THE MICRO AND MACRO OF MANAGERIAL BELIEFS

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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 profitability is more persistent and stable than it really is. 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.

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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. If biases are a pervasive feature of managerial beliefs, the sum of individual managers’ mistakes may additionally affect the macroeconomy. While it is easy to make this string of arguments, the question is ultimately an empirical and quantitative one: how—and by how much—do biases in managerial beliefs matter?

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 macroeconomy. I use data from a confidential survey of US managers to test whether they have biased 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, rational 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 Atlanta Fed/Chicago-Booth/Stanford 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 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 measure both their subjective expectations (i.e. their forecasts) and their subjective uncertainty about future sales growth and assess whether both their first and second moments are consistent with ex-post realizations.

How biased do managers appear in the SBU data? I answer this question by documenting 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. 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'  

\[ \text{See Bachmann and Elstner (2015) for a similar finding among German manufacturing firms.} \]
subjective distributions would imply an average absolute forecast error of about 4 percentage points, 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 during the quarter of the forecast the manager overestimates future performance by an additional 0.2 percentage points. 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 managerial 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 the model against the SBU data, structurally estimating the parameters that empirically account for: (1) the extent of managerial optimism, 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 existing paper structurally estimates a micro-to-macro model by jointly targeting moments from managerial probability assessments and moments related to endogenous outcomes and choices like sales and employment.

\(^2\)See La Porta (1996) and Bordalo et al. (2018a) for similar results about professional analysts, as well as Rozsypal and Schlafmann (2017) for a similar finding for US households.
Quantitatively, how and by how much do biases in managerial beliefs affect firm value and macroeconomic outcomes? Using my estimated model, I consider two types of counterfactual 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 account 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 destroy 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 the firm’s 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 pervasive overreaction results in excessive reallocation. Rational managers instead 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 when managers are rational. It may seem counterintuitive to find higher static "misallocation" in the economy with rational managers. The reason is that there are costs to hiring and firing workers, so more reallocation is not necessarily better in my model economy. 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. Accordingly, I show that taxing firms’ hiring and firing can help reduce some of the excessive reallocation and thus mitigate some of the welfare costs of managerial overconfidence and overextrapolation.

I also ask whether overextrapolation or overconfidence is quantitatively more consequential. While both biases contribute to managerial overreaction and excess reallocation, my results show

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3Dispersion 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). In the benchmark case with no misallocation and all inputs chosen statically, marginal products are equalized across firms.
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 impact of biases in managerial beliefs may want to consider how to curb 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’ worth of forecast data to establish whether any individual manager is biased. Even rational managers are 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 find in the SBU. 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. A key feature of my analysis is I use data on hundreds of managers at different firms, enabling me to draw conclusions about the average extent of bias. In a second possibility, biased individuals may be endogenously selected for managerial roles, for example if managers have multiple traits, 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.4

To consider how my findings relate to oversight and agency conflicts, as well as prior proxies for managerial bias, I re-estimate my model across subsamples firms that differ by the extent of managerial oversight, empire-building tendencies, and whether the CEO is biased according her stock option exercise behavior (see Malmendier and Tate 2005; 2015). These exercises show consistently that firms with weaker 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

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4For example see Goel and Thakor (2008) for a formal model in which such tournament incentives optimally result in hiring overconfident managers.
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 find larger real costs biased beliefs at the micro and macro levels relative to earlier work, with the interplay between biased beliefs and reallocation frictions playing a key role. Finally, I model several biases and investigate which are most costly for individual firms and for the aggregate economy.

Related Literature

My paper is part of a new wave of empirical studies of 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) reviews this literature and points the promise of using subjective probability assessments 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. Additionally, I provide new evidence that managers are biased with regards to their own firm’s future performance, which should have 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.

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 consists of integrating empirical evidence on beliefs, decisions, and endogenous outcomes with a heterogeneous-agent general equilibrium framework. This approach contrasts with earlier contributions that make descriptive comparisons of managers who appear more biased versus more rational and show empirically that the two groups behave differently, including seminal contributions by Malmendier and Tate (2005) who identify biased managers based on stock option exercise behavior, and Ben-David et al. (2013),

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5 See, for example Bachmann and Elstner (2015) and Ma, Sraer, and Thesmar (2018).
6 Evidence of this sort of phenomena among the broader population goes back at least to Tversky and Kahneman (1974).
7 For household expectations, see for example Dominitz and Manski (1997) and Dominitz (1998). For business expectations see 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 .
8 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. (2018a) 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.
who show using survey data that CFOs are overconfident about future S&P 500 returns. There
are also several papers that build models with managerial biases to study how biases might impact
manager and firm behavior theoretically, but lack data on managerial beliefs to quantify the implications.\textsuperscript{9} In closely related work, Alti and Tetlock (2014) take a different approach, using asset-pricing
anomalies rather than survey evidence on beliefs to structurally estimate the extent of overextrap-
olation and overconfidence among managers and investors, arguing that rational-expectations models
cannot explain certain asset pricing patterns. A separate literature in finance has documented that
investors and mutual fund managers are also biased and studied how that affects their decisions.\textsuperscript{10}

A handful of existing papers that do integrate empirical evidence on beliefs with behavioral
models of firm behavior find small real costs of biased beliefs, especially at the macro level. For
example Bachmann and Elstner (2015) study optimism and pessimism among German manufact-
urers, and a Ma, Sraer, and Thesmar (2018) use publicly-traded firms’ sales guidance as a proxy
for managerial beliefs. Relative to both these 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. I also go
beyond this earlier work by testing for and modeling several biases simultaneously, also assessing
which biases appear to be more costly.

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.\textsuperscript{11} 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).

More broadly, I contribute to a long literature in corporate finance focusing on the impact of
business executives on their organizations, especially when there are agency frictions or biases in
beliefs and a literature on managerial style.\textsuperscript{12} 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.\textsuperscript{13} Finally, my paper follows the long

\textsuperscript{9}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.
overconfidence affects CEO compensation and portfolio choice, both form a theoretical standpoint.
\textsuperscript{10}See, for example, Odean (1998), Barber and Odean (1999) Puetz and Ruenzi (2011), and Bailey et al. (2011).
\textsuperscript{11}More recent papers have attempted to uncover specific distortions that impact aggregate outcomes, for example
\textsuperscript{12}See Stein (2003) for a comprehensive survey, Bertrand and Schoar (2003) for a study on the impact of CEOs on
theoretically why biased individuals may end up in managerial positions. My paper also relates to the literature on
CEOs’ personalities and style, including Kaplan et al. (2012) and Kaplan and Sorensen (2017), which show that 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.
\textsuperscript{13}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
tradition of modeling firm behavior and managerial decision-making within a dynamic framework subject to adjustment costs and other frictions.\textsuperscript{14}

The rest of the paper is structured as follows: Section 2 introduces the Atlanta Fed/Chicago-Booth/Stanford 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.

2 Managerial Beliefs in the Survey of Business Uncertainty

In this section I use data from the Atlanta Fed/Chicago-Booth/Stanford Survey of Business Uncertainty to document three facts about managerial 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 underestimate risk and 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 managerial beliefs may be biased in other ways, first and second moments seem a reasonable place to start. Additionally, I validate that responses in the SBU data do appear to reflect managerial beliefs and decisions.

My analysis throughout this section exploits the fact that the SBU is a panel that tracks firm performance across time and allows me to compare realized performance against managers’ ex-ante beliefs. 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.

\textsuperscript{14} 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).
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, company directors, 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 observe in the SBU data, regardless of why those biases may arise.

2.1 The Survey of Business Uncertainty

My data on managerial beliefs comes from the Atlanta Fed/Chicago-Booth/Stanford Survey of Business Uncertainty (SBU), fielded by the Federal Reserve Bank of Atlanta.\textsuperscript{15} The SBU surveys high-level firm managers of US firms 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. The survey then asks these managers to provide subjective probability distributions about their own firms’ real outcomes, looking ahead over the next year. Interested readers should refer to Altig et al. (2018) for more details about the survey’s development and methodology.

The SBU’s sampling frame comes from Dunn & Bradstreet and includes firms from the entire private business sector of the US and from all regions of the country. The survey over-samples larger and older firms, as well as firms in cyclical, highly capital-intensive sectors (esp. durables manufacturing). This sampling arises partly because small young firms are relatively scarce in the Dunn & Bradstreet sampling frame, partly due to deliberate over-sampling of larger enterprises that also carry more weight in the macro-economy, and partly due to higher response rates among larger firms. The ultimate sample is broadly representative of the US business sector in employment-weighted terms. In Appendix A.1, I reproduce figures from Altig et al. (2018) showing the share of employment by firm size, sector, and region in the SBU in comparison to the overall US economy based on Census data.

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 managerial beliefs and behavior, including Ben-David et al. (2013), Malmendier and Tate (2005), and Ma, Sraer, and Thesmar (2018). Specifically, the mean and median employment of SBU respondents as of June 2018 is 152 and 632. In Appendix A I report other summary statistics pertaining to SBU respondents and specifically pertaining to the sample of observations with forecast errors that are my focus in this section of the paper.

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 (= fraction of all emails sent that result 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

\textsuperscript{15}This paper and Altig et al. (2018) are the first ever to analyze the SBU data.
sample sizes across months. For my purposes, it is convenient that macroeconomic volatility has been low by historic standards during the sample period. Thus I interpret variation in managerial beliefs and firm performance as stemming primarily from firm-specific conditions. Low aggregate volatility during my sample also lends credence to my empirical analysis, since large aggregate shocks could generate the appearance of systematic discrepancies between beliefs and outcomes even if the underlying beliefs were truly rational.

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. 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.

The survey is also well-suited for studying managerial beliefs because elicits subjective probability distributions from 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. The survey also asks a similar set of questions about the firm’s level of employment twelve months into the future, shown in Appendix Figure A.11.

