecasts looking four quarters ahead are highly predictive of actual sales growth. Similarly, I show sales growth forecasts predict managers' hiring plans (i.e. their forecast for the firm's employment growth looking a year ahead), and those plans in turn predict actual employment

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[17]Many well-known surveys SPF, the Michigan Survey of Consumers, or Duke Fuqua's CFO Survey (see Ben-David et al. (2013)) all ask about "expectations" in this manner. See Cochrane (2017) for an example of the critique.

growth. In Appendix A.4 I additionally document that current hiring in the quarter in which a firm makes its forecast also co-moves with sales growth forecasts looking ahead over the next four quarters, although less strongly. Instead, current hiring correlates strongly with innovations to the firm's sales growth. These dynamics suggest managers beliefs are one of several inputs into their current hiring decisions, which motivates my attention to the role of hiring frictions in the model I present in Section 3 and my quantitative results in Section 5.

Having established the validity of the data in the Survey of Business Uncertainty, I proceed to document whether and to what extent managers' beliefs about their own firm's future sales are biased. I summarize my findings in three facts I describe throughout the rest of this section.

2.2 Fact 1: Managers are Neither Over-Optimistic nor Pessimistic

I find no evidence of systematic optimism or pessimism among managers in the SBU. Table 1 displays the mean forecast for sales growth (looking four quarters ahead), the mean realized sales growth, and finally the mean forecast error (= forecast minus realized sales growth) pooling across firms and dates.

Looking at the first two columns it is already clear that the typical forecast and realization are not far from each other, at 0.038 and 0.045. In column (3) the mean forecast error is -0.0078 with a standard error of 0.0078, clustering by firm. Two-way clustering by firm and date increases the standard error to 0.010, maintaining the result. So we cannot not reject the null hypothesis that managerial forecasts deviate on average from the actual sales growth that subsequently occurs. This finding does not mean that managers systematically predict their future performance accurately (they may make big mistakes), only that their forecasts do not systematically exceed or understate ex-post performance.

We can also see this lack of systematic optimism or pessimism looking at forecasts versus realizations across time. In Figure 3 I plot the time series of the average forecast error by month, along with 95 percent confidence bands based on firm-clustered standard errors. In any given month, the average forecast error is rarely ever as close in magnitude to zero as the overall mean. The near-zero overall average forecast error is a result of averaging positive and negative forecast error months. In fact, the mean forecast error in any given month is often, but not always, statistically indistinguishable from zero, and a test of the null that all forecast errors are zero rejects with 1 percent confidence.[18] This pattern highlights the benefit of using panel data rather than a cross section to test for optimism, namely because we can average out date-specific macro shocks to managers' beliefs and realizations that might appear like optimism or pessimism in a cross section. For my paper, it is also convenient that macroeconomic volatility has been low by historic standards during my sample period, starting in late 2014 and ending in mid-2018, and thus I am less concerned about

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[18]For many months in my sample in which the mean forecast error is not statistically distinct from zero, the insignificance may be due to smaller samples. Months prior to September 2016 when fewer firms answered questions about sales or sales growth in a given month have large point estimates for the forecast error that are insignificant presumably due to this small sample issue. In more recent months, when sample sizes are bigger there seem to be a few individual months where the typical forecast minus realization is statistically different from zero.

the influence of aggregate shocks than I would be in other periods.

Looking at the mean forecast error in each sector in Figure 4 we can also see no evidence of systematic optimism or pessimism in managers' forecasts. Most of the mean sectoral forecast errors are statistically indistinguishable from zero. Of the two that are significant (for retail trade and finance and insurance) one is positive and the other negative, showing no clear pattern. Furthermore, a test of the null hypothesis that the mean forecast minus realization is zero in all sectors yields a p-value of 0.33.

Larger and smaller firms also do not appear to under- or overestimate future sales growth differently from each other. Figure 5 shows the mean forecast error for each decile of quarterly sales as reported at the time of the forecast, with none of the decile means statistically different from zero. Accordingly, the p-value on the F-test that the mean forecast error for each decile of sales is exactly zero is 0.69.

My finding of no detectable optimism or pessimism is consistent with the result in Bachmann and Elstner (2015) that two-thirds or more of firms responding to Germany's IFO Business Climate Survey appear neither systematically over- or under- optimistic about their future sales growth. My contribution in this regard is to document this result among US firms using high quality panel data that includes managers' subjective probability distributions and tracks performance across time. The main limitation of my analysis relative Bachmann and Elstner (2015) is that my panel is short so I do not attempt to determine whether any individual firms are over-optimistic or pessimistic, showing instead on that the typical firm is neither.

2.3   Fact 2: Managers are Overconfident

Managers responding to the SBU appear to be overconfident, namely they underestimate the risks their firms face and overestimate the accuracy of their forecasts. Figure 6 shows this overconfidence by superimposing two histograms. The blue bars show the empirical distribution of forecast minus realized sales growth that I observe in the data. The red bars show how forecast minus realized sales growth would be distributed if sales growth realizations were instead drawn from managers' the five-point subjective probability distributions as provided in the survey. 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 unbiased beliefs, the empirical and subjective distributions of forecast errors should lie on top of each other. What we can see in Figure 6 is a sounding rejection of that hypothesis. The subjective distribution of forecast errors is much less dispersed than what we see empirically, indicating that the magnitude of managers' actual forecast errors is much larger than what they expect ex-ante. Under managers' subjective distributions, realized sales growth over the next four quarters should be within 5 percentage points of their forecasts nearly 75 percent of the time. Empirically, such an outcome happens with about 25 percent probability. Looking again at Figure 6 it is also clear that managers understate the probability of being off by 10 to 20 percentage points, which are very much within the realm of normal under

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the empirical distribution. The difference in the magnitude of the errors across the empirical and subjective distributions is not due to a few extreme realizations or "Black Swans" that managers ignore ex-ante; rather, managers appear simply unrealistic about how accurate they expect their forecasts to be.

Table 2 quantifies the degree of overconfidence more formally by comparing the mean absolute forecast error (= absolute distance between forecast and realized sales growth) that I observe empirically versus what would arise if realizations were distributed according to managers' subjective distributions (i.e. the average, subjective mean absolute deviation from forecast). Pooling across firms and months, the mean absolute forecast error is 0.184 with a standard error of 0.007 (clustered by firm) under the empirical distribution, but only 0.039 with a standard error of 0.002 under the subjective distribution. So quantitatively, I observe an "excess absolute forecast error" of about 0.146 with a standard error of 0.006. The discrepancy between subjective and empirical absolute errors is still highly significant if I use two-way clustered standard errors by firm and date.

The stylized fact that managers are overconfident about their forecasts' accuracy also holds looking across time and across sectors, without a particular month or sector driving the result. In Figure 7, I plot the mean excess absolute forecast error (again, equal to the empirical absolute forecast error minus ex-ante subjective mean absolute deviation) for forecasts made in each month between October 2014 and August 2017. Although there is some variation in the degree of overconfidence across time, the mean excess error typically ranges from 0.10 to 0.20 across months and is highly significant in all months but one since the survey began in October 2014. Repeating this exercise in Figure 8, but now focusing on differences across sectors, I find some heterogeneity in the mean excess absolute forecast error across sectors, but all are significantly different from zero and again range from about 0.10 to 0.20.

Looking across the firm size distribution managers appear to be overconfident regardless of firm size, but those at the smallest firms in the survey appear particularly overconfident and others at the largest firms appear somewhat less overconfident than the rest. We can see this in Figure 9 which shows the mean excess absolute forecast error for each decile of the distribution of current sales (measured at the time of the forecast). While the degree of overconfidence hovers around 0.15 for the top nine deciles, it is closer to 0.25 and 0.10 for the bottom and top deciles. This finding suggests that the degree of overconfidence may be related to long-run firm-level productivity. Smaller firms that are likely to be less productive and less well-managed appear to have managers who are particularly overconfident.

Economically, I interpret managerial overconfidence as a failure to recognize the amount of risk the firm is actually exposed to over the four-quarters following a forecast. In Appendix A.5 I show that this is not because managers are unable to express how uncertain they feel their firm's performance looking ahead over the next year. Specifically, differences in managers' ex-ante uncertainty are highly predictive of the magnitude of the absolute forecast errors they ultimately make. Instead, they underestimate the *level* of those errors by a fixed amount regardless of how uncertain they claim to be ex-ante.

2.3.1 Overconfidence or measurement error?

If managers report the dollar value of current sales with some error in quarter t when they make their forecasts, and potentially also when they report their realized sales again in quarter $t + 4$, the realized sales growth I measure could hypothetically differ from managers' ex-ante forecasts mostly due to measurement error in the SBU and not due to fundamental shocks to the firm's profitability. In that case, the large excess absolute forecast errors I measure would not be evidence of overconfidence but rather of serious measurement error. A key challenge to testing whether large excess errors are overconfidence or measurement error is that I cannot at this stage link the firms in the SBU to another reliable data source containing realized sales data. So I proceed by testing whether the magnitude of the forecast errors I observe empirically is plausible in comparison with analyst forecasts for the sales of publicly traded firms as stated in the Institutional Brokers' Estimate System (I/B/E/S).

After comparing the magnitude of analyst errors about publicly-traded firms and managers' errors in the SBU, I argue that measurement error is unlikely to be responsible for the large excess absolute forecast errors I find in the SBU data. In Appendix A.6 I show that analysts' forecast errors for the sales growth of publicly-traded firms from a horizon of four quarters (the same horizon as in the SBU) are about as large as managers' errors in the SBU. Accordingly, the magnitude of the forecast errors that managers expect to make under their subjective distributions looks implausibly small. In light of this evidence, I conclude that the large excess errors I find in the SBU are more likely a result of managers being overconfident, underestimating the full extent of the risk their firms are facing.

2.3.2 Is overconfidence a consequence of the SBU's discrete, five-point distributions?

I argue that expressing managers' beliefs about sales growth in the SBU using five-point discrete subjective distributions does not mechanically generate the appearance of overconfidence. The reason is respondents have nine degrees of freedom in specifying their beliefs (five bins plus five probabilities, but the probabilities must add up to 100 percent), which is an extremely flexible specification for a distribution. Furthermore, recall they are in no way constrained about what value or probability to assign to each of the possible scenarios, so are certainly able to treat the highest and lowest values as true tail-risk outcomes that happen with a small probability.

In Appendix A.7 I demonstrate that discretization on a five-point grid is not responsible on its own for the large excess absolute forecast errors I observe empirically. Using two distinct discretization approaches, I approximate the continuous distribution of sales growth outcomes on five points while disregarding some mass at the tails of the target continuous distribution. This sort of procedure is commonly used in the discrete-time dynamic programming literature to approximate Gaussian autoregressive processes on a discrete grid (Tauchen (1986)), with five grid points viewed as adequate for many applications [19]. With either of the two discretization approaches I try in

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[19]For example Terry (2016) uses a three-point grid to represent an i.i.d. Gaussian shock. Khan and Thomas (2008) use 11 grid points for a Markov chain representing idiosyncratic shocks and 15 for aggregate productivity. Finer grids

Appendix A.7, I am unable to generate excess absolute forecast errors of the magnitude I observe in the SBU data even if I exclude the most extreme 40 percent of the mass of potential outcomes and then approximate the distribution of the remaining mass on five points. These exercises suggest that managers simply place the five scenarios of their subjective distribution too close together, resulting in an overly-narrow subjective distribution.

2.4   Fact 3: Managers Overextrapolate

Although managers in the *SBU* do not appear systematically optimistic or pessimistic about their firms' future sales growth they do appear to overextrapolate. Specifically, managers' ex-ante forecasts tend to overstate ex-post realizations when those forecasts are made during high-performing quarters, and vice versa. Figure 10 shows this pattern with a bin-scatter of forecast minus realized sales growth growth between quarters t and $t+4$ on the vertical axis, against the firm's sales growth between quarters $t-1$ and t on the horizontal axis. We can see a strong positive relationship, indicating that managers' forecast errors are highly predictable based on their firms' sales growth during the quarter prior to making the forecast. This pattern is consistent with overextrapolation, whereby managers overestimate the degree to which the current state of affairs will continue into the future. There is ample evidence in the literature of this sort of behavior, for example in Bordalo et al. (2018) and Bordalo et al. (2017) among analyst forecasts of macro variables and public firms earnings growth, respectively.

To conclude that overextrapolation is indeed responsible for the patterns that we see in Figures 10 and A.20, idiosyncratic, firm-level shocks must be the main source of dispersion in the sales growth rates on the horizontal axis, as well as variation in the forecast errors on the vertical axis. Namely, overextrapolation arises when an individual firm receives a positive shock in quarter t and its manager overestimate how much of that shock will persist between t and $t+4$. Hypothetically, the pattern in Figure 10 could arise if managers had rational expectations, but aggregate or sector-level shocks affected the performance of all firms (or all firms in a given sector) in quarter t and also potentially between t and $t+4$. The relationship between errors and lagged performance would, similarly, not be the result of overextrapolation if some firms consistently grow at a fast rate and also consistently overestimate their subsequent performance. That would reflect differing optimism or pessimism across subpopulations of firms.

In Table 3 I show that correlated shocks across all firms, across firms in the same one-digit sector, or persistent differences in optimism across firms are not driving the relationship between performance at the time managers record their beliefs and their subsequent errors. In column (1) I report the estimate from the firm-level regression corresponding to Figure 10, namely a cross-sectional regression of managers' forecast errors for sales growth between quarters t and $t+4$ against their firms' sales growth between quarters $t-1$ and t pooling all observations across firms and months. The highly significant coefficient quantitatively implies that firms growing one standard

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are more useful for representing highly persistent shock processes, so the five points in the SBU seems adequate for thinking about a one-shot probability distribution.

deviation above average overestimate their firm's subsequent sales growth by about 0.07, while the unconditional mean forecast error is approximately zero. In column (2) I add date fixed effects and in column (3) sector-by-date effects, so that the coefficient now reflects differences in forecast errors across firms subject to the same aggregate or sector-specific shocks. In both of these specifications the coefficient on sales growth between quarters $t-1$ and t barely changes relative to column (1), and actually increases in column (3), effectively ruling out the possibility that aggregate shocks are driving the relationship. In column (4) I use firm fixed effects and time dummies to control for persistent firm-level differences and the aggregate environment, with the estimated coefficient barely moving once again. This last estimate means that the sign and magnitude of errors made by the same manager differ across periods of better or worse performance for her firm.

The stability of the relationship between lagged sales growth and forecast errors across specifications in Table 3 also suggests that the relationship in the raw data is truly driven by idiosyncratic, firm-level variation in performance. Intuitively, this robustness makes sense to the extent that high-frequency, idiosyncratic shocks are the primary source of dispersion in one-quarter sales growth rates across firms and within firms over time. By contrast, we might not expect temporary idiosyncratic shocks to be the main driver of differences in the *level* of productivity or persistent differences in longer-run growth rates across firms.

In Figure 11 I explore whether managers at small or large firms appear to overextrapolate more. Once again, I regress forecast minus realized sales growth for quarters t to $t+4$ on the firm's lagged sales growth from $t-1$ to t, now computing a separate coefficient for each quintile of the distribution of sales level. These estimates are noisy since the sample is small, but the point estimates are all positive and consistent with there being no systematic difference in how predictable managers' forecast errors are across the firm size distribution. In particular, managers in the top and bottom quintiles both overextrapolate significantly and by a similar magnitude.

2.4.1 Additional evidence of overextrapolation

In Appendix A.8 I show other evidence that managers overextrapolate. The literature usually tests for overextrapolation based on serial correlation in forecast errors, for example see Bordalo et al. (2018), Coibion and Gorodnichenko (2015), or Ma et al. (2018). In particular, overextrapolation is consistent with negative serial correlation across forecast errors, as managers who overestimate their firm's sales growth between quarters t and $t+4$ due to a bad shock realization overstate the persistence of that bad shock and end up underestimating the firm's performance between $t+4$ and $t+8$. As detailed in Section A.8, I find that forecast errors for sales growth t and $t+4$ are indeed negatively correlated with the subsequent error for $t+4$ to $t+8$. I do not use this as my baseline specification as this requires a respondent to remain in my sample for a minimum of two years, which lowers my sample size and means that selection might be a greater concern.

Similarly in Appendix A.8 I show that forecast errors about sales growth between t and $t+4$ also covary positively with rate of sales growth managers report the firm experiencing in the 12 months prior to answering the survey. We can interpret that reported sales growth rate at face

value, or alternatively, this reported growth rate may capture the respondents' sentiment about the company's current performance. In either case, managers' tendency to overestimate the firm's subsequent growth when they report higher growth in the year prior to the survey, and vice versa for when they report lower growth, suggests their forecasts are subject to overextrapolation bias.

3   General Equilibrium of Model of Employment Dynamics with Subjective Beliefs

This section develops my baseline model of employment dynamics carried out by managers of heterogeneous firms subject to idiosyncratic risk. At its heart the model contains many of the canonical features of dynamic models based on Hopenhayn (1992) and Hopenhayn and Rogerson (1993). I extend the standard setup by allowing the managers who make dynamic business decisions to have biased subjective beliefs about future idiosyncratic shocks. Specifically, managers may misperceive the unconditional mean, persistence, and volatility of those shocks and end up making sub-optimal hiring and firing decisions. Since aggregate outcomes depend on managers' decisions, widespread beliefs biases may also have an impact on the aggregate economy.

My goal in writing down this model is to provide enough structure to consider counterfactual scenarios in which managers face the same environment but have different beliefs. In Section 4 below, I describe how I solve the model and estimate its parameters using data from the *Survey of Business Uncertainty*. Based on these estimates, in Section 5 I show how individual firms and aggregate outcomes differ quantitatively when managers are unbiased.

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:

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

where $\alpha \in [0, 1)$. I remain agnostic about the specific reasons behind these decreasing returns. Potential candidates include imperfect competition that forces the firm to lower prices in order to sell larger quantities, or limited managerial attention or span-of-control following Lucas (1978).

Each firm's idiosyncratic shock z_t follows a log-normal autoregressive Markov process, as is standard in the literature on business dynamics and heterogeneous firm macroeconomic models:

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

I refer to this stochastic process as the state of "business conditions" capturing changes in the state of either demand or supply conditions. There is no aggregate risk.

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:

$$y(z_t, n_t; w_t) = z_t n_t^\alpha - w_t n_t.$$

Every firm in the model has a manger 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:

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

The firm's workforce next quarter includes labor already working at the firm less exogenous separations (occurring at a rate q) plus net hiring and firing h_t. I assume managers make hiring decisions under uncertainty about the next quarter's shock to business conditions z_{t+1}. These dynamics capture real-world lags in searching, interviewing and training new employees, as well as time spent 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 severance payments for laid-off workers and revenue lost as the firm rebalances duties across workers who were not laid off. In my baseline specification I assume these adjustment costs are quadratic in the gross rate of hiring and scale with the firm's size:

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

Each firm in the model obtains cash flow $\pi(\cdot)$ in quarter t, equal to its earnings less hiring and firing costs 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:

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

The magnitude and form of adjustment costs is an important feature of the quantitative exercise I conduct in Section 5. [20] When managers decide how many workers to hire or lay off today, they trade off spending on adjustment costs today against adjusting the firm's labor force towards the optimal level implied by the managers' forecast for business conditions next quarter (i.e. the manager's forecast for z_{t+1}). With adjustment costs, managers' uncertainty about z_{t+1} may also impact their dynamic hiring and firing decisions for standard real-options motives. In my baseline specification with quadratic adjustment costs they do not choose to delay hiring and firing altogether but rather

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[20]Ma et al. (2018) is a closely-related and contemporaneous paper that omits this channel as a potential source of the costs of beliefs biases.

adjust the firm's employment more cautiously.

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 baseline quadratic specification follows standard practice involving firm-level data that aggregates several establishments, product lines, and divisions belonging to the same firm. That said, in Section 6 I show how my quantitative results differ in a specification that focuses on capital investment subject to quadratic adjustment costs as well as partially irreversible investment.

3.2 Managers' Subjective Beliefs

Firms in the model are exposed to idiosyncratic shocks to business conditions z_t following a standard log-Normal autoregressive process, shown in Equation 1. Managers in the model observe their firms' current shock $\log(z_t)$, but believe the distribution of future shocks 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 each manager's sense of optimism, persistence, and uncertainty about future business conditions relative to the objective process in Equation 1. If $\tilde{\mu} > \mu$, managers tend to overestimate their firms' future conditions. If $\tilde{\rho} > \rho > 0$ they overestimate the persistence of current conditions $\log(z_t)$, leading them to overextrapolate from current conditions when they make forecasts. 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 of managers' subjective 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.

3.3 Managers' Optimization Problem

Managers in my model economy aim to maximize the risk-neutral, *subjective* present value of their firms' cash flows. Formally, I assume managers are risk neutral and are compensated with a share $\theta \in (0, 1]$ of their firm's equity.[21] Managers are thus incentivized to optimize the net present value of their firms' cash flows, abstracting from other agency frictions. In pursuit of this goal they make dynamic hiring and firing decisions that require forecasting future business conditions. They key feature of my model is that managers use their own subjective beliefs process when making those forecasts.