I exploit the fact that the SBU elicits five-point subjective probability distributions by constructing moments of these subjective distribution. I measure each manager’s forecast as the mean of the distribution, namely by taking the inner product of the vector of potential outcomes and the vector of probabilities. I similarly construct measures of subjective uncertainty by computing the mean absolute deviation and standard deviation of managers’ subjective distributions. See Appendix A.2 for the full formulas. 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

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16For 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.

17For 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).
subjective probability distribution.\textsuperscript{18}

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. By tracking the history of these current conditions, I can ex-post compare managers’ beliefs against actual performance and thus infer how accurate or how biased those beliefs appear to be. 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.

2.2 Validating the SBU Data

As with all survey data, the quality of respondents’ answers is crucial to the credibility of the empirical results. First, I validate that managerial beliefs expressed in the SBU are reasonable probability distributions. In nearly all cases the outcome scenarios are monotonic (the lowest bin’s value is less than the low bin, which is less than the middle bin, 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 that lacked that restriction over 90 percent of responses to questions about sales growth include probabilities that add up to 100 percent.

Second, I validate that beliefs expressed in the SBU predict outcomes and decisions. Figure 3 shows, first, that managerial sales growth forecasts looking ahead over the next four quarters are highly predictive of actual sales growth. Similarly, I show that sales growth forecasts predict managers’ hiring plans (i.e. their forecast for the firm’s employment growth looking a year ahead), and finally that those plans in turn predict actual employment growth.

I further show in Table 1 that managerial forecasts for sales and employment growth have strong predictive power over and above the firm’s current sales growth, current hiring, current capital expenditures, and current employment, as well industry, region, and firm age fixed effects. In columns (1) and (4) I regress actual sales and employment growth in the four quarters following a survey on all of these potential explanatory variables, which comprise almost anything that would be ordinarily available to a forecaster. In columns (2) and (5) I additionally include the manager’s forecast and we can see that the resulting coefficients are positive, significant and statistically indistinct from one. The R-squared additionally jumps by some 7 percentage points in both cases. Finally, in columns (3) and (6) I show that the forecast’s predictive power does not hinge on the inclusion of the other controls, remaining positive and significant and with non-trivial R-squareds of about 0.15 in both columns.

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

\textsuperscript{18}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.
sales growth. These dynamics suggest managerial beliefs are one of several inputs into 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.

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

I find no evidence of systematic optimism or pessimism among managers in the SBU. Table 2 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. So we cannot reject the null hypothesis that managerial forecasts are on average equal to the sales growth that actually arises over the following year. This finding does not mean that managers systematically predict their future performance accurately (they may make big mistakes), only that forecasts do not systematically exceed or understate ex-post performance.

The lack of systematic optimism or pessimism is a robust feature of managerial beliefs, which we can see by looking at the mean forecast error across time, sectors, and firms of different sizes. In Figure 4a 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 sometimes statistically distinguishable from zero, and a test of the null that all forecast errors are zero rejects with 1 percent confidence.19 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.

Looking at the mean forecast error in each sector in Figure 4b 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

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19For 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.
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 4c 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 relative contribution 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. Ma, Sraer, and Thesmar (2018) similarly find no optimism or pessimism in public US firm’s official sales guidance. New techniques developed by D’Haultfoeuille et al. (2018) may help us understand whether these null results arise from averaging the forecasts of differentially optimistic or pessimistic managers that are similar in number.

2.4 Fact 2: Managers are Overconfident

Managers responding to the SBU are overconfident or overprecise; namely they underestimate the risks their firms face and overestimate the accuracy of their forecasts. Figure 5 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 according to managers’ 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 rational beliefs, the empirical and subjective distributions of forecast errors should be the same. What we can see in Figure 5 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 5 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 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
Table 3 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 6a, 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 6b, 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 somewhat more overconfident and the largest firms appear somewhat less overconfident than the rest. We can see this in Figure 6c 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 middle eight 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, or overall volatility. Smaller firms that are likely to be less productive and less well-managed as well as more volatile 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.
2.4.1 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. A key challenge to testing whether large excess errors are driven by 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.\(^{20}\)

I proceed to test 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). 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.

2.4.2 Is overconfidence a consequence of the SBU’s discrete, five-point distributions?

I argue that expressing managerial 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. Indeed, the dynamic programming literature has used discrete probability mass functions to approximate Gaussian autoregressive processes on a discrete grid since at least Tauchen (1986), with five grid points viewed as adequate for many applications.\(^ {21}\)

In Appendix A.7 I demonstrate that using reasonable truncation and discretization procedures to approximate the continuous distribution of sales growth outcomes on a five-point grid does not inherently generate large excess absolute forecast errors as I observe empirically. Using two distinct discretization methods, even if I truncate the distribution so as to disregard the most extreme 40 percent of the mass of potential outcomes and then distribute the remaining mass on five points I

\(^{20}\)In the medium run, I plan to match up the SBU data into the US Bureau of Census’ business register and thus obtain third-party measures of sales and employment from the Longitudinal Business Database.

\(^{21}\)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 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.
generate excess absolute forecast errors that are about half as large as I measure in the SBU. These exercises suggest that managers place the five scenarios of their subjective distribution too close together, resulting in an overly-narrow subjective distributions.

2.5 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 from current conditions. Specifically, managers’ ex-ante forecasts tend to overstate ex-post realizations when those forecasts are made during high-performing quarters, and vice versa. Figure 7 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 managerial forecast errors are highly predictable based on their firm’s 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. (2018a) 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 7 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 overestimates how much of that shock will persist between $t$ and $t+4$. The pattern in Figure 7 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 4 I show that correlated shocks across all firms, across firms in the same 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 7, namely a cross-sectional regression of managerial forecast errors for sales growth between quarters $t$ and $t+4$ against their firm’s 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 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 4 also suggests that the relationship in the raw data is truly driven by idiosyncratic, firm-level variation in performance. 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 8 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 levels. These estimates are noisy since each sub-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.

### 2.5.1 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. (2018a), Coibion and Gorodnichenko (2015), or Ma, Sraer, and Thesmar (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 $t + 8$. In Appendix A.8, I show that forecast errors for sales growth between $t$ 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. 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. In the Appendix I also show evidence of managerial overextrapolation in employment growth forecasts, corroborating my findings.
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 beliefs about their firm’s future idiosyncratic profitability. Specifically, managers may misperceive the unconditional mean, persistence, or volatility of shocks to profitability and may thus make sub-optimal hiring and firing decisions. Since aggregate outcomes depend on the sum of all managers’ decisions, widespread beliefs biases also affect 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. Later, in Section 4, I discuss 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 rational.

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:

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

I refer to this stochastic process as the state of "business conditions" capturing changes in the state of either demand or supply. 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 manager who makes hiring and firing decisions on a quarterly basis. After observing her firm’s current idiosyncratic shock $z_t$, each manager decides how many workers
to hire or lay off to obtain labor $n_{t+1}$ the following quarter:

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

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:

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

Each firm in the model obtains cash flow $\pi(z_t, n_t, n_{t+1}; w_t)$ in quarter $t$, equal to its 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.\textsuperscript{22} 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’ beliefs about business conditions next quarter. With adjustment costs, managerial 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 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,\textsuperscript{22}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.
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

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

$$\log(z_{t+1}) = \tilde{\mu} + \tilde{\rho} \log(z_t) + \tilde{\sigma} \epsilon_{t+1}, \quad \epsilon_{t+1} \sim N(0, 1)$$

The parameters $\tilde{\mu}$, $\tilde{\rho}$, and $\tilde{\sigma}$ distort managers’ sense of optimism, persistence, and uncertainty about future business conditions relative to the objective process in Equation 1. If $\tilde{\mu} > \mu$, managers overestimate $\log(z_{t+1})$ on average; that is they are over-optimistic. If $\tilde{\rho} > \rho > 0$ they overestimate the persistence of current conditions $\log(z_t)$, leading them to overextrapolate. If $\tilde{\sigma} < \sigma$, managers are overconfident or too sure about the future because they underestimate how risky innovations to $\log(z_t)$ really are.

This explicit specification 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. An alternative specification for managerial beliefs could consider a more parsimonious distortion of the subjective distribution, for example based on diagnostic expectations as developed in Bordalo et al. (2017), Bordalo et al. (2018b), and Bordalo et al. (2018a).

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. 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 many workers to hire or fire to obtain labor $n_{t+1}$ the following quarter, incurring adjustment costs.

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23 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 space, 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 $\theta$. 

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$AC(n_t, n_{t+1})$ according to equation 2. Adjusting the firm’s labor entails a trade off between reducing in 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 $(1 + r_{t+1})$:

$$\hat{V}(z_t, n_t; w_t, r_{t+1}) = \max_{k_{t+1}>0} \left[ \pi(z_t, n_t, n_{t+1}; w_t) + \frac{1}{1+r_{t+1}} \hat{E}_t[\hat{V}(z_{t+1}, n_{t+1}; w_{t+1}, r_{t+2})] \right]$$

(4)

Here the operator $\hat{E}_t[\cdot]$ 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, $\hat{V}(z_t, n_t; \cdot)$ denotes the manager’s subjective value of the business.

3.3.1 Managerial control of firms

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. These assumptions capture the first order features of how managers make decisions, whether as primary owners of smaller businesses or based on incentive contracts set up by shareholders of larger firms. Implicit in these assumptions is the notion that the manager has some ability or information that an outside shareholder does not and so cannot come in an replace the biased manager. In Appendix D I explore how my parameter estimates differ across subsamples of firms in which managers are plausibly subject to more or less oversight from directors or shareholders, and subsamples in which managers appear to be either less well behaved or more biased.

I also take as given my finding from the data that managers are biased and abstract from why biased individuals end up as managers. As I discuss in Appendix A.10, it is not obvious that firms can easily determine whether an individual manager is biased given that individual realizations of firm performance could be inconsistent with ex-ante beliefs even if those beliefs are correct. So boards may stick with biased managers for years without knowing for certain whether they are biased, or by how much, which I capture here by assuming managers are biased. Also, there are certainly models in which biased individuals are endogenously selected for managerial roles if, say, managerial ability is not observable and so boards and shareholders promote individuals who have the best past performance. In such a setup, overconfident individuals could be disproportionately selected for managerial roles, for example, as in Goel and Thakor (2008).