In quarter t, each manager observes her firm's current shock to business conditions z_t, the firm's current labor force n_t, and the current market wage w_t. The manager then chooses how

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[21]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 6 below I show how my general equilibrium counterfactuals differ with alternative choices for θ.

many workers to hire or fire to obtain labor n_{t+1} the following quarter, incurring adjustment costs $AC(n_t, n_{t+1})$ according to equation 2. Adjusting the firm's labor entails a trade off between reducing in the firm's current cash flows $\pi(\cdot)$ and increasing the managers' expected valuation of the firm (under her subjective beliefs) next quarter, discounted by the equilibrium risk-free rate $(1 + r_{t+1})$:

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

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

3.3.1 Ownership and control of firms in the model

I assume that managers in the model control the firm's policies and make decisions based on their subjective beliefs, abstracting from corporate governance and interactions with other shareholders. I thus abstract from how biases may arise, or why biased individuals end up as managers. There are certainly models in which biased individuals are selected for managerial roles as a result of agency conflicts of various sorts, so in that sense my results help us understand new mechanisms for how agency conflicts can impact firm-level performance.

Having said that, the existence of agency conflicts is not necessary for firms to end up with biased managers. Since individual forecasts and realizations may differ due to random shocks even if managers have rational expectations, it may take boards of directors or shareholders decades before they can conclusively say whether a manager is biased or not. So boards may stick with biased managers for years without knowing for certain whether they are biased, or by how much.[22]

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. This true value of the firm is the net present value of cash flows, forecasting future conditions under the *true* 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 managers' choice for next quarter's labor as a function of the firm's idiosyncratic states and equilibrium prices. Then, $V(z_t, n_t; \cdot)$ is the solution to the following functional equation:

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[22]The literature has posed at least two hypotheses for why high-level firm managers may have biased beliefs. The first, more widespread in the psychology and behavioral literatures (e.g. see Tversky and Kahneman (1974)), argues that humans are not naturally apt at handling probabilities and biases are simply part of how managers think. The second argues that biased individuals are differentially selected into becoming managers, for example in Goel and Thakor (2008) as a result of tournament-style promotion incentives.

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

Equation 5 uses the objective expectations operator $\mathbf{E}_t[\cdot]$ to forecast the firm's continuation value, in contrast with the manager's valuation in 4.

A firm's true value $V(z_t, n_t; \cdot)$ in general differs from the managers' subjective valuation of the firm $\tilde{V}(z_t, n_t; \cdot)$, but the two are identical when the managers' subjective beliefs about the evolution of z are unbiased. Additionally, $V(z_t, n_t; \cdot)$ in general fails to achieve the optimal value of the firm, except (again) if the manager is unbiased. One of my key contributions in what follows is to quantify how much more firm value could be generated by replacing the typical manager with another, unbiased manager[23].

3.5 Household

There is an infinitely-lived representative household who consumes firms' output and supplies their labor. The household owns a "mutual fund" that holds the remaining share $1 - \theta \in [0, 1)$ of the equity of all firms in the economy (recall that each manager owns the other $\theta \in (0, 1]$ share of the firm she runs). The mutual fund provides the household with lump-sum capital income

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

where $\phi_t(z, n)$ is the measure of firms with business conditions z and labor n in quarter t. Again, $\kappa(z_t, n_t)$ 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.

In full, the representative household maximizes its lifetime utility from consumption and leisure

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

subject to its budget constraint

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

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[23]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 of individual firms in the model, but I am hesitant to make predictions about asset-pricing without more evidence on how rational or biased the beliefs of investors are. 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.

The household's optimality conditions are the usual intertemporal Euler equation and intratemporal labor-leisure tradeoff:

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

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

The household's problem is standard because the focus of my analysis is on managers' dynamic employment decisions. However, the household's optimality conditions pin down equilibrium prices that are crucial for my quantitative evaluation of general equilibrium counterfactuals.

3.6 Stationary General Equilibrium

Let $Pr(z'|z) = Pr(z_{t+1} = z'|z_t = z)$ stand for the conditional density of idiosyncratic shocks z_t under the objective driving process from equation 1. Once again let $n_{t+1} = \kappa(z_t, n_t; w_t, r_{t+1})$ be the target employment choice of a manager whose firm is currently in state (z_t, n_t), facing equilibrium prices w_t and r_{t+1}.

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 valuations $\tilde{V}(z_t, n_t; w, r)$ by managers, and a stationary distribution $\phi : \mathcal{Z} \times \mathcal{N} \to [0, 1]$ such that:

1. $\tilde{V}(z_t, n_t; w, r)$ solves each managers' problem in 4.

2. The household optimally chooses steady-state consumption C, labor supply N^S, and savings B.

3. The distribution of firms $\phi(\cdot)$ is invariant across quarters and consistent with managers' hiring decisions and exogenous fluctuations in business conditions:

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

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

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

This 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 $\{w_t, r_t\}_{t=0}^{\infty}$, a time varying distribution of firms $\phi_t(z, n; w_t, r_t)$, and managers' and household's optimality conditions as well as market clearing hold period-by-period, taking the price sequence as given.

My model abstracts from aggregate risk and instead focuses on managers' subjective beliefs about idiosyncratic shocks and the decisions they make based on those beliefs. This abstraction makes the model tractable and means that biases in my model economy affect aggregate outcomes only to the extent that they change the allocation 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 biased with respect to aggregate shocks, my analysis below should *underestimate* the quantitative implications of biases for the macro-economy in a broader setting that also allows for such aggregate shocks.

4   Model Solution and Estimation

Once again, my goal in this paper is to quantify the implications of biased beliefs for the value of individual firms and for the macro-economy. This quantification requires estimating many of the parameters of the model economy described in Section 3. This section describes: (1) how I compute the aggregate steady state of the model, 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. 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 receive Gaussian shocks, the model in Section 3 satisfies this requirement[24].

To solve the model, I first note that the household's inter-temporal Euler equation 7 pins down the steady-state risk-free rate as a function of the household's discount factor: $r = 1/\beta - 1$. To solve for the rest of the equilibrium conditions, including the wage w that clears the labor market I use the following algorithm (see Appendix C for details):

1. Given a guess for w, I solve for managers' optimal subjective valuation of the business in 4 numerically using standard techniques. Specifically, I solve for managers' value and policy functions over a discretized (z, n) state space with policy function iteration (i.e. value function iteration aided by Howard's improvement algorithm). The key element here is that I use managers' subjective beliefs for the evolution of z_t (instead of the true stochastic process) to forecast managers' expectation of the firm's future value.

2. I compute the stationary distribution $\phi(z, n; w)$ of firms that arises from (1) managers' biased policy functions $n_{t+1} = \kappa(z_t, n_t; w)$ (obtained from step 1.) and (2) the *true* stochastic process

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[24]Formally, this requires the subjective conditional variance $\tilde{\sigma}$ to be strictly greater than zero, although it could be arbitrarily small.

for idiosyncratic shocks z_t from Equation 1. I exploit the Markovian structure of the model and compute $\phi(\cdot)$ numerically using non-stochastic simulation based on the procedure outlined in Young (2010). This is equivalent to simulating a long panel of firms, with the added benefit that I do not need to draw random numbers and thereby avoid introducing simulation error into any 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) under the current guess for the manager's policies. Then I find the household's desired labor supply N^s given C and w according to its intratemporal labor-leisure tradeoff in equation 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

To analyze the impact of subjective beliefs on firm-level and aggregate outcomes through the lens of my model I need to pick appropriate values for the parameters governing the technology, preferences, and objective and subjective stochastic processes for idiosyncratic shocks.

I calibrate the parameters relating to the household's labor supply and consumption-savings decision using standard values from the literature, see Table 4 for details. Most of these household parameters do not affect managers' investment decision and output dynamics in the economy's stationary general equilibrium. The main exception is the household's discount factor β, which maps directly to the risk-free rate that enters managers' problem in 4. I pick β to obtain a risk-free rate of 4 percent per year in the economy's stationary equilibrium. I set the share of equity owned by managers in the model θ equal to 0.05, following estimates by Nikolov and Whited (2014) of the typical amount of equity held by managers. This figure includes equity held directly and through stock options. On the firm side of the economy, I also 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). Table 4 lists the values for all these externally-calibrated parameters.

I structurally estimate the main parameters governing managers' investment decisions and their outcomes. Specifically, I estimate the persistence and volatility of shocks in the true driving processes from equation 1 ρ and σ, the subjective parameters governing managers' beliefs about persistent shocks to fundamentals in 3 $\tilde{\rho}$ and $\tilde{\sigma}$, the elasticity of revenue with respect to labor, α, and the magnitude of labor adjustment costs, λ.

I undertake the estimation via GMM, matching moments from my model's stationary distribution to corresponding data moments I obtain from the SBU .This procedure finds the vector of parameters $\theta = (\alpha, \lambda, \rho, \tilde{\rho}, \sigma, \tilde{\sigma}, \tilde{\mu})'$[25] that minimizes the weighted distance between a vector of population moments in the stationary distribution of the model $m(\theta)$ and their counterparts in the

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[25]Recall that I set $\mu = 0$ without loss of generality.

SBU data $m(X)$. I use a simulated annealing algorithm to undertake this numerical minimization problem to ensure I find a global rather than a local minimum for my econometric objective:

$$\min_\theta \quad [m(\theta) - m(X)]'W[m(\theta) - m(X)].$$

I use the efficient moment-weighting matrix W that has been shown to have good small-sample properties in this sort of structural estimation exercises on firm-level data (see Bazdresch et al. (2017)). Concretely, W is the inverse of the firm-clustered variance-covariance matrix of data moments $m(X)$.

To identify the seven parameters in θ, I need at least as many data moments that are informative about the parameters. My GMM estimation procedure implies a many-to-many rather than one-to-one mapping between moments and parameters, but I guide my choice of target moments aiming to pick moments that intuitively identify particular parameters.

To begin, I include three moments that correspond directly to the statistics from the SBU that I use to test whether managers' subjective beliefs are in Section 2:

- The mean forecast minus realized sales growth;

- The mean excess absolute forecast error (= absolute forecast error minus subjective mean absolute deviation); and

- The covariance of forecast minus realized sales growth for quarters t to $t + 4$ and the firm's sales growth between quarters $t - 1$ and t.

Intuitively, these three forecast error moments provide discipline for $\tilde{\mu} - \mu$, $\tilde{\sigma}/\sigma$, and $\tilde{\rho} - \rho$ conditional on the true σ and ρ as well as α and λ.