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:

$$V(z_t, n_t; w_t, r_{t+1}) = \left[ \pi(z_t, n_t, \kappa(z_t, n_t; w_t, r_{t+1}); w_t) + \frac{1}{1+r_{t+1}} \mathbb{E}_t[V(z_{t+1}, \kappa(z_{t+1}, n_t; w_{t+1}, r_{t+1}); w_{t+1}, r_{t+1+2})] \right]$$  (5)

Equation 5 uses the objective expectations operator $\mathbb{E}_t[\cdot]$ 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.24

3.5 Household

There is an infinitely-lived representative household who consumes the output of the firms in the model and supplies their labor. The household owns a "mutual fund" that holds the remaining share $1 - \theta \in [0, 1)$ of the equity of 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

$$\Pi_t = (1-\theta) \int_{Z,N} \pi(z_t, n_t, \kappa(z_t, n_t); w_t) \phi_t(z,n)dzdn$$  (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

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

24I 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.
subject to its budget constraint

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

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

\[ \frac{1}{(1 + r_t)} = \beta \left( \frac{C_{t+1}}{C_t} \right)^{-\gamma} \]

\[ w_t = \chi C_t^\gamma N^\eta \]  

(7)  

(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 in which all firms are now run by rational managers. Changing all firms’ dynamic hiring policies collectively changes the economy’s aggregate labor demand and thus the market-clearing wage that is consistent with the household’s labor supply tradeoff.

### 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 \( z_{t+1} \) under the objective driving process from equation 1. Once again let \( n_{t+1} = k(z_t, n_t; w_t, r_{t+1}) \) 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 \( \phi : \mathcal{Z} \times \mathcal{N} \rightarrow [0, 1] \) such that:

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

2. The household optimally chooses steady-state consumption \( C\), labor supply \( N^S\), and savings \( B\) to satisfy its optimality conditions in 7 and 8 and its budget constraint.

3. The distribution of firms \( \phi(z, n) \) is invariant across quarters and consistent with managers’ hiring decisions and exogenous fluctuations in business conditions, namely:

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

\[ \phi(z', n') = \int_{\mathcal{Z} \times \mathcal{N}} \phi(z, n) \cdot Pr(z'|z) \cdot 1(n' = \kappa(z, n; w, r))dzdn \]
4. The labor and risk-free bond markets clear:

\[ N^S = \int_{\mathbb{Z},N} n \cdot \phi(z,n) dz dn \]
\[ B = 0 \quad \text{in zero net supply by assumption} \]

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 \( \{w_t, r_{t+1}\}_{t=0}^{\infty} \), a time varying distribution of firms \( \phi_t(z,n; w_t, r_{t+1}) \), and managers' and household's optimality conditions as well as market clearing hold period-by-period, 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 quantitatively 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 overconfident and extrapolate 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

To quantify the implications of biased beliefs for the value of individual firms and for the macroeconomy I estimate 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.

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):

\( ^{25} \)Formally, this requires the subjective conditional variance \( \hat{\sigma} \) to be strictly greater than zero, although it could be arbitrarily small.
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 using 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 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 my estimates of model-implied moments.

3. Using the stationary distribution $\phi(\cdot; w)$ I compute the household’s implied consumption $C = wN^D + \Pi$, where $N^D = \int_{Z \times N} n \cdot \phi(z, n; w)dzdn$ is aggregate labor demand and $\Pi$ 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 $\varepsilon$, 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 a number of my model’s parameters to standard values from the literature, shown in Table 5. Many of these parameters are part of the household’s problem and so do not affect managerial behavior or firm-level output dynamics in the economy’s stationary general equilibrium. The main exception is the household’s discount factor $\beta$, which maps directly to the risk-free rate that enters managers’ problem in 4. I pick $\beta$ 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 $\theta$ 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. The value of $\theta$ drops out of the manager’s optimization problem in equation 4, so it does not affect my parameter estimates. However, it does affect outcomes in my general equilibrium counterfactuals because it affects the household’s capital income and thus labor supply decisions. On the firm side of the economy, I also normalize the objective mean of the driving process $\mu$ to zero, and set the exogenous separation rate for labor $q$ to 30 percent annually, following Shimer (2005).
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 $\rho$ and $\sigma$, 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, $\alpha$, and the magnitude of labor adjustment costs, $\lambda$.

I undertake the estimation using GMM, namely by matching moments from my model’s stationary distribution to corresponding data moments I obtain from the SBU. This procedure finds the vector of parameters $\theta = (\alpha, \lambda, \rho, \tilde{\rho}, \sigma, \tilde{\sigma}, \tilde{\mu})$ 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 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:

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

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 $\theta$, 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 $\sigma$ and $\rho$ as well as $\alpha$ and $\lambda$.

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 $t$;

26Recall that I set $\mu = 0$ without loss of generality.
• 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 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 $\sigma$, while the variance of hiring and its covariance with sales growth are jointly informative of the revenue-elasticity of labor $\alpha$ and the magnitude of adjustment costs $\lambda$. 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 $\rho$. 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 $\lambda$ and $\alpha$.

This intuitive description of how moments map to parameters is based on comparative static exercises in which I simulate the model for different sets of parameters and see what moments change with what parameters. That said, it is well-known in the structural estimation literature that nearly all parameters – particularly fundamental ones like the extent of decreasing returns $\alpha$ – 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 6 shows the results from my structural estimation exercise.

Sub-table 6a displays the value of the eight targeted moments in the data and the model, showing my estimated model accounts 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 6b shows my parameter estimates and their standard errors. My estimate of the revenue-elasticity of capital, $\alpha$ 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 $\lambda$
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 $\lambda$ 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, $\rho$, 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 overex-
trapolate 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 $\sigma$ 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 $\sigma$ (equal to 0.212). Managers also believe the autocorrelation of $\log(z)$, $\tilde{\rho}$, is 0.91,
significantly higher than the true autocorrelation $\rho$ 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

I quantify the implications of managerial beliefs biases for the value of individual firms and for the
aggregate economy by conducting two different types of counterfactual exercises:

1. I ask how much firm value would increase for the typical firm in my estimated economy if
   it hired an unbiased manager in quarter $t$, holding all else constant. In particular, I fix the
   firm’s initial business conditions $z_t$ and labor force $n_t$, as well as general equilibrium prices
   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 rational managers and compare
   aggregate outcomes between this efficient, unbiased economy and my estimated economy with
   biased managers.
5.1 Managerial Beliefs and Firm Value

Table 7 shows the potential 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 of the parameters of the persistent shock process in equation 1, holding all else equal.

To compute each line in Table 7 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 \(V^c(z,n;wr)\). I first obtain the biased and unbiased managers’ policy functions \(\kappa(\cdot)\) and \(\kappa^c(\cdot)\) and then compute \(V(\cdot)\) and \(V^c(\cdot)\) to satisfy 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 7.

The bottom line of Table 7 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 7 show how much firm value would increase by replacing the typical manager with another who either appreciates the true risk in innovations to fundamentals \(\tilde{\sigma} = \sigma\) or appreciates the true degree of mean reversion in fundamentals \(\tilde{\rho} = \rho\). Firm value would increase substantially in the latter case, by 1.3 percent, while there is a smaller increase in firm value of 0.4 percent from removing overconfidence and keeping overextrapolation.\(^{27}\) 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

\(^{27}\)Since \(z\) is a lognormal process, removing overconfidence on its own \((\tilde{\sigma} = \sigma)\) also has effects on managerial optimism via a Jensen’s inequality term. Specifically, removing overconfidence makes managers more optimistic, which may actually hurt firm value. My baseline results control for this effect by using \(\tilde{\mu} - \frac{1}{2}(\sigma^2 - \tilde{\sigma}^2)\) as the overall mean of the subjective process in the no overconfidence \((\tilde{\sigma} = \sigma)\) counterfactual. Not performing this correction makes the change in firm value from removing overconfidence close to zero because the positive effect of removing overconfidence roughly cancels against the added optimism form the Jensen’s effect.
in the next section when I consider the impact of biased beliefs on the aggregate economy, but 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 in Section 4.2 and Sub-table 6b. 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 estimates in prior literature of managerial misbehavior or entrenchment. 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 7 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 Biased Beliefs

Table 8 shows my headline results on the impact of biases in managerial beliefs. 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. Each of the counterfactual economies is at its long-run steady state and in equilibrium. 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. For comparison, 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 than 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 overreact to shocks. This behavior is evident in Figure 9, 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 an innovation to firm-level profitability $\log(z_t)$, they overestimate how persistent it is, which leads them to overestimate how many workers they should hire or lay off. They are also overconfident and thus too certain about the firm’s future marginal product of labor, so they are also more willing to pay the costs associated with adjusting the firm’s labor force.

Overconfidence and overextrapolation are costly for the aggregate economy because pervasive overreaction to shocks results in excess, costly reallocation in the economy with biased managers. Indeed, Table 9 shows that the rate of reallocation (= the sum of all hiring and firing as a fraction of aggregate labor) in the biased economy 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. This drop in reallocation means firms in the unbiased economy are on average farther from their optimal scale. Dispersion in the marginal product of labor is thus higher by about 6.6% in the unbiased economy.

Based on the drop in reallocation and higher dispersion in the marginal product of labor, it would appear that biased managers are better at allocating scarce labor across firms and should therefore generate higher welfare. This is not the case reallocation is costly and biased managers overestimate
its marginal benefit relative to its costs. Rational managers efficiently choose a slower pace of reallocation and thus increase welfare. We can see this in Table 9 by comparing the share of GDP spent on reallocation in each economy. 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.