I also target five moments that describe the joint behavior of employment and output at the firm level, namely:

- The variances and covariance of net hiring in quarter t and sales growth between quarters $t - 1$ and t;

- The covariance of sales growth between quarters $t - 1$ and t with sales growth between quarters t and $t + 4$; and

- The covariance of net hiring in quarter t with sales growth between quarters t and $t + 4$.

These additional moments intuitively help identify the true stochastic process and firm technology conditional on managers' beliefs. They would be natural choices for identifying the technology and true stochastic process under the assumption of rational expectations. The variance of sales growth across quarters is particularly informative of the variance of idiosyncratic shocks σ, while the variance of hiring and its covariance with sales growth are jointly informative of the revenue-elasticity of labor α and the magnitude of adjustment costs λ. The covariance of recent sales growth (between $t - 1$ and t) with sales growth over the ensuing year (between t and $t + 4$) is

informative about the true rate of mean reversion or persistence of idiosyncratic shocks ρ. In turn, the covariance of longer-run sales growth with current hiring is additionally informative about the extent of adjustment costs and the extent to which hiring today results in sales growth in the future, so also λ and α.

This intuitive description of how moments map to parameters is meant to be heuristic, however. It is well-known in the structural estimation literature that nearly all parameters – particularly fundamental ones like the extent of decreasing returns α– impact many moments of firm's dynamic behavior. This many-to-many mapping justifies my joint estimation of all parameters, given that my model is ultimately non-linear and over-identified. See Appendix C for more details on how I construct my model and data moments and the estimation procedure. In C I also report the sensitivity of my estimated parameters to moments following the procedure in Andrews et al. (2017).

4.3 Estimation Results

Table 5 shows the results from my structural estimation exercise. The top panel, Sub-table 5a displays the value of the eight targeted moments in the data and the model, showing my estimated model accounts reasonably well for both the extent of beliefs biases in the data and the joint dynamics of sales and employment. That said, managers in my estimated model appear slightly less biased than they do in the data. The top three forecast error moments are somewhat smaller in absolute value in the model than in the data (they would all be zero if managers had rational expectations). However, the differences do not appear economically significant. My model also understates the variances of sales growth and (particularly) net hiring, possibly because there is measurement error in the SBU data that is absent from the model. However, the model is able to match the covariance of net hiring in quarter t with sales growth between $t - 1$ and t, and the pairwise covariances of sales growth over quarter t to $t + 4$ with sales growth and hiring in quarter t.

Sub-table 5b shows my parameter estimates and standard errors . My estimate of the revenue-elasticity of capital, α is 0.61, consistent with the firms in my model implicitly having a more or less fixed capital stock, a constant returns production function for physical output (with capital's output elasticity of about one-third), and decreasing returns to scale in revenue of about 0.8 to 0.9 in labor and capital together. My estimate for the the quadratic adjustment cost parameter λ is about 27.3. Since this parameter is model and context dependent, this value is hard to interpret and indeed there is virtually no consensus in the adjustment cost literature regarding what an appropriate value for λ might be. To give an idea, the typical ratio of adjustment costs paid relative to revenue in the stationary distribution of my estimated model is close to 13 percent.

Moving to my estimates of the objective stochastic process, I find the standard deviation of the shocks to business conditions is 0.21, a typical value for a quarterly model with adjustment costs. Similarly, the autocorrelation of the persistent shocks, ρ, is 0.80, a reasonable value for quarterly shocks to firm-level profitability.

4.3.1 Interpreting the magnitude of beliefs biases in my estimated model

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

Managers' lack of systematic optimism or pessimism is evident in my estimate of $\tilde{\mu}$ equal to -0.003 – not far in economic terms from the true value of $\mu = 0$. Quantitatively, my estimated value for $\tilde{\mu}$ means managers underestimate the mean of innovations to $\log(z_t)$ by a mere 1 percent of the true standard deviation σ of those innovations.

By contrast, managers seem significantly overconfident and overextrapolative. They believe the volatility of shocks to business conditions is $\tilde{\sigma}$ equals 0.098, about 46 percent as large as the true volatility σ (equal to 0.212). Managers also believe the autocorrelation of $\log(z)$, $\tilde{\rho}$, is 0.91, significantly higher than the true autocorrelation ρ of 0.80. This discrepancy quantitatively means managers believe the half-life of innovations to $\log(z)$ is 7.6 quarters, while the true half life is only 3.1 quarters, less than half as long.

5 Micro and Macro Implications of Beliefs Biases

Having estimated my baseline model, in this section I quantify the implications of managerial beliefs biases for the value of individual firms and for the aggregate economy. I do so by conducting two different types of counterfactuals:

1. I ask how much firm value would increase for the typical firm in my estimated economy if it hired an unbiased manager in quarter t, holding all else constant. In particular, I hold the firm's business conditions z_t, labor force n_t, and general equilibrium prices fixed and compute the change in value that results from hiring rationally for all date $\tau \geq t$.

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

5.1 Firm Value Destruction and Beliefs Biases

Table 6 shows the potential immediate gain in firm value from replacing a biased manager with another who is either fully unbiased, or at least knows the true value of some the parameters of the persistent shock process in equation 1, holding all else equal.

To compute each line in Table 6 I need to know the true value generated by a biased manager at each point in the (z, n) state space of the model, $V(z, n; w, r)$, and also the true value generated by the counterfactual unbiased manager $V^c(z, n; wr)$. To compute these true values $V(\cdot)$ and $V^c(\cdot)$ I first obtain the biased and unbiased managers' policy functions $\kappa(\cdot)$ and $\kappa^c(\cdot)$. Then solve the functional equation in 5 taking each managers' policy as given. 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 across the stationary distribution of firms in the economy, reporting this last value in Table 6[26].

The bottom line of Table 6 considers the benchmark case, in which a manager with correct beliefs (whose $\tilde{\mu} = \mu$, $\tilde{\sigma} = \sigma$, and $\tilde{\rho} = \rho$) takes over running the firm and generates 1.9 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 ($\tilde{\rho} = \rho$) and isn't overconfident ($\tilde{\sigma} = \sigma$) but slightly understates the mean innovation to $\log(z_t)$ to the extent I estimate in Section 4.2 ($\tilde{\mu} = -0.003 < \mu = 0$). This result is consistent with the evidence in Section 2 that managers are not systematically optimistic or pessimistic, and accordingly their estimated misperception of the mean innovation to business conditions appears marginally inconsequential for firm value.

The top two rows of Table 6 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 ($\tilde{\rho} = \rho$). Firm value would increase substantially in the latter case, by 1.3 percent, while there is essentially no change in firm value from removing overconfidence and keeping overextrapolation. This result is fairly intuitive since overextrapolation distorts managers' conditional expectations while overconfidence distorts their uncertainty about future business conditions. Removing overextrapolation should have first order impact on managers' chosen policies while overconfidence should have second order impact, especially in my setting with smooth, symmetric adjustment costs. That said, removing overconfidence after removing overextrapolation on its own (namely moving from the second to the third row of the table) delivers the last 30 to 35% of the full gain in firm value that we could get by employing a rational manager. So ultimately it would be wrong to conclude that overconfidence is inconsequential even in a setting with smooth, symmetric adjustment costs.

Biased managers destroy firm value because they overreact to shocks. I explore this more fully in the next section when I consider the impact of biased beliefs on the aggregate economy. However, it is already intuitive that a manager who observes her firm receiving a large positive shock in quarter t will hire more aggressively in response if she believes the shock to be more persistent. Thus, a manager who overextrapolates responds more strongly to the shock than a rational manager who knows the true extent of the shock's mean reversion. Similarly, a manager who is overconfident and thus less uncertain about future conditions may respond less cautiously to realized shocks, being more willing to spend on adjustment costs. The prospect of receiving a shock next quarter that could make today's hiring decision look completely inadequate, by contrast, will encourage a rational manager to hire and fire workers with more caution.

My results show that firms would perform significantly better by replacing biased managers with unbiased ones. However, I would argue the potential gains in firm value I find in this section are modest in light of the substantial deviations from rational expectations I find in my estimation

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[26]An alternative calculation would be one where I calculate how much more valuable the typical firm would be in the long-run if it had an unbiased manager, relative to the value of the typical firm today.

in Section 4.2 and Sub-table 5b. Recall that managers underestimate the standard deviation of the firm's shocks by over 50 percent. They also overestimate the half life of shocks by more than double. One key reason why these significant deviations from rational expectations have relatively limited impact for firm value is that managers cannot really take actions that have catastrophic or irreversible consequences in the model. The firm's long-run productivity is invariant to managers' actions ($\mu = 0$), 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 to what extent managers' beliefs biases may destroy firm value through those additional channels.

Although modest, my estimates of the firm-value cost of biases are of a similar order of magnitude as in prior literature. For comparison, Terry (2016) quantifies the gains to firm value from eliminating incentives to distort R&D investment to meet earnings targets at about 1 percent of firm value. Taylor (2010) estimates the potential gains from eliminating CEO entrenchment at 3 percent. Finally, Nikolov and Whited (2014) quantify the change in firm value resulting from modest changes to the severity of agency conflicts that affect managers' cash-holding policies at amounting to 3 to 7 percent of firm value.

One caveat about results from Table 6 is they represent a shift to a first-best that might not be attainable in reality, as there may be no candidates in the pool of potential managers with correct beliefs. This potential lack of unbiased candidates may be due to particularly biased individuals being selected or self-selecting themselves into managerial roles – for example due to tournament-style incentives in Goel and Thakor (2008)– or possibly also due to a generalized lack of rational expectations among the general population. In either case, it is not obvious that it would be feasible to replace the typical biased manager with another who was fully rational.

5.2   Macro Implications of Subjective Beliefs Biases

Table 7 shows my headline results. Each entry in the table shows the percent difference between an 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 the biased economy I estimate in Section 4. Aggregate consumer welfare is larger in the unbiased economy by 0.99 percent in consumption equivalent terms (i.e. considering changes in both aggregate consumption and labor supply). Aggregate output or GDP (after subtracting output spent on adjustment costs) is also higher by 1.6 percent, and labor productivity is higher by 0.17 percent. These figures are sizable. Recent estimates of the cost of business cycles amount to about 1 percent in consumption equivalent terms (Krusell et al., 2009), and only after considering the impact of long-term unemployment. Similarly, estimates of the welfare gains from trade liberalization range from about 1 to 8 percent in Melitz and Redding (2015). In other papers about managerial misbehavior, the welfare cost of short-termism in Terry (2016) is 0.44 percent, somewhat smaller my estimates for the implications of beliefs biases.

Why is welfare higher in the economy with unbiased managers? As I argued intuitively in Section 5.1, overextrapolation and overconfidence lead managers in the model to respond to shocks

excessively and overspend on adjustment costs. This behavior is evident in Figure 12, in which I show how the joint distribution of labor productivity (i.e. the marginal product of labor) and net hiring differs in my estimated model with biases from the counterfactual economy with rational managers. Each point on the graph depicts one of twenty quantiles of the distribution 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.