In Table 10 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 relative to the baseline economy with biased managers. For ease of comparison, the bottom line replicates the results from Table 8 for the economy with fully rational managers. We can see that eliminating either overconfidence or overextrapolation (or both) improves consumer welfare and results in less reallocation, higher dispersion in the marginal product of labor, and fewer resources spent on adjustment costs. As with the micro impact of biases in Table 7, 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 10 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 10, 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 sizable given the modest accompanying reduction in reallocation and and spending on adjustment costs. This apparent contradiction shows that behind the results from Table 10 there are general equilibrium effects that matter quantitatively. This analysis highlight one my contributions in this paper, namely quantifying the cost of biases taking those general equilibrium effects into account. While a few recent papers have started to consider the impact of these effects, specifically Ma, Sraer, and Thesmar (2018), this feature of my paper and theirs contrasts with earlier regression-based work as in Malmendier and Tate (2005) and Ben-David et al. (2013). In Appendix C.5 I explore in more
detail how general equilibrium effects quantitatively relate to welfare and other aggregate outcomes across counterfactual economies.

My headline result that managerial overconfidence and overextrapolation are costly because they encourage excessive hiring and firing begs the question: what can policy-makers possibly do to mitigate the costs of managerial biases? In Figure 10 I use my model to show that taxing business spending on adjustment costs and rebating the proceeds to consumers can help discourage some of the excess spending on adjustment costs and improve consumer welfare. Specifically, I modify firm’s cash flow function and the representative household’s budget constraint, respectively:

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

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

subject to the constraint that the government’s budget balances (taking managers’ policy \( \kappa(\cdot) \) as given:

\[
T_t = \tau_f \int_{Z \times N} \phi(z, n) AC(n, \kappa(z, n; w_t, r_{t+1})) dz dn.
\]

Then, I solve for the model’s stationary equilibrium for a range of taxes (or subsidies) on hiring and firing \( \tau_f \in [-0.1, 0.6] \) and compare consumer welfare in the equilibrium with the tax (or subsidy) versus my baseline estimated model. Figure 10 plots the results from this exercise.

Taxing firm-level adjustment costs, namely their expenditures on hiring and firing, increases the marginal cost of adjustments, which encourages managers to react to profitability shocks less aggressively. The resulting slower pace of reallocation increases consumer welfare. Subsidizing hiring and firing, by contrast, exacerbates the costs of managerial biases, as seen by the loss in consumer welfare under negative \( \tau_f \) taxes. Too a high tax can also discourage reallocation too much and result in lower welfare. These results stand in contrast with canonical analyses of regulatory impediments to resource reallocation that argue such policies are detrimental to welfare.\(^{28}\) In my setting, the presence of overconfident and overextrapolative managers breaks the standard result, making moderate, tax-based frictions to reallocation welfare-improving.

I take two broad lessons from this exercise. First, even if we cannot change the nature of managerial beliefs, there may exist public policies that can mitigate the costs of their mistakes. Second, the effects of public policies can depend on managerial beliefs. In Appendix C.6 I expand on the latter point by explicitly considering the interaction of managerial overconfidence and overextrapolation with distortionary payroll and labor income taxes. I show that the welfare cost of taxation is higher with biased managers, and similarly that the cost of managerial biases can also be higher when there are distortionary labor income and payroll taxes.

\(^{28}\)For example see the arguments by Decker et al. (2018) on the potential role of reallocation frictions for US productivity growth slowdown.
6 Robustness

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, 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 mistakes stemming from 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.

6.1 Alternative parameterizations and specifications

Table 11 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 11a and 11b respectively replicate the baseline results from Tables 7 and 10 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 three potentially important features of the model’s parameterization: (1) the magnitude of adjustment costs, (2) the durability of labor, and (3) the extent of decreasing returns to scale. To start, I consider the effect of tripling or cutting my adjustment cost parameter $\lambda$ to one third, corresponding to the columns labels "High" and "Low" adjustment costs in Tables 11a and 11b. Intuitively, the presence and magnitude of adjustment costs is a 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 $\lambda$.

Looking at Table 11a, 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. With high adjustment costs, the impact of biases on firm value is actually even smaller because in this case hiring and firing frictions are so large that both the biased and unbiased (or less biased) managers react more weakly 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.

Looking instead at Table 11b, the impact of biases on aggregate welfare under high versus low adjustment costs 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 adjust-
ment costs. 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
11a and 11b is one where the exogenous worker separation rate $q$ is lower at $q = 0.026$ (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. 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 11a confirm this intuition, with modestly larger changes in firm value
from replacing biased managers with others who lack one or more biases than the baseline. Having
said that, in Table 11b I find the change in welfare from eliminating biases to be of a similar order
of magnitude as in the baseline case.

The incentive to reach a target firm size, conditional on beliefs and adjustment costs, depends
crucially on the extent of decreasing returns to scale parameter, $\alpha$. I estimate $\alpha = 0.61$, which
is reasonable if think this reflects decreasing returns to labor on its own, with the firm effectively
having a fixed capital stock quarter to quarter. However, my estimated value of $\alpha$ seems low if we
interpret it as the total extent of decreasing returns to revenue, considering all factors of production,
for which typical estimates range from about 0.75 to 0.9. I thus consider how my quantitative results
change if I increase the extent of decreasing returns to 0.8, finding larger costs of biases at both the
micro and macro levels. I believe the intuition for this result is that less strongly decreasing returns
provide added motives to overreact to shocks, while also having the wrong amount of labor becomes
more consequential. In the end, my seemingly low estimate of $\alpha$ turns out to be conservative.

In Table 11b I also explore how the share of equity held by managers $\theta$, 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 $\theta$ drops out of their optimization problem in equation 4 and does
not directly affect their hiring and firing decisions. The value of $\theta$ does matter for my macro
counterfactuals because it changes the share of total profits $\Pi_t$ that the representative household
receives as capital income, and thus affects the household’s labor supply decision and the general
equilibrium wage. Since $\theta$ 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

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29 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)).

30 See Hsieh and Klenow (2009) for a similar discussion, whereby increasing substitutability of firms output within
sectors – equivalent to increasing the returns to scale – leads to larger gains from eliminating misallocation in India
and China.
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 11b consider how the welfare impact of beliefs biases changes if I triple or cut by one third the share of equity held by managers. The welfare impact is modestly larger for $\theta = 0.15$ and lower for $\theta = 0.017$, 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,\textsuperscript{31} though the 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.7 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 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.7.2 for details on this estimation. I find somewhat larger changes in firm value – up to 3 percent relative to 1.9 percent in my baseline – from replacing biased managers in Table 11a. This result is in accordance with the intuition that capital choice is more consequential. By contrast, I find the change in consumer welfare to be smaller than in the baseline labor model, looking at the final column of Table 11b and even negative for the counterfactual that eliminates overextrapolation on its own. Upon closer examination, this seems to be a result of general equilibrium effects. Wages typically drop in the capital-based model while they rise in the labor-based model, so while the economy becomes more efficient consumers reap a smaller share of those gains because declining wages tend to hurt them. Adding the increase in consumption by the capitalist managerial class to the numbers in this last column shows there are about as large welfare gains – considering both consumers and managers – when we eliminate biases.\textsuperscript{32}

\textsuperscript{31}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.

\textsuperscript{32}Considering the welfare of both consumers and managers, I find eliminating biases results in a consumption-equivalent welfare increase of about 0.8 percent in both the capital and labor-based specifications.
6.2 Heterogeneity across subsamples

One important question that I do not address in my main analysis concerns how my model estimates and quantitative results might vary across subsamples of firms in which managers are subject to more versus less oversight, managers are more badly behaved, or plausibly more biased. In Appendix DI re-estimate my model splitting my SBU sample by median employment, with smaller firms being more plausibly owner operated and thus subject to less managerial oversight by directors and outside investors. I also re-estimate my investment-based model on subsamples of Compustat firms with weak versus strong governance according to Bebchuk et al. (2008), with recent M&A activity versus no acquisitions as a proxy for empire-building preferences, and with managers who appear more biased based on their stock option exercise behavior as identified in 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.\textsuperscript{33} I find, as expected, that managers who appear to be badly behaved and those at firms with less oversight 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 seem to face somewhat 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. However, managers are overconfident, overestimating their ability to make accurate forecasts and underestimating the amount of risk their firms are exposed to. They also appear to overextrapolate from current conditions, leading them to overestimate their firm’s future sales growth when the firm is growing and underestimate it when it is shrinking.

I quantify the micro and macroeconomic implications of overconfidence and overextrapolation by building a general equilibrium model in which managers may have biased beliefs and make dynamic hiring decisions subject to adjustment costs. Estimating the beliefs, frictions, and true shock process that are consistent with the empirical evidence about managerial beliefs and the joint dynamics of employment and output in firm-level data, I find that that managers underestimate the volatility of shocks to firm-level profitability by over 50 percent. They also believe the half-life of those shocks is close to 8 quarters, while the true half life is less than half as long.

Comparing outcomes in my estimated model against outcomes from a counterfactual economy in which managers have correct beliefs, I find that the value of the typical firm would be higher by about 1.9 percent if its manager were rational. Aggregate welfare in an economy with rational managers would additionally be 1 percent higher and GDP would be 1.6 percent higher, taking into account shifts in general equilibrium prices. My model reveals that biased managers destroy

\textsuperscript{33}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.
firm value and welfare because they believe firm-level profitability is persistent and stable, so they overreact shocks overspend on costly reallocation. Rational managers appreciate the true costs of hiring and firing workers, efficiently choosing a slower pace of reallocation.

This paper makes one of the first serious attempts to quantify the micro and macro implications of biases in firm managers’ beliefs. However, my analysis also points to several new questions. Most importantly, why do firms hire and seemingly retain managers who have biased beliefs? Are there quantitatively-plausible agency or information frictions that may explain why firms hire 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 developed in this paper may serve as useful starting points to consider these and other questions in corporate finance and macroeconomics.
References


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


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

Notes: This figure shows the share of SBU panel members whose job title falls into each of the following categories as of July 2018.
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: Sales and Employment Growth Forecasts Predict Outcomes

(a) Sales Growth Forecast Predict Sales Growth

(b) Sales Growth Forecasts Predict Hiring Plans
Notes: This figure shows bin-scatter plots of sales growth forecasts on the horizontal axis against (top) realized sales growth and (middle) forecast employment growth, and employment growth forecasts (bottom) actual employment growth. Sales growth forecasts are made in quarter $t$ and forecast sales growth are for the period between quarter $t$ and $t + 4$. Employment growth forecasts are made in month $m$ and forecast employment growth between $m$ and $m + 12$. All data are from the SBU with the sample period covering 10/2014 to 6/2018.
Figure 4: Optimism and Pessimism Across Time, Sector, and Firm Sizes

(a) Time

(b) Sectors
Notes: This figure shows (top) the mean forecast error for each month, (middle) the mean forecast error in each sector, and (bottom) the mean forecast error for each decile of firm-level sales. 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 $t+4$. $N = 1,574$. 

(c) Firm Sizes
Figure 5: Managers are Overconfident

Notes: This figure plots the empirical distribution of forecast errors as well as the distribution of forecast errors that would arise if sales growth realizations were drawn from SBU respondents' subjective probability distributions. I scale each distribution so that the sum of the heights of the bars is equal to one, and fix the width of the bars to 0.05. The sample period includes all months between 10/2014 to 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: Overconfidence Across Time, Sectors, and Firm Sizes

(a) Time

(b) Sectors
Notes: This figure shows the mean excess absolute forecast error (top) by month, (middle) by industry, and (bottom) by decile of firm-level sales. 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 7: 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 8: Managerial Overextrapolation 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.
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.
Figure 10: **Welfare Effects of a Tax on Hiring & Firing Expenditures**

**Notes:** This figure shows the change in welfare across the steady state in an economy with a tax on hiring/firing expenditures relative to the baseline estimated economy. In both cases managers are biased. The curve shown uses a third-order polynomial to smooth out kinks due to numerical approximation of equilibrium.
### Table 1: Managerial Forecasts have Predictive Power

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<tr>
<td></td>
<td>Realized Sales Growth, t to t+4</td>
<td>Actual Hiring, t to t+4</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Sales Growth Forecast, t to t+4</td>
<td>1.013***</td>
<td>0.662**</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forecast (Planned) Hiring, t to t+4</td>
<td>0.718***</td>
<td>0.715***</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Sales Growth, t-1 to t</td>
<td>-0.020</td>
<td>-0.037*</td>
<td>0.024</td>
<td>0.010</td>
<td></td>
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<tr>
<td>Net Hiring, t</td>
<td>-0.056</td>
<td>-0.042</td>
<td>-0.243**</td>
<td>-0.180</td>
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<td></td>
</tr>
<tr>
<td>log(Cap. Expenditures), t</td>
<td>0.008**</td>
<td>0.008**</td>
<td>0.013**</td>
<td>0.011**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(Employees), t</td>
<td>-0.021**</td>
<td>-0.021***</td>
<td>-0.017*</td>
<td>-0.017*</td>
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<td></td>
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<td>Industry FE (14)</td>
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<td>Y</td>
<td>Y</td>
<td>Y</td>
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<td>Region FE (9)</td>
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<td>Y</td>
<td>Y</td>
<td>Y</td>
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<td>Age FE (22)</td>
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<td>Y</td>
<td>Y</td>
<td>Y</td>
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<tr>
<td>Observations</td>
<td>517</td>
<td>517</td>
<td>1,313</td>
<td>609</td>
<td>609</td>
<td>1,604</td>
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<tr>
<td>R-squared</td>
<td>0.452</td>
<td>0.523</td>
<td>0.160</td>
<td>0.241</td>
<td>0.310</td>
<td>0.142</td>
</tr>
</tbody>
</table>

**Notes:** Columns (1) to (3) regress actual sales growth between quarters t and t+4 on information available in the quarter of the forecast. Columns (4) to (6) do the same for actual net hiring between t and t+4. I respectively include the respondent’s forecast for sales growth or net hiring to show it has significant predictive power and its inclusion increases the marginal R-squared. I weight regressions by measures of accuracy for realized sales growth and actual hiring. Standard errors in parentheses, clustered by firm. Data are from the SBU covering 10/2014 to 6/2018 collapsed to quarterly frequency. *** p<0.01, ** p<0.05, * p<0.1
Table 2: Managers and Neither Over-Optimistic Nor Pessimistic

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
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<tbody>
<tr>
<td></td>
<td>Sales Growth</td>
<td>Forecast Error</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Forecast</td>
<td>Realized</td>
</tr>
<tr>
<td>Mean</td>
<td>0.0379</td>
<td>0.0458</td>
<td>-0.0078</td>
</tr>
<tr>
<td>SE</td>
<td>(0.0039)</td>
<td>(0.0081)</td>
<td>(0.0078)</td>
</tr>
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<td>Obs.</td>
<td>1,574</td>
<td>1,574</td>
<td>1,574</td>
</tr>
<tr>
<td>Firms</td>
<td>397</td>
<td>397</td>
<td>397</td>
</tr>
</tbody>
</table>

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 3: Managers are Overconfident About Their Forecasts’ Accuracy

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
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<th>(3)</th>
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<tbody>
<tr>
<td></td>
<td>Absolute Forecast Error</td>
<td>Excess Error</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Empirical</td>
<td>Subjective</td>
<td>Empirical - Subjective</td>
</tr>
<tr>
<td>Mean</td>
<td>0.1845</td>
<td>0.039</td>
<td>0.146</td>
</tr>
<tr>
<td>SE</td>
<td>(0.007)</td>
<td>(0.002)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Obs.</td>
<td>1,574</td>
<td>1,574</td>
<td>1,574</td>
</tr>
<tr>
<td>Firms</td>
<td>397</td>
<td>397</td>
<td>397</td>
</tr>
</tbody>
</table>

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 4: Managers Overextrapolate: Forecast Errors versus Recent Performance

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

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 5: Externally-Calibrated Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
<th>Target/Source</th>
</tr>
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<tbody>
<tr>
<td>$q$</td>
<td>0.08</td>
<td>Quarterly separation rate</td>
<td>Shimer (2005)</td>
</tr>
<tr>
<td>$\mu$</td>
<td>0</td>
<td>Mean $\log(z)$</td>
<td>Normalization</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>2</td>
<td>Inverse EIS</td>
<td>Hall (2009)</td>
</tr>
<tr>
<td>$\eta$</td>
<td>2</td>
<td>Inverse Frisch elasticity of lab. supply</td>
<td>Chetty et al. (2011)</td>
</tr>
<tr>
<td>$\beta$</td>
<td>$0.96^{1/4}$</td>
<td>Household discount factor</td>
<td>Annual Interest Rate of 4%</td>
</tr>
<tr>
<td>$\chi$</td>
<td>29.7</td>
<td>Disutility of work</td>
<td>Steady-state labor $N^* = 1/3$</td>
</tr>
<tr>
<td>$\theta$</td>
<td>0.05</td>
<td>Managers' share of equity</td>
<td>Nikolov and Whited (2014)</td>
</tr>
</tbody>
</table>
Table 6: **Structural Estimation Results**

(a) **Data and Model Moments**

<table>
<thead>
<tr>
<th>Moment</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean(Forecast Error)</td>
<td>-0.013</td>
<td>-0.010</td>
</tr>
<tr>
<td>Mean(Excess Absolute Forecast Error)</td>
<td>0.143</td>
<td>0.129</td>
</tr>
<tr>
<td>Cov(Forecast Error_{t,t+4}, Sales Growth_{t-1,t})</td>
<td>0.011</td>
<td>0.008</td>
</tr>
<tr>
<td>Var(Sales Growth)</td>
<td>0.060</td>
<td>0.049</td>
</tr>
<tr>
<td>Var(Net Hiring)</td>
<td>0.019</td>
<td>0.001</td>
</tr>
<tr>
<td>Cov(Net Hiring, Sales Growth)</td>
<td>0.003</td>
<td>0.004</td>
</tr>
<tr>
<td>Cov(Sales Growth_{t,t+4}, Sales Growth_{t-1,t})</td>
<td>-0.012</td>
<td>-0.011</td>
</tr>
<tr>
<td>Cov(Sales Growth_{t,t+4}, Net Hiring_{t+1})</td>
<td>-0.002</td>
<td>-0.004</td>
</tr>
</tbody>
</table>

(b) **Estimated Parameters**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Explanation</th>
<th>Estimate (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>Revenue curvature</td>
<td>0.6132 (0.036)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Quadratic adjustment costs</td>
<td>27.3 (0.800)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>True shock persistence</td>
<td>0.801 (0.005)</td>
</tr>
<tr>
<td>$\tilde{\rho}$</td>
<td>Subjective Sshock persistence</td>
<td>0.913 (0.005)</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>True shock volatility</td>
<td>0.212 (0.0006)</td>
</tr>
<tr>
<td>$\tilde{\sigma}$</td>
<td>Subjective shock volatility</td>
<td>0.098 (0.0006)</td>
</tr>
<tr>
<td>$\tilde{\mu}$</td>
<td>Subjective shock mean</td>
<td>-0.003 (0.00003)</td>
</tr>
</tbody>
</table>

**Notes:** This table shows the results from my structural estimation of the model from Section 3. Sub-table 6a *(top)* shows my target moments in the data and the corresponding model moments 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 6b *(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 7: Eliminating Beliefs Biases Increases Firm Value

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>$\Delta$ True Firm Value (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{\sigma} = \sigma$ only</td>
<td>0.4</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho$ only</td>
<td>1.3</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho$, and $\tilde{\sigma} = \sigma$</td>
<td>1.9</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, and $\tilde{\mu} = \mu$</td>
<td>1.9</td>
</tr>
</tbody>
</table>