Labor productivity is positively associated with net hiring in both the biased and efficient economies. Intuitively, firms receiving positive shocks have a high marginal product of labor and find it worth spending some resources in the current quarter to hire more workers for next quarter, and vice versa for firms receiving negative shocks. But the relationship is steeper for the economy with biased managers. Again, this is due to both overextrapolation and overconfidence. When biased managers observe a shock they overestimate how persistent it is, which leads them to overestimate how many workers they should hire or lay off. They are also overconfident and thus too certain about the firm's future marginal product of labor, making them more willing to pay the costs associated with adjusting the firm's labor force.

Because unbiased managers do not hire or fire as many workers in response to shocks, the rate of reallocation in the unbiased economy is lower than in the baseline economy with biased managers. Table 8 shows that the rate of reallocation in the biased economy (= the sum of all hiring and firing as a fraction of aggregate labor) is about 5.7 percent, but only about 1.1 percent in the unbiased economy. This drop amounts to an 81 percent reduction in the pace of reallocation. Because unbiased managers' reactions to shocks are modest, firms in the unbiased economy end up farther from their optimal scale on average. Dispersion in the marginal product of labor is higher by about 6.6% in the unbiased economy. It appears as if biased managers are better at allocating scarce labor across firms, but this line of reasoning ignores that reallocation is costly and biased managers overestimate the benefits to reallocation relative to its costs. Looking again at Table 8, the unbiased economy spends 2.2 fewer percentage points of GDP on adjustment costs, a 13.1% reduction. With fewer resources devoted to unnecessary (and costly) reallocation, the economy with unbiased managers delivers higher welfare to the household even though on its face the drop in reallocation might seem concerning. Less reallocation is welfare improving, again, because biased managers overestimate the benefit of responding to shocks they believe to be persistent and stable. Rational managers recognize the true marginal benefit of reallocation and so spend fewer resources on adjustment costs.

In Table 9 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. In all cases I compute how these outcomes differ from the baseline economy with biased managers. For ease of comparison, the bottom line replicates the results from Table 7 for the fully unbiased economy. 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 for the micro impact of biases in Table 6,

eliminating both overconfidence and overextrapolation keeping managers' mild pessimism ($\tilde{\rho} = \rho$ and $\tilde{\sigma} = \sigma$) delivers welfare and efficiency gains that are almost as large as the ones we would see if we eliminated all biases. So managers' estimated pessimism is, again, fairly inconsequential, even looking at long-run aggregate outcomes.

Table 9 also shows there is an optimal level of reallocation and dispersion in the marginal product of labor, given the magnitude of adjustment costs and the objective stochastic process for idiosyncratic firm shocks. An economy with managers who are overconfident but do not overextrapolate ($\tilde{\rho} = \rho$ only) sees less reallocation, higher dispersion in the marginal product of labor, and the smallest share of GDP spent on adjustment costs across all counterfactuals. Yet the gains in consumer welfare are only about two-thirds as large as for the economy with fully unbiased managers ($\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, and $\tilde{\mu} = \mu$) and only about three-quarters as large as in the economy that removes overconfidence and overextrapolation together ($\tilde{\rho} = \rho$ and $\tilde{\sigma} = \sigma$). Both of those higher-welfare counterfactuals have higher reallocation and static "misallocation". The managers in each of those economies are apt at handling the tradeoff between reallocation's benefits and its costs, ultimately choosing the right amount of resources to spend on adjustment. The economy with overconfident, non-extrapolative managers ($\tilde{\rho} = \rho$ only) instead reallocates too little and would benefit if more labor moved to firms where that extra workers are most productive.

Still looking at Table 9, eliminating overconfidence on its own ($\tilde{\sigma} = \sigma$ only) has the smallest welfare effect –about one third as large as for the case that eliminates all biases– but it is a sizable one given the modest accompanying reduction in reallocation and and spending on adjustment costs. This apparent contradiction shows that behind the results from Table 9 there are general equilibrium effects that matter quantitatively. In Appendix C.5 I explore how these price effects quantitatively relate to welfare and other aggregate outcomes across counterfactual economies.

6   Robustness and Extensions

An obvious drawback of taking a structural approach is that the explicit assumptions embedded in the model and the particular choice of target moments and calibrated parameters all affect the quantitative results in counterfactuals. To address these concerns, in this section I first consider how my quantitative micro and macro result change under modest changes to my model parameterization. Additionally, I address concerns that my baseline model focuses on the dynamics of labor, which is a short-lived, flexible input. We might expect that mistakes based on biased beliefs could be more consequential for longer-lived, less adjustable inputs like capital, so I estimate a version of my model focusing on investment dynamics. Finally, I briefly discuss how my parameter estimates and results vary if I estimate my investment-based model on subsamples of Compustat firms for which managers appear to be badly behaved, or agency conflicts to be more severe.

Table 10 contains two sub-panels showing how my key counterfactual outcomes, namely firm value at the micro level and consumer welfare at the macro level, vary for different model specifications. The first column of Table 10a and 10b respectively replicate the baseline results from Tables

6 and 9 concerning the change in firm value or consumer welfare from replacing a biased manager with another who is more biased or moving to an economy in which all managers display fewer biases.

For both my macro and macro counterfactuals, I consider the effect of two potentially important features of the model's parameterization: (1) the magnitude of adjustment costs, and (2) the durability of labor. To start, I consider the effect of tripling or cutting my adjustment cost parameter λ to one third, corresponding to the columns labels "High" and "Low" adjustment costs in Tables 10a and 10b. Intuitively, the presence and magnitude of adjustment costs is the key friction in manager's forward-looking hiring decision. Biased managers in my model destroy firm value and reduce aggregate welfare because they overspend on adjustment costs as they hire or lay off too many workers in response to shocks. I structurally estimate the baseline quadratic adjustment cost parameter $\hat{\lambda} = 27.3(0.800)$, whose identification comes primarily from the covariance of quarterly sales growth and net hiring in my SBU data, but there is still a question of how much my quantitative results depend on this particular value for λ.

Looking at Table 10a, the impact of biases on firm value is actually lower under both high $(3 \times \hat{\lambda})$ and low $(1/3 \times \hat{\lambda})$ adjustment costs. The intuition for the lower impact of low adjustment costs is straightforward. Overreaction due to overconfidence and overextrapolation is less costly if the upfront costs of mistakenly hiring or firing too many workers are smaller. [27] With high adjustment costs, the impact of biases on firm value is actually even smaller because in this case hiring and frictions are so large that both the biased and unbiased (or less biased) managers make limited responses to shocks. So even though biased managers want to overreact, the upfront costs of hiring or laying off workers are so large that a higher fraction of them end up staying put and thus making the same choice as unbiased managers. That said, the impact of removing overconfidence on its own is positive for high adjustment costs because now managers' perception of uncertainty has first order impact on their choices via standard real options motives that are weaker when adjustment costs are smaller.

Looking instead at Table 10b, the impact of biases on aggregate welfare under high versus low adjustment costs, however does follow the intuitive pattern. With high adjustment costs, welfare gains from moving to an economy with unbiased or less biased managers are larger than with low adjustment costs. In particular, with high adjustment costs removing overconfidence on its own (the $\tilde{\sigma} = \sigma$ case) is significantly more consequential, resulting in welfare gains that are almost as large as the full move to rational expectations. With low adjustment costs eliminating biases still carries significant consequences for aggregate welfare, but they are about two-thirds as large as in the baseline cast.

The second alternative parameterization I consider for both the micro and macro results in Tables 10a and 10b is one where the exogenous worker separation rate q is lower at $q = 0.026$

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[27]Eliminating overconfidence on its own ($\tilde{\sigma} = \sigma$) actually diminishes firm value because with low adjustment costs, overextrapolative managers' perceptions of uncertainty primarily impact their policy function through Jensen's and Hartman-Abel effects. Specifically, removing overconfidence with low adjustment costs effectively creates over-optimism that negatively affects firm value.

(10 percent annually) relative to the baseline level of $q = 0.083$ (30 percent annually). In my baseline analysis, I calibrate q to this higher value, following the evidence from Shimer (2005) on the typical duration of jobs in the US.[28] At higher separation rates (i.e. with lower job durations) managers effectively get to re-optimize a larger fraction of their firm's work force each quarter and thus hiring mistakes are less consequential because they undo themselves exogenously and quickly. At lower separation rates, managers instead need to actively reverse more of their mistakes and potentially pay for those reversals. The results in Table 10a confirm this intuition, with modestly larger changes in firm value from replacing biased managers with other who lack one or more biases than the baseline. Having said that, in Table 10b I find the change in welfare from eliminating biases to be of a similar order of magnitude as in the baseline case.

In Table 10b I also explore how the share of equity held by managers θ, which I did not estimate, affects my macro counterfactual exercises. Since manager's compensation only comes in the form of equity, the specific value of θ drops out of their optimization problem in equation 4 does not directly affect their hiring and firing decisions. The value of θ does matter for my macro counterfactuals because it changes the share of total profits Π_t that the representative household receives as capital income, and thus affects aggregate labor supply and the general equilibrium wage. Since θ does not affect managers' decisions, it is not identified by my target moments so I pick a value of $\theta = 0.05$ following estimates in Nikolov and Whited (2014) on the typical share of equity held by managers, combining equity held in the form of actual shares as well as stock options. The fifth and sixth columns of Table 10b consider how the welfare impact of beliefs biases changes if I double or halve the share of equity held by managers. The welfare impact is modestly larger for $\theta = 0.10$ and lower for $\theta = 0.025$, intuitively corresponding to larger changes in the general equilibrium wage in the former than the latter case. If managers own a larger share of the firm's equity, less of the increases in profitability that emerge from eliminating biases get ultimately rebated to the household via capital income. Thus, the household requires larger changes in the wage to accommodate the change in aggregate labor demand that occurs when managers are no longer biased.

Finally, I consider whether I would obtain different results if I built and estimated a model of capital investment with adjustable labor. Dynamic models of investment subject to adjustment costs are arguably the standard way of modeling firm behavior,[29] though the traditional focus on physical capital is arguably due at least in part to the literature's traditional focus on manufacturing. In Appendix B.5 I modify my baseline model to focus on dynamic capital investment decisions (making labor a static choice) and in Appendix C.6 estimate this investment model targeting moments from Compustat firms' investment and output decisions and my three forecast error moments from the SBU. My investment model also features both quadratic adjustment costs and partially irreversible

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[28]Note that because my target moments concern *net* rather than gross hiring (I only observe employment growth rather than gross hires and fires) the value of q barely changes the value of the model moments I target in my estimation exercise from Section 4.2. So q would be hard to identify and estimate with the data I have available. Indeed, the literature that estimates capital depreciation rates in using structural models similar to mine typically targets a mean *gross* investment rate to identify this parameter (e.g. see Bazdresch et al. (2017)).

[29]For example, see Cooper and Haltiwanger (2006), Khan and Thomas (2008), and Winberry (2015). Sraer and Thesmar (2018) derive general results for the impact of frictions in this sort of standard setup.

capital, to see how much my results change with multiple forms of adjustment frictions. I employ moments from two separate data sources – Compustat and the SBU– for this exercise because the SBU does not have reliable data on capital stocks and capital expenditures. I acknowledge that publicly-traded firms are well known not to be representative of the economy as a whole (e.g. see Davis et al. (2007)) so this analysis is not as clean of an empirical exercise. Readers should refer to Appendix C.6.2 for details on this estimation. While my results for the macro counterfactuals in the final column of Table 10b are similar in magnitude to those of the baseline labor-based model, I find larger changes in firm value – up to 6.2 percent relative to 1.9 percent in my baseline – from replacing biased managers in Table 10a.

In Appendix D I also use my investment model to test how my estimates of model parameters – in particular beliefs biases — differ across subsamples of Compustat firms for which agency conflicts appear to be larger, or in which managers may be badly behaved. Specifically, I consider firms with strong versus weak governance based on the index in Bebchuk et al. (2008), firms that have recently been engaged in mergers and acquisitions (as a crude proxy for empire-building preferences), and firms whose managers appear to be "overconfident" and over-optimistic based on their stock option exercise behavior using data from Malmendier and Tate, 2015. For each of these estimations I target the investment and output moments of the subsample of firms, holding constant my beliefs moments from the SBU.[30] I find, as expected, that managers who appear to be badly behaved and those at firms with more severe agency conflicts behave in ways that are consistent with them being more biased, specifically subject to more severe overextrapolation. Other parameter estimates also move in expected ways. For example, firms with weak governance face lower adjustment costs, which may reflect managers' greater freedom to enact their investment plans without having to justify them with the board and shareholders.

7 Conclusion

Managers of US firms do not appear to be systematically over-optimistic or pessimistic about their firm's future performance. But they do appear to overextrapolate from current conditions, leading them to overestimate their firm's future sales growth in good times and underestimate in bad times. Managers are also overconfident, overestimating their ability to make accurate forecasts and underestimating the amount of risk their firms are exposed to.

I quantify the micro and macroeconomic costs of overconfidence and overextrapolation by estimating the beliefs, frictions, and true shock process that are consistent with this evidence about managerial beliefs and the joint dynamics of employment and output in firm-level data. My estimates imply that managers underestimate the volatility of shocks hitting the firm by over 50 percent. They also believe the half-life of those shocks is close to 8 quarters, when the true half life is less than half as long.

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[30]Given I can't link my SBU data to publicly-traded firms, this approach means that differences in estimated parameters across subsamples come entirely from differences investment and output dynamics.

Comparing outcomes in my estimated model against outcomes from a counterfactual economy in which managers have correct beliefs about the evolution of business conditions, I find sizable implications. At the micro level, firm value would be higher by 1.9 percent in my preferred specification if managers did not overextrapolate and were not overconfident. At the macro level, an economy with unbiased managers would have 1.0 percent higher welfare in consumption-equivalent terms, and GDP would be 1.6 percent higher. Both the micro and macro implications are a result of biased managers' overreacting shocks and thus overspending on costly reallocation. Unbiased managers appreciate the true costs and benefits of reallocation, increasing aggregate welfare.

This paper is one of the first serious attempts at quantifying the micro and macro implications of biases in firm managers' beliefs. Having ascertained that the costs of biases are significant, my results also points to a number of questions for future work. Are there quantitatively-plausible agency or information frictions that may explain why firms hiring biased managers? What do managerial beliefs about aggregate dynamics look like? How do biases in managerial beliefs impact business cycle dynamics, or long-run innovation, creative destruction, and growth? The analyses and methods used here may serve as useful starting points to consider these and other important questions in corporate finance and macroeconomics.

References

ABEL, A. B. AND J. C. EBERLY (1997): "An exact solution for the investment and value of a firm facing uncertainty, adjustment costs, and irreversibility," *Journal of Economic Dynamics and Control*, 21, 831–852.

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, M. BRYAN, S. J. DAVIS, B. H. MEYER, AND N. PARKER (2018): "The Survey of 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.

BAKER, S. R., T. MCELROY, AND X. S. SHENG (2018): "Expectation Formation Following Large Unexpected Shocks," .

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.

BERNANKE, B. S. (1983): "Irreversibility, Uncertainty, and Cyclical Investment," *The Quarterly Journal of Economics*, 98, 85–106.

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," .

BOLTON, P., M. K. BRUNNERMEIER, AND L. VELDKAMP (2012): "Leadership, coordination, and corporate culture," *Review of Economic Studies*, 80, 512–537.

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

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

BOUTROS, M., J. R. GRAHAM, AND C. R. HARVEY (2018): "Managerial Recalibration: Do CFOs Learn?" .

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.

COIBION, O. AND Y. GORODNICHENKO (2012): "What can survey forecasts tell us about information rigidities?" *Journal of Political Economy*, 120, 116–159.

——— (2015): "Information rigidity and the expectations formation process: A simple framework and new facts," *American Economic Review*, 105, 2644–78.

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., H. A. HOPENHAYN, AND V. VENKATESWARAN (2016): "Information, misallocation and aggregate productivity," *The Quarterly Journal of Economics*, qjw006.

DAVIS, S. J., J. HALTIWANGER, R. JARMIN, AND J. MIRANDA (2007): "Volatility and dispersion in business growth rates: Publicly traded versus privately held firms," in *NBER Macroeconomics Annual 2006, Volume 21*, MIT Press, 107–180.

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.

ERICKSON, T. AND T. M. WHITED (2002): "Two-step GMM estimation of the errors-in-variables model using high-order moments," *Econometric Theory*, 18, 776–799.

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

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.

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

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.

HAN, C. AND P. C. PHILLIPS (2010): "GMM estimation for dynamic panels with fixed effects and strong instruments at unity," *Econometric theory*, 26, 119–151.

HENNESSY, C. A. AND T. M. WHITED (2005): "Debt dynamics," *The Journal of Finance*, 60, 1129–1165.

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 (2009): "Misallocation and manufacturing TFP in China and India," *The quarterly journal of economics*, 124, 1403–1448.

——— (2017): "The Reallocation Myth," *Fostering a Dynamic Global Economy*.

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

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.

Khan, A. and J. K. Thomas (2008): "Idiosyncratic shocks and the role of nonconvexities in plant and aggregate investment dynamics," *Econometrica*, 76, 395–436.

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.

——— (2015): "Behavioral CEOs: The role of managerial overconfidence," *Journal of Economic Perspectives*, 29, 37–60.

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.

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

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

Pindyck, R. S. (1988): "Irreversible Investment, Capacity Choice, and the Value of the Firm," *The American Economic Review*, 969–985.

Restuccia, D. and R. Rogerson (2008): "Policy distortions and aggregate productivity with heterogeneous establishments," *Review of Economic dynamics*, 11, 707–720.

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.

Sraer, D. and D. Thesmar (2018): "A sufficient statistics approach for aggregating firm-level experiments," Tech. rep., National Bureau of Economic Research.

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

Stokey, N. L., R. E. Lucas, and w. E. C. Prescott (1989): *Recursive methods in economic dynamics*, Harvard University Press.

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

Tauchen, G. (1986): "Finite state markov-chain approximations to univariate and vector autoregressions," *Economics letters*, 20, 177–181.

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," .

TVERSKY, A. AND D. KAHNEMAN (1974): "Judgment under uncertainty: Heuristics and biases," *science*, 185, 1124–1131.

WINBERRY, T. (2015): "Lumpy investment, business cycles, and stimulus policy," *Job market paper, University of Chicago Booth School of Business*.

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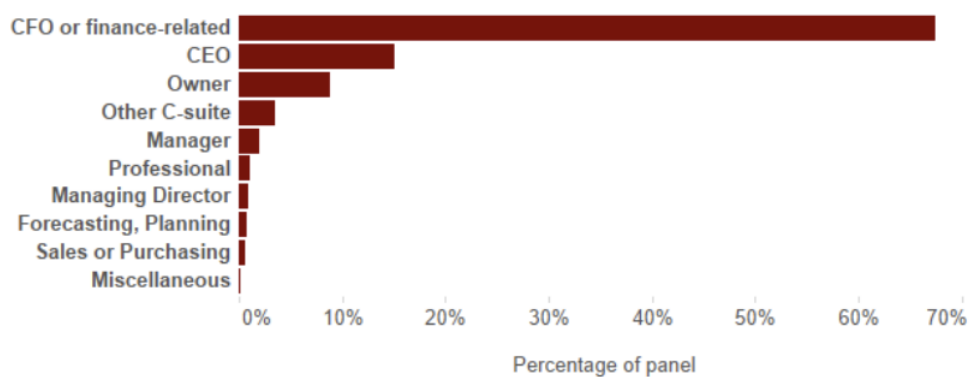
Notes: This figure shows the share of SBU panel memebers whose job title falls into each of the following categories as of July 2018.

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

**Notes:** Sales growth questions in the *Survey of Business Executives* as they have appeared since September 2016. In months prior to September 2016, the *SBE* asked for sales growth beliefs in levels rather than growth rates. See Figure A.1. The rates of sales growth assigned to the five scenarios and their associated probabilities shown in this example are consistent with the typical responses provided by actual survey participants.