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

### Table 8: Aggregate Impact of Beliefs Biases

<table>
<thead>
<tr>
<th>$\Delta$ Consumer Welfare %</th>
<th>$\Delta Y$ %</th>
<th>$\Delta (Y/N)$ %</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.99</td>
<td>1.6</td>
<td>0.17</td>
</tr>
</tbody>
</table>

**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 9: Biases Encourage Excessive Reallocation

<table>
<thead>
<tr>
<th></th>
<th>Reallocation $\times 100$</th>
<th>$\sigma(\log(MPN))$</th>
<th>$AC/Y \times 100$</th>
</tr>
</thead>
<tbody>
<tr>
<td>With Biases</td>
<td>5.7</td>
<td>0.33</td>
<td>16.6</td>
</tr>
<tr>
<td>No Biases</td>
<td>1.1</td>
<td>0.35</td>
<td>14.4</td>
</tr>
<tr>
<td>Difference</td>
<td>-81.5%</td>
<td>6.6%</td>
<td>-13.1%</td>
</tr>
</tbody>
</table>

**Notes:** This table compares steady-state values of the rate of reallocation (= total hiring and firing $\Delta n_{t+1}$ 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 10: **Macro Impact of Individual Biases**

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>Δ C. Welfare %</th>
<th>Δ Realloc. %</th>
<th>Δ(\sigma(\log(MPN))) %</th>
<th>Δ(AC/Y) x 100</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\hat{\sigma} = \sigma) only</td>
<td>0.28</td>
<td>-11.4</td>
<td>0.8</td>
<td>-0.3</td>
</tr>
<tr>
<td>(\hat{\rho} = \rho) only</td>
<td>0.68</td>
<td>-89.1</td>
<td>7.7</td>
<td>-2.5</td>
</tr>
<tr>
<td>(\hat{\rho} = \rho) and (\hat{\sigma} = \sigma)</td>
<td>0.91</td>
<td>-79.6</td>
<td>6.4</td>
<td>-2.2</td>
</tr>
<tr>
<td>(\hat{\rho} = \rho), (\hat{\sigma} = \sigma), and (\hat{\mu} = \mu)</td>
<td>0.99</td>
<td>-81.5</td>
<td>6.6</td>
<td>-2.2</td>
</tr>
</tbody>
</table>

**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 (\(\hat{\sigma} = \sigma\)), overextrapolation (\(\hat{\rho} = \rho\)), or pessimism (\(\hat{\mu} = \mu\)) 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 11: Quantitative Results Robustness

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

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>Baseline</th>
<th>High Adj. Costs</th>
<th>Low Adj. Costs</th>
<th>Low q (separation rate)</th>
<th>High α</th>
<th>Investment Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{\sigma} = \sigma$ only</td>
<td>0.4</td>
<td>0.2</td>
<td>0.2</td>
<td>0.1</td>
<td>0.7</td>
<td>0.4</td>
</tr>
<tr>
<td>$\bar{\rho} = \rho$ only</td>
<td>1.3</td>
<td>0.6</td>
<td>1.0</td>
<td>1.5</td>
<td>3.2</td>
<td>2.8</td>
</tr>
<tr>
<td>$\bar{\rho} = \rho$ and $\bar{\sigma} = \sigma$</td>
<td>1.9</td>
<td>0.7</td>
<td>1.5</td>
<td>2.1</td>
<td>5.5</td>
<td>3.0</td>
</tr>
<tr>
<td>$\bar{\rho} = \rho$, $\bar{\sigma} = \sigma$, and $\bar{\mu} = \mu$</td>
<td>1.9</td>
<td>0.7</td>
<td>1.5</td>
<td>2.1</td>
<td>5.5</td>
<td>3.0</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>Baseline</th>
<th>High Adj. Costs</th>
<th>Low Adj. Costs</th>
<th>Low q (sep. rate)</th>
<th>High α (manager’s equity)</th>
<th>Low θ (manager’s equity)</th>
<th>Investment Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{\sigma} = \sigma$ only</td>
<td>0.28</td>
<td>0.26</td>
<td>0.14</td>
<td>0.29</td>
<td>0.32</td>
<td>0.50</td>
<td>0.21</td>
</tr>
<tr>
<td>$\bar{\rho} = \rho$ only</td>
<td>0.68</td>
<td>0.38</td>
<td>0.48</td>
<td>0.68</td>
<td>1.13</td>
<td>0.59</td>
<td>0.70</td>
</tr>
<tr>
<td>$\bar{\rho} = \rho$ and $\bar{\sigma} = \sigma$</td>
<td>0.91</td>
<td>1.03</td>
<td>0.64</td>
<td>0.87</td>
<td>1.50</td>
<td>1.13</td>
<td>0.85</td>
</tr>
<tr>
<td>$\bar{\rho} = \rho$, $\bar{\sigma} = \sigma$, and $\bar{\mu} = \mu$</td>
<td>0.99</td>
<td>1.41</td>
<td>0.66</td>
<td>0.90</td>
<td>1.58</td>
<td>1.27</td>
<td>0.90</td>
</tr>
</tbody>
</table>

**Notes:** Table 11a (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 correspond to different model specifications. Table 11b (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 $\lambda$, 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. The columns labeled "high $\alpha$" impose decreasing returns to scale on the order of $\alpha = 0.8$, higher than my baseline estimated value of $\alpha = 0.61$. Specifications with high and low manager’s equity share $\theta$ respectively triple and cut by a third the manager’s equity share from its baseline level of $\theta = 0.05$. (Note, $\theta$ does not affect the micro counterfactuals in Table 11a). 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.7 for details on its estimation.
Online Appendix: The Micro and Macro of Managerial Beliefs

A Data Appendix

A.1 Representativeness of the SBU

Figures A.7 to A.10 explore how representative SBU data are of the broader US Economy. Similar figures appear in Altig et al. (2018), each showing the share of employment accounted for by firms in different size categories, ages, sectors, or regions in the Survey of Business Uncertainty and the US Economy. To compute employment shares by size, sector, and region I use the US Census Bureau’s Statistics on US Businesses for 2015. For firm age I use the Census’ Business Dynamics statistics.

The SBU is more or less representative of the US in employment-weighted terms. In Figure A.7 we can see the share of employment accounted for by firms with more than 500 employees is somewhat higher for the SBU, as is the share of employment born prior to 1990 in Figure A.8. The survey’s industrial composition includes firms from all sectors, as we can see in Figure A.9, but relatively more firms in durables manufacturing and finance and insurance, and relatively fewer in the health care sector. Deviations in the share of employment for particular groups of firms versus the US economy stem partly from the survey’s Dunn & Bradstreet sampling frame, in which smaller and younger firms may be under-represented. It may also be that older and larger firms are more willing to respond to the survey.

A.2 Measuring Subjective Moments and Forecast Errors in the SBU

My analysis focuses on managers’ subjective beliefs about the growth rate of quarterly sales looking four quarters into the future as reported in the SBU. Managers and analysts pay significant attention to sales and earnings as indicators of firm-level performance, so focusing on sales growth as a performance outcome seems a reasonable choice. Anecdotally, managers also use sales figures and projections for planning, budgeting, and hiring. As I report in Appendix A.9, my three facts concerning managers’ beliefs about sales growth are also present in their beliefs about employment growth looking 12 months ahead, suggesting they are a robust feature managerial beliefs rather than a one-off finding.

The SBU is an unbalanced monthly panel, and an individual respondent receives the questionnaire that includes questions about sales every two months\textsuperscript{34}. Throughout my analysis of managers’ beliefs in Section 2 I preserve the survey’s structure as a monthly panel with gaps, but the results are similar if I collapse the panel to a quarterly frequency, picking the last response of the quarter. Indeed, for my structural estimation exercise in Section 4.2, I compute the target moments that come from the SBU using the last response of each calendar quarter for conformity with my quarterly model.

A.2.1 Measuring subjective moments

I focus on SBU respondents’ subjective beliefs for sales growth over the next four quarters. Responses from prior to September 2016 report subjective probability distributions over the dollar level of sales looking four quarters ahead. Thus, I first compute the rate of sales growth implied by the respondent’s reported sales level in quarter \( t \), \( s_t \), and each of the five potential quarterly sales levels \( s_{j,t+4} \) for \( j = 1, 2, 3, 4, 5 \).\textsuperscript{35} Following the convention in the literature on business dynamics, I measure these five potential growth rates as the difference across periods divided by the average:

\[
g_{j,t+4} = \frac{s_{j,t+4} - s_t}{\frac{1}{2}(s_{j,t+4} + s_t)}. \tag{9}
\]

\textsuperscript{34}Since the last major survey update in September 2016, respondents receive questionnaires about sales and employment in one month and then questionnaires about capital expenditures and unit costs the next month. Prior to September 2016, the SBU also asked questions about pricing and profit margins, so respondents received the same questionnaire approximately once every three months.

\textsuperscript{35}For simplicity of notation I do not use respondent-level subscripts throughout this section, but responses in the SBU belong to a respondent manager \( i \) in month \( m \) which belongs to quarter \( t \).
Survey responses from September 2016 and later report subjective distributions over sales growth rates directly. I assume a respondent’s estimate for her firm’s sales growth rate between quarters $t$ and $t+4$ under scenario $j = 1, 2, 3, 4, 5$, $x_{j,t+4}$, corresponds to a traditional growth rate, so that $x_{j,t+4} = (s_{j,t+4} - s_t)/s_t$. Here again, $s_t$ is the current sales level and $s_{j,t+4}$ is the potential sales level in quarter $t + 4$ under scenario $j = 1, 2, 3, 4, 5$. Therefore, I translate these raw data growth rates to conform with the formula in 9, measuring

$$g_{j,t+4} = \frac{2 * x_{j,t+4}}{2 + x_{j,t+4}}.$$

For each survey response, I now have a five-point subjective probability distribution over sales growth between quarters $t$ and $t+4$. These subjective distributions consist of a potential growth rate for each of 5 scenarios $\{g_{j,t+4}\}_{j=1}^5$ and their associated subjective probabilities, $\{p_{j,t+4}\}_{j=1}^5$. I then calculate a firm’s forecast for her firm’s sales growth between quarters $t$ and $t+4$, $g_{t+4}$ is:

$$\tilde{E}_t[g_{t+4}] = \tilde{E}_t[g_{t+4}|I_t] = \sum_{j=1}^5 p_{j,t+4}g_{j,t+4}.$$

Here $\tilde{E}_t[\cdot]$ is my notation for the respondent’s subjective expectation on date $t$ when she responded to the survey. I use $I_t$ to denote the managers’ information set at $t$, which includes other information reported in the survey — for example the firm’s current sales level $s_t$ — and other information about the firm’s current and future prospects that may be known to the manager but is unobservable to researchers. Throughout my analysis I assume managers’ subjective beliefs, and thus any moments based on those subjective distributions condition on $I_t$, as do any ex-post realized outcomes I observe.