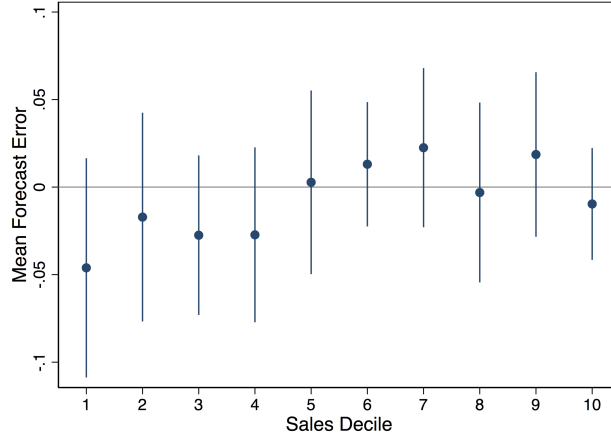Figure 3: **Managers are Neither Over-Optimistic Nor Pessimistic: Across Time**
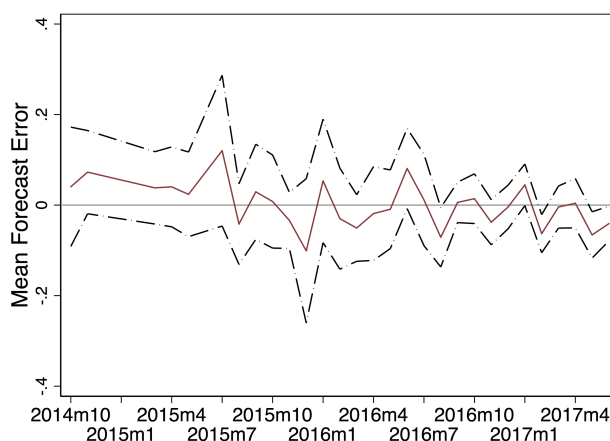
Notes: This figure shows the mean forecast error for each month. Data are from the *Survey of Business Uncertainty,* with the sample including all forecast error observations concerning sales growth, looking four quarters ahead. The sample period includes all months between 10/2014 to 6/2018. A forecast 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 $t+4$. $N = 1,574$.

Figure 4: **Managers are Neither Over-Optimistic Nor Pessimistic: Across Sectors**
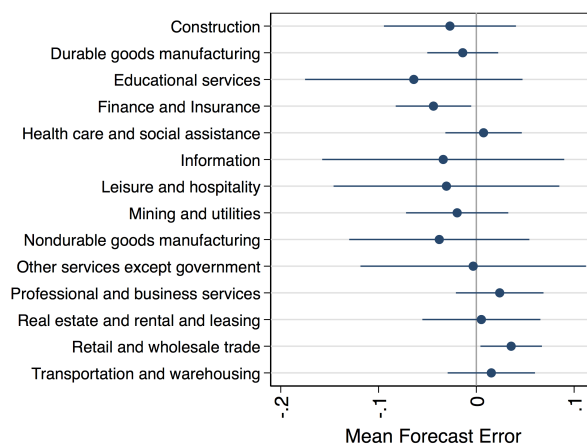
Notes: This figure shows the mean forecast error for each one-digit sector. Data are from the *Survey of Business Uncertainty,* with the sample including all forecast error observations concerning sales growth, looking four quarters ahead. The sample period includes all months between 10/2014 to 6/2018. 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 $t+4$. $N = 1,574$.

Figure 5: **Managers are Neither Over-Optimistic Nor Pessimistic: Across Firm Sizes**
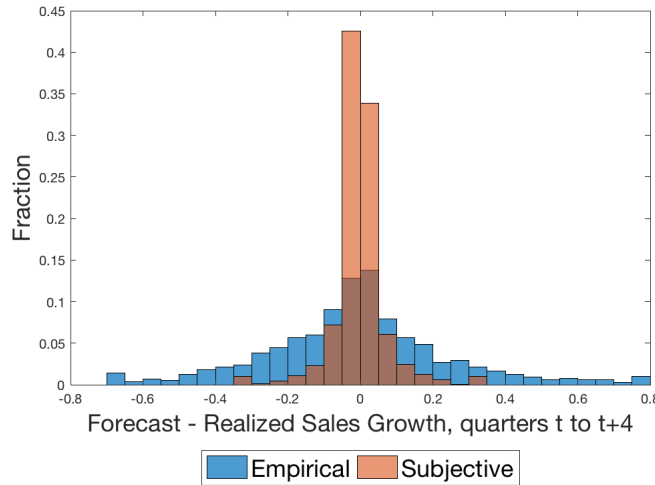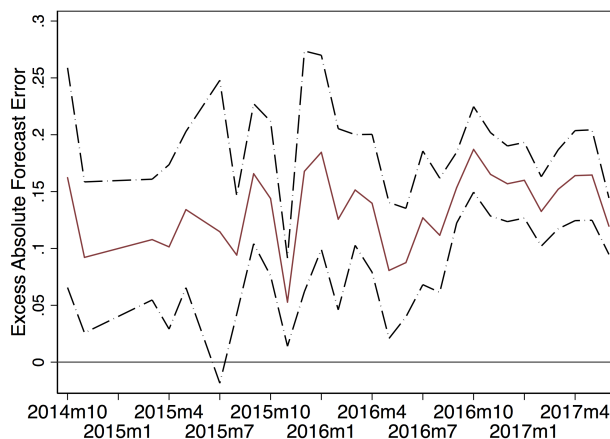

Notes: This figure shows the mean forecast error for each decile of the distribution of current sales (at the time of forecast). Data are from the *Survey of Business Uncertainty,* with the sample including all forecast error observations concerning sales growth, looking four quarters ahead. The sample period includes all months between 10/2014 to 6/2018. 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 $t+4$. $N = 1,574$.

Figure 6: **Managers are Overconfident About Their Forecasts' Accuracy**

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 6/2018. 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 $t+4$. $N = 1,574$.

Figure 7: **Managers are Overconfident About Their Forecasts' Accuracy: Across Months**

Notes: This figure shows the mean excess absolute forecast error for each month. The broken lines are 95 percent confidence bands, clustering by firm. A respondent's excess absolute forecast error is her realized absolute error minus her ex-ante subjective mean absolute deviation from her forecast. Data are from the *SBU* and sample period includes all months between 10/2014 to 6/2018. 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 $t + 4$. $N = 1,574$.

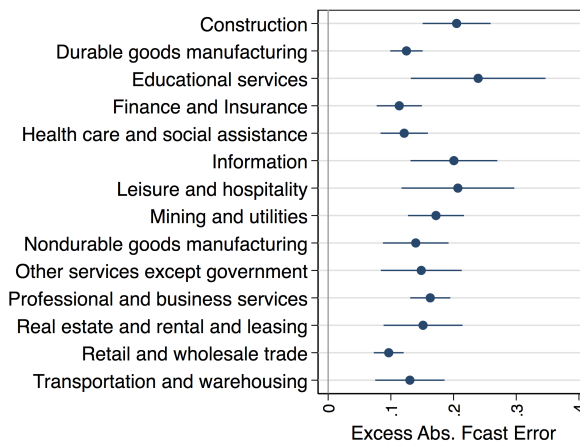Figure 8: **Managers are Overconfident About Their Forecasts' Accuracy: Across Sectors**

Notes: This figure shows the mean excess absolute forecast error by one-digit sector, with confidence intervals based on standard errors clustered by firm. A respondent's excess absolute forecast error is her realized absolute error minus her ex-ante subjective mean absolute deviation from her forecast. Data are from the *SBU* and sample period includes all months between 10/2014 to 6/2018. 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 $t + 4$. $N = 1,574$.

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Figure 9: **Managers are Overconfident About Their Forecasts' Accuracy: Across Firm Sizes**
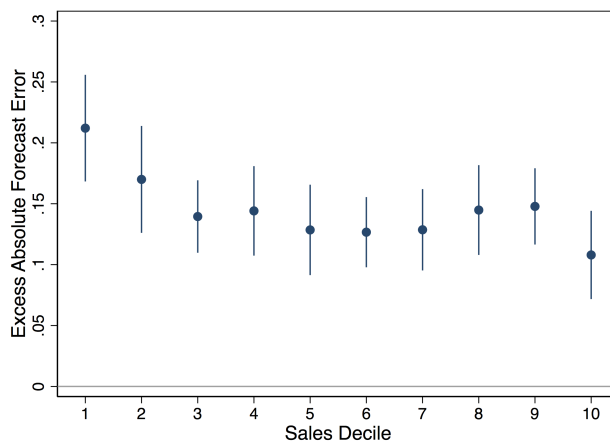
Notes: This figure shows the mean excess absolute forecast error by decile of current sales at the time of forecast, with confidence intervals based on standard errors clustered by firm. A respondent's excess absolute forecast error is her realized absolute error minus her ex-ante subjective mean absolute deviation from her forecast. Data are from the SBU and sample period includes all months between 10/2014 to 6/2018. 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 $t + 4$. $N = 1,574$.

Figure 10: Managers Overextrapolate from Current Conditions
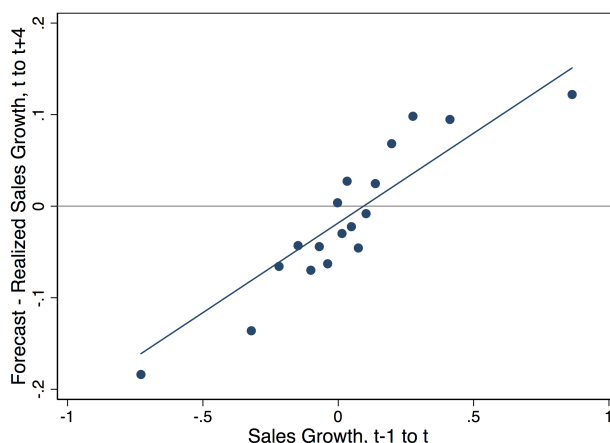
Notes: This figure shows a bin-scatter of realized forecast errors for sales growth between t and $t+4$ on the vertical axis against realized sales growth between quarters $t-1$ and t, just prior to the survey response. Data are from the SBU and sample period includes all months between 10/2014 to 6/2018. 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 $t + 4$. $N = 919$.

Figure 11: **Managers Overextrapolate: Across Firm Sizes**
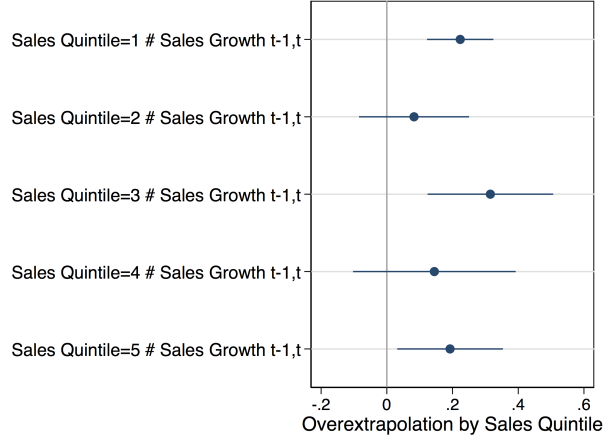
**Notes:** This figure shows the coefficients from regressing forecast minus realized sales growth between quarter t and $t + 4$ on the firm's lagged sales growth from $t - 1$ to t separately for each of five quintiles of the distribution of sales level. The horizontal bars are 95 percent confidence intervals based on firm-clustered standard errors.

Figure 12: **Net Hiring vs. Labor Productivity in the Economies with Biased and Unbiased Managers**
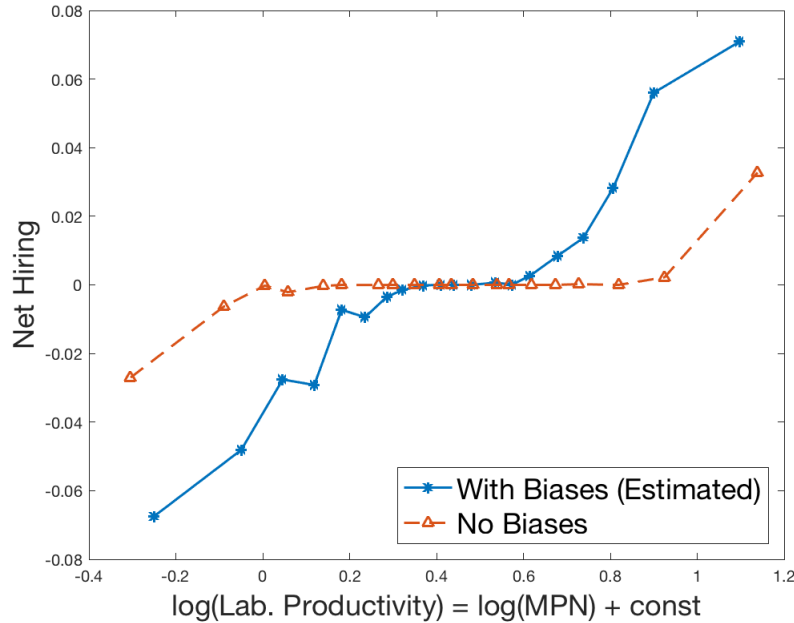
Notes: This figure shows the joint distribution of log(labor productivity) on the horizontal axis and net hiring on the vertical axis in my baseline economy with biases and a counterfactual economy in which all managers are unbiased. To construct the figure, I sort the stationary distribution of each 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.

Table 1: **Managers and Neither Over-Optimistic Nor Pessimistic**

	(1)	(2)	(3)
	Sales Growth		**Forecast Error**
	Forecast	Realized	Forecast - Realized
Mean	0.0379	0.0458	-0.0078
SE	(0.0039)	(0.0081)	(0.0078)
Obs.	1,574	1,574	1,574
Firms	397	397	397

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. Standard errors are clustered by firm. Data are from the SBU and sample period includes all months between 10/2014 to 6/2018. 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 2: **Managers are Overconfident About Their Forecasts' Accuracy**

	(1)	(2)	(3)
	Absolute Forecast Error		**Excess Error**
	Empirical	Subjective	Empirical - Subjective
Mean	0.1845	0.039	0.146
SE	(0.007)	(0.002)	(0.006)
Obs.	1,574	1,574	1,574
Firms	397	397	397

Notes: Means of empirical absolute forecast errors and subjective absolute forecast errors. A respondent's subjective absolute forecast error is the subjective mean absolute deviation from her forecast. Standard errors are clustered by firm. Data are from the *SBU* and sample period includes all months between 10/2014 to 6/2018. 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 Overextrapolate: Forecast Errors versus Recent Performance**

	(1)	(2)	(3)	(4)
Dependent Variable	**Forecast - Realized Sales Growth, quarters t to t+4**			
Sales Growth, quarters $t-1$ to t	0.196***	0.196***	0.231***	0.211***
	(0.039)	(0.038)	(0.040)	(0.043)
Constant	-0.018*			
	(0.010)			
Date FE		Y		Y
Date x Sector FE			Y	
Firm FE				Y
Observations	919	919	869	862
R-squared	0.059	0.092	0.254	0.451

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 6/2018. 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 4: **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 5: **Structural Estimation Results**

(a) **Data and Model Moments**

Moment	Data	Model
Mean(Forecast Error)	-0.013	-0.010
Mean(Excess Absolute Forecast Error)	0.143	0.129
Cov(Forecast Error$_{t,t+4}$, Sales Growth$_{t-1,t}$)	0.011	0.008
Var(Sales Growth)	0.060	0.049
Var(Net Hiring)	0.019	0.001
Cov(Net Hiring, Sales Growth)	0.003	0.004
Cov(Sales Growth$_{t,t+4}$,Sales Growth$_{t-1,t}$)	-0.012	-0.011
Cov(Sales Growth$_{t,t+4}$, Net Hiring$_{t,t+1}$)	-0.002	-0.004

(b) **Estimated Parameters**

Parameter	Explanation	Estimate (SE)
α	Revenue curvature	0.6132 (0.036)
λ	Quadratic adjustment costs	27.3 (0.800)
ρ	True shock persistence	0.801 (0.005)
$\tilde{\rho}$	Subjective Sshock persistence	0.913 (0.005)
σ	True shock volatility	0.212 (0.0006)
$\tilde{\sigma}$	Subjective shock volatility	0.098 (0.0006)
$\tilde{\mu}$	Subjective shock mean	-0.003 (0.00003)

Notes: This table shows the results from my structural estimation of the model from Section X. Sub-table 5a *(top)* shows my target moments in the data and the corresponding model moments after choosing the vector of parameters that minimize the weighted distance between model and data moments. I estimate all data moments using SBU data with the sample period covering 10/2014 to 6/2018. All of the variances and covariances I target correspond to within-firm variation. Namely, before computing my target covariances and variances I regress all observations of a full set of firm and date fixed effects to purge variation due to aggregate shocks and persistent differences across firms and then compute the variances and covariances on the residual of those regressions. I compute model moments numerically from the stationary distribution of firms across the (z, n) state space of the model. Sub-table 5b *(bottom)* shows the values and standard errors of the parameters that minimize the weighted distance between model and data moments. Note that I normalize the true mean of the stochastic process for $\log(z)$ to $\mu = 0$. My choice of weighting matrix is the firm-level clustered covariance matrix of SBU data moments, namely the GMM efficient weighting matrix. I perform the numerical optimization of the econometric objective using a simulated annealing algorithm.

Table 6: **Eliminating Beliefs Biases Increases Firm Value**

Counterfactual	Δ True Firm Value (%)
$\tilde{\sigma} = \sigma$ only	0.0
$\tilde{\rho} = \rho$ only	1.3
$\tilde{\rho} = \rho$, and $\tilde{\sigma} = \sigma$	1.9
$\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, and $\tilde{\mu} = \mu$	1.9

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 7: **Aggregate Impact of Beliefs Biases**

Δ Consumer Welfare %	ΔY %	$\Delta (Y/N)$ %
0.99	1.6	0.17

Notes: This 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.

Table 8: **Biases Encourage Excessive Reallocation**

	Reallocation $\times 100$	$\sigma(\log(MPN))$	$AC/Y \times 100$
With Biases	5.7	0.33	16.6
No Biases	1.1	0.35	14.4
Difference	-81.5%	6.6%	-13.1%

Notes: This table compares steady-state values of the rate of reallocation (= total hiring and firing Δn_{t+1} 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 in an efficient economy with unbiased managers. Y is aggregate GDP after subtracting output spent on adjustment costs. Both the baseline economy with biases and the counterfactual economy with no biases are in general equilibrium.

Table 9: **Macro Impact of Individual Biases**

Counterfactual	Δ C. Welfare %	Δ Realloc. %	$\Delta\sigma(\log(MPN))$ %	$\Delta AC/Y \times 100$
$\tilde{\sigma} = \sigma$ only	0.40	-8.9	0.5	-0.04
$\tilde{\rho} = \rho$ only	0.68	-89.1	7.8	-2.4
$\tilde{\rho} = \rho$ and $\tilde{\sigma} = \sigma$	0.91	-79.7	6.4	-2.2
$\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, and $\tilde{\mu} = \mu$	0.99	-81.5	6.6	-2.2

Notes: This 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 in the steady state of an economy whose managers lack one or more of overconfidence ($\tilde{\sigma} = \sigma$), overextrapolation ($\tilde{\rho} = \rho$), or pessimism ($\tilde{\mu} = \mu$) relative to the steady state of my baseline economy with beliefs biases. Both the baseline economy with biases and the counterfactual economies with no biases are in general equilibrium.

Table 10: **Quantitative Results Robustness**

(a) **Micro Counterfactuals: Make a single manager unbiased**

| Counterfactual | Baseline | Δ True Firm Value (%) | | | Investment Model |
		High Adj. Costs	Low Adj. Costs	Low q (separation rate)	
$\tilde{\sigma} = \sigma$ only	0.0	0.1	-0.3	0.1	0.2
$\tilde{\rho} = \rho$ only	1.3	0.5	1.0	1.5	6.1
$\tilde{\rho} = \rho$ and $\tilde{\sigma} = \sigma$	1.9	0.7	1.5	2.1	6.2
$\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, and $\tilde{\mu} = \mu$	1.9	0.7	1.5	2.1	6.2

(b) **Macro Counterfactuals: Make all managers unbiased in general equilibrium**

| Counterfactual | Baseline | Δ Consumer Welfare (%) | | | | | Investment Model |
		High Adj. Costs	Low Adj. Costs	Low q (sep. rate)	High θ (manager's equity)	Low θ (manager's equity)	
$\tilde{\sigma} = \sigma$ only	0.40	1.36	0.27	0.36	0.94	0.24	0.33
$\tilde{\rho} = \rho$ only	0.68	0.38	0.48	0.68	0.58	0.70	0.29
$\tilde{\rho} = \rho$ and $\tilde{\sigma} = \sigma$	0.91	1.03	0.64	0.87	1.13	0.85	0.64
$\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, and $\tilde{\mu} = \mu$	0.99	1.41	0.66	0.89	1.27	0.90	0.62

Notes: Table 10a *(top)* 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. Columns corresponds to different model specifications. Table 10b *(bottom)* shows the change in consumer welfare we would obtain from moving to a counterfactual economy in which all managers have fewer or no subjective beliefs biases. Each of these welfare changes correspond to a comparison of the aggregate steady state of the baseline economy with biased managers and the aggregate steady state of the counterfactual economy under consideration.

The baseline column refers to the estimated economy in from Section X. Specifications with high and low adjustment costs respectively have three times and one third my estimated adjustment cost parameter λ, which equals 27.3 in the baseline. The specification with low separation rate q sees 0.026 of the firm's workforce separate exogenously each quarter down from 0.083 in the baseline, corresponding to 10 percent annually rather than 30 percent in the baseline. Specifications with high and low manager's equity share θ respectively double and halve the manager's equity from its baseline level of θ = 0.05. (Note, θ does not affect the micro counterfactuals in Table 10a). Finally, the column for the investment model shows results from a model in which labor is chosen statically and capital is subject to adjustment costs which I estimate using data from the Survey of Business Uncertainty as well as from Compustat. See Appendix B.5 for a description of this model and Appendix C.6 for details on its estimation.