I compute other moments of managers’ subjective distributions by analogously taking the inner product of subjective probabilities and some function of potential sales growth outcomes. For example a manager’s subjective mean absolute deviation from her forecast (on average how far she expects to be from her forecast) is:

$$\tilde{\text{MAD}}_t[g_{t+4}] = \tilde{E}_t[\|g_{t+4} - \tilde{E}_t[g_{t+4}]\|]$$

$$= \sum_{i=1}^5 \tilde{p}_{j,t+4} \|g_{j,t+4} - \sum_{k=1}^5 \tilde{p}_{k,t+4}g_{k,t+4}\|.$$

Parts of Section 2 use managers’ subjective mean absolute deviations as a measure of their expected forecast accuracy, or equivalently their ex-ante uncertainty.

A.2.2 Realized sales growth and forecast errors

I measure a respondent’s firm’s actual sales growth between quarters $t$ and $t+4$, $g_{t+4}$ based on the respondent’s reported sales level in quarter $t$ when she makes her forecast as well as four quarters later. Specifically, I exploit the fact that the $SBU$ is a panel, and measure this ex-post realized sales growth as

$$g_{t+4} = \frac{s_{R,t+4} - s_t}{\frac{1}{2}(s_{R,t+4} + s_t)}.$$

\[36\] Here I am making some abuse of notation. Although $\tilde{E}_t[\cdot]$ does denote the respondent’s subjective expectation at the time of the survey, I may observe multiple forecasts for sales growth between quarters $t$ and $t+4$ if the respondent answered questions about sales in more than one month belonging to quarter $t$. Again, restricting my analysis to the final response of the quarter does not materially change any of the main results.
where \( s_t \) is the firm’s sales level as reported in quarter \( t \), and \( s_{R,t+4} \) is the realized sales level in quarter \( t + 4 \). Although seemingly straightforward, the fact that the SBU asks questions about sales every two months (three months prior to September 2016) means that there may be more than one forecast and more than one reported sales level within a calendar quarter. Individual respondents may also drop out of the sample or fail to respond to the survey in a particular month.

To accommodate these circumstances, I aim to measure sales growth realizations based on sales levels reported exactly twelve months apart. If I do not observe a sales level response exactly twelve months after observing the original sales level \( s_t \) I proceed as follows:

- If \( s_t \) belongs to the first month of the quarter (e.g. January), I record \( s_{R,t+4} \) based on the sales level thirteen months after observing \( s_t \). If there is also no sales level reported thirteen months later I use the sales level fourteen months after.
- If \( s_t \) belongs to the second month of the quarter (e.g. February), I record \( s_{R,t+4} \) based on the sales level eleven months after observing \( s_t \). If there is no sales level reported eleven months later I use the sales level thirteen months after.
- If \( s_t \) belongs to the third month of the quarter (e.g. March), I record \( s_{R,t+4} \) based on the sales level eleven months after observing \( s_t \). If there is no sales level reported eleven months later I use the sales level ten months after.

Following this procedure, I increase the number of sales realizations I observe four quarters after recording a subjective distribution, namely because I don’t require exactly twelve months between beliefs and realizations. But I am also careful to record the realized level of quarterly sales in the appropriate quarter, that is quarter \( t + 4 \) for a subjective distribution recorded in quarter \( t \).

Having obtained data on realized sales levels \( s_{R,t+4} \), I can compute the realized growth rates \( g_{t+4} \) and managers’ forecast errors by taking the difference between their sales growth forecast (i.e. their subjective mean sales growth for quarters \( t \) to \( t + 4 \)) and the ex-post sales growth realization:

\[
\text{ForecastError}_{t,t+4} = \bar{E}_t[g_{t+4}] - g_{t+4}.
\]

Using this definition, a positive forecast error occurs when a respondent’s subjective mean exceeds the realized sales growth over the ensuing four quarters, and vice versa for a negative forecast error. For much of my analysis in 2 I winsorize forecast errors at the 1st and 99th percentiles to limit the influence of outliers but my results are similar without winsorizing.

A.3 Sample selection and descriptives

My main sample in 2 consists of all firm-months for which I can construct a forecast error for sales growth looking four quarters ahead. Namely I include in my sample all responses to the sales module in the SBU with well-formed probability distributions for which I can observe a subsequent sales level realization four quarters later.

Following Altig et al. (2018), I review any forecast errors with magnitude greater than unity\(^{37}\) and correct units mistakes (e.g. reporting $5 instead of $5,000,000 in quarterly sales) or other common patterns (e.g. reporting annual rather quarterly sales) based on the history of responses. After this review, I exclude forecast errors for which there is no obvious mistake and are significantly larger than one in absolute value. To conduct this review I exploit the fact that respondents provide estimates of their firm’s current quarterly sales every two months, so looking at this history of responses I can easily determine whether individual responses appear anomalous in comparison with the months immediately before and after.

\(^{37}\)Note that under my sales growth measure \( g_{t+4} \) is bounded by plus and minus two. A forecast error equal to positive one will arise, for example, if the firm predicts sales growth of zero and the firm’s sales subsequently drop by two-thirds.
The sample I use in the rest of this empirical section is an unbalanced monthly panel with gaps, including 1,574 forecast error observations pooling across all firms and months. Prior to September 2016 (when firms answered questions about sales only every three months), my sample contains about 20 to 30 forecast errors per month, while months since September 2016 have about 100 forecast errors per month.

Again, the firms who have forecast errors are larger, well-established organizations, covering a mix of privately-held and publicly-traded firms. Table A.1 displays basic summary statistics about the sample. The median and mean employment in the sample are 175 and 477, the median and mean quarterly sales are $8 Million and $38.1 Million. See Figures A.3 and A.4 for histograms of the distribution of current employment and current quarterly sales across all forecast error observations. The firms in the sample are also fairly old, with about half of all forecast errors belonging to firms that hired their first paid employee prior to 1970, and only 3 percent since 2000, as we can see in Figure A.5.

Performance across the sample is highly heterogeneous, as we should expect from a large cross section of firms. While the mean sales growth over four quarters is 0.046 (on the DHS scale ranging from -2 to +2), its standard deviation is 0.270. Figure A.6 shows the distribution of four-quarter sales growth realizations for my main sample.

A.4 How do Beliefs About Sales Growth in the SBU Relate to Outcomes?

This section elaborates further on my results from Section 2.2 about whether managerial beliefs about future outcomes from the SBU can predict future outcomes and decisions. These exercises aim to rule out the hypothesis that the beliefs recorded in the survey are mostly or all noise. If that were the case, my empirical results arguing that managers have biased beliefs would carry little weight. It would be hard to argue that my data show managers are biased if the data is too noisy to represent beliefs in the first place.

I additionally want to rule out the case that managerial forecasts for sales growth are completely unrelated to current hiring and hiring plans. My quantitative analysis assumes that managers employ the beliefs they provide in the survey when they make business decisions, which is why biases affect decisions. If current hiring and hiring plans are orthogonal to sales growth forecasts and uncertainty, it is hard to argue that the biases I identify in the SBU affect businesses’ decisions.

A.4.1 Realized sales growth and employment vs. their ex-ante forecasts

Figure A.12 reproduce the results shown in the main text, namely that sales and employment growth forecasts (where a forecast equals the mean of a manager’s subjective distribution) have extremely high predictive power for actual sales and employment growth over the next four quarters or twelve months, as appropriate. The t-statistics for these regressions, based on firm-clustered standard errors, are respectively 4.9 and 7.7, confirming the visual intuition from the figure that ex-ante subjective forecasts can predict realized outcomes. Although in both cases the coefficient in the implied regressions is less than one, this may be attenuation bias due to classical measurement error in the forecast. Previous literature typically finds highly significant coefficients (often less than one) in these sorts of regressions, for example in Gennaioli et al. (2016). My findings are also consistent with an older literature studying the subjective beliefs of households, which shows that people are willing and able to answer surveys and that their answers are highly predictive of future events (see Manski, 2004 and 2018, for a survey of this literature).

A.4.2 Sales growth forecasts predict planned hiring

Figure A.13 shows that hiring plans (i.e. managers’ forecast for employment growth over the next twelve months) correlate highly with with their sales growth forecasts for a four-quarter horizon, with a t-statistic of 8.5. This result is highly encouraging, as it means managers’ sales forecasts are highly consistent with their best guess for their own actions looking ahead to the next year. Given we already saw in Figure A.12 that these hiring plans are also highly predictive of actual hiring, this is even more evidence that managers’ beliefs as stated in the SBU are an important input into hiring plans and hiring decisions.

---

38The SBU asks managers for beliefs about sales growth over a horizon of four quarters, while the horizon for employment questions is twelve months.
A.4.3  Actual sales growth predicts actual hiring

Figure A.14 validates that actual hiring and actual sales growth are correlated in the SBU. Namely, when firms record positive sales growth they also hire more workers as we would expect in most economic models. This is an additional validity check for the data, having shown that sales and employment growth forecasts are consistent and predict realizations.

A.4.4  Actual hiring versus forecast sales growth

In Figure A.15 I show that there is a positive but potentially nonlinear relationship between actual hiring in the year after managers’ make a sales growth forecast and the forecast itself. The weak linear relationship may be due to nonlinearities in the relationship between sales growth forecasts and actual hiring decisions that may take place throughout the year following the forecast. Given my earlier findings that forecasts predict hiring plans and hiring plans predict actual hiring, and finally sales growth forecasts predict actual sales growth I view this as consistent with the need to use a nonlinear model to understand how sales growth forecasts ultimately result in hiring decisions.

A.4.5  Current hiring versus sales growth forecasts and current sales growth

Figure A.16 explore how hiring in the current quarter relates to managers’ beliefs about sales growth looking ahead over the next four quarters, and the firm’s recent performance. In Figure A.16a we can see that there is a weak but positive relationship between the firm’s current net hiring and managers’ medium-run sales growth expectations. Turning to Figure A.16b, there is by contrast a clear relationship between hiring in quarter $t$ and the firm’s performance in quarter $t$ relative to quarter $t-1$. This pattern suggests managers’ current decision to hire or lay-off workers incorporates several different pieces of information, including both their medium-run forecasts for the firm’s performance and also the firm’s current business conditions.

That innovations in the firm’s sales predict their hiring more strongly than longer run forecasts resembles the dynamics in my estimated model in the main text, in which overconfident and overextrapolative managers are constantly reacting to changes in their firms’ business conditions. Furthermore, I interpret the weaker relationship between expectations and hiring this quarter relative to hiring plans for the next twelve months as evidence that hiring is not frictionless, but rather subject to adjustment costs and frictions that are at the center of the economic model I use to quantify the impact of beliefs biases.

Based on the evidence in this subsection, I therefore argue managers’ beliefs about their firm’s future performance do enter their current hiring decisions and – more importantly – their hiring plans. These results are consistent with the evidence in the literature on beliefs and expectations, in particular the finding by Gennaioli et al. (2016) that survey-based expectations can predict outcomes and actions like investment above and beyond model-implied proxies like Tobin’s $q$. However, since my SBU data is confidential and mostly comes from privately-held firms, so I cannot at the moment link it to rich data sources to test whether beliefs predict outcomes above and beyond other variables.

A.5  Managerial Overconfidence Underestimates the Level of Risk, Rather than Differences in Risk

How does managerial overconfidence manifest itself for firms that experience more versus less ex-ante subjective uncertainty? I find managers underestimate an approximately fixed level of risk regardless of their firm’s subjective uncertainty, while being highly sensitive to differences in risk across firms. To see this, I explore the relationship between ex-ante uncertainty and ex-post absolute forecast errors in Figure A.18. The horizontal axis shows 20 equally sized quantiles of subjective uncertainty – the standard deviation of managers’ subjective distribution for sales growth between $t$ and $t+4$. The blue circles on vertical axis show the average absolute forecast error that arises empirically in each of those twenty quantiles, while the orange triangles show what those average forecast errors would look like if sales growth realizations were distributed according to managers’ subjective distributions.

The two bin-scatters in Figure A.18 are upward sloping and essentially parallel, showing that managers
who report higher ex-ante subjective uncertainty make larger ex-post errors both empirically and under the subjective distribution (the latter by construction). This result is consistent with existing work, including Bloom et al. (2017), who find that managers in industries and firms with higher historical and option-implied volatility report higher uncertainty. The similarity in the slope of the relationship across the empirical and subjective errors implies that differences in risk as perceived across managers reflects differences in true risk fairly accurately. But the vertical gap between the empirical and subjective errors in Figure A.18 visually captures the degree of overconfidence, which appears to be constant. At all levels of uncertainty, managers appear to underestimate the magnitude of their forecast errors by a fixed amount. To my knowledge, this is the first paper to document that managers seem to underestimate a fixed level of risk, while remaining sensitive to differences in risk across firms and time.

Repeating this exercise focusing on within-firm variation in subjective uncertainty the results are similar, but the slope of the relationship between empirical absolute forecast errors and subjective uncertainty decreases by about half. This decrease in the slope suggests that managers are better at recognizing differences in subjective uncertainty across rather than within firms.

A.6 Overconfidence or Measurement Error?

In this section I argue that measurement error is unlikely to be responsible for the large excess absolute forecast errors I find in the SBU data. Recall that the mean excess absolute forecast error is the key statistic I use to quantify the degree of managerial overconfidence. My measures of realized sales growth in the SBU are almost certainly measured with error, for example because managers report their firm’s current sales level in the SBU in round numbers before official accounting figures are published. It’s true that SBU respondents don’t have strong incentives to be perfectly accurate, and may answer the survey without paying much attention. The question is whether these potential sources of measurement error can explain why I measure large forecast errors (in absolute terms), while managers’ subjective distributions imply they should be making much smaller errors.

To test whether the magnitude of my measured forecast errors seems implausible, in Figure A.19a I compare the distribution of forecast errors for sales growth I obtain from the SBU, against the distribution of errors made by professional analysts in IBES, both from a horizon of four quarters. We should expect sales data released by public firms to have significantly less measurement error than there might be in the SBU, given realized values come from official accounting releases that are meant for public distribution. They definitely should not suffer from rounding, units, and inattention issues that that we might worry about in the SBU data.

Owing to the structure and variables available in IBES I construct forecast errors somewhat differently from the main analysis in the paper. IBES reports forecasts and realizations of the level of sales. Therefore I construct implied forecasts for the growth rate of sales (looking four quarters ahead) by taking the growth rate implied by the current level and the forecast. In the SBU I compute the implied subjective expectation for the sales level four quarters ahead and then the growth rate implied by that expected future level with the current reported level. Then I define forecast errors in both the SBU and IBES as the difference between these growth forecasts and actual growth.

Looking at Figure A.19a, it seems that managers do make slightly larger forecast errors in the SBU than do analysts in IBES. This may be partly due to additional measurement error in the SBU, but it is also a well-known fact (see, for example Davis et al., 2007) that larger firms are less volatile. Firms in IBES are some of the larger publicly-traded firms in the US so makes sense that their sales to be more predictable than the sales of firms my SBU sample of smaller (though still fairly large in absolute terms) firms. In Figure A.19b I confirm that the distribution of SBU forecast errors under managers’ subjective distributions for realized sales growth look implausible. There I show the distribution of empirical forecast errors from IBES and the subjective distribution of forecast errors in the SBU. As in Figure 5 in the main text, it is the subjective distribution of errors that looks implausible in comparison with the distribution of actual analyst errors in IBES.
A.7 Is Overconfidence Mechanically Generated from the SBU’s Five-Point Subjective Probability Distributions?

Responses in the SBU elicit managers’ beliefs about future sales growth using a five-point discrete distribution. Realized sales growth, however, is a continuous variable. This discrepancy raises the concern that my key measures of overconfidence – excess absolute forecast errors – may be mechanically large because discrete approximations simply have a hard time capturing continuous distributions. I argue that is not correct.

Looking at Figure 5 in the main text, it is clear that the managers’ subjective distributions overestimate the probability of small forecast errors, not that actual forecast errors are occasionally very large because the distribution of sales growth realizations has continuous support. Managers place nearly 75 percent probability on the possibility that forecast sales growth will be within 5 percentage points of realizations. Empirically this only happens with about 25 percent probability. Managers in turn underestimate the probability of being off by about 10 percentage points, which is actually very much within the realm of normal (the standard deviation of actual forecast errors is close to 0.25). These patterns suggest that managers place the five bins corresponding to the lowest, low, middle, high, and highest scenarios too close together, ignoring a large amount of mass at the tails of the true distribution.

To verify this intuition I demonstrate that making a discrete five-point approximation of the continuous distribution of realized sales growth, ignoring modest amounts of mass at the tails, need not generate large excess absolute forecast errors \(^{39}\). I consider two potential approaches. Under a first approach based on the Tauchen (1986) algorithm, I first pick some amount of tail mass \(p \in (0, 1)\) of the empirical distribution \(^{40}\) to disregard. Then I pick five equidistant bins \(q_i, \ i = 1, 2, 3, 4, 5\) where \(q_1\) and \(q_5\) are the endpoints of remaining support. Finally, I distribute probabilities across bins based on the cumulative distribution \(F(\cdot)\) of realized sales growth:

\[
\begin{align*}
p_1 & = F\left(\frac{q_1 + q_2}{2}\right) \\
p_2 & = F\left(\frac{q_2 + q_3}{2}\right) - F\left(\frac{q_1 + q_2}{2}\right) \\
& \quad \ldots \\
p_5 & = 1 - F\left(\frac{q_4 + q_5}{2}\right).
\end{align*}
\]

Once I have this approximate discrete distribution I use it to construct a forecast \(E = \sum_{i=1}^5 p_i q_i\) and a mean absolute deviation \(MAD = \sum_{i=1}^5 p_i |q_i - E|\). Then I find the mean absolute forecast error implied by the discretization, \(MAFE = \sum_{n=1}^N (E - g_n)\) where \(n\) indexes observations of the empirical sales growth distribution I am targeting. Finally I find the excess absolute forecast error generated by my discrete approximation, \(EAFE = MAFE - MAD\), which is analogous to my measure of overconfidence in Section 2. Table A.2a shows how this excess error changes across discretizations that ignore the outermost \(p\) mass of the target empirical distribution. Ignoring modest amounts of tail mass \((p \leq 0.2)\) results in modest excess absolute forecast errors, on the order of a couple of percentage points. Ignoring the outermost 40 percent of the mass (i.e. placing the outermost bins at the 20th and 80th percentiles of the target distribution) only generates an excess absolute forecast error half as large as the excess error I observe empirically.

I find similar results using an alternative approach to discretizing the empirical distribution. The mean probability vector SBU respondents assign is approximately \((p_1, p_2, p_3, p_1, p_2)' = (0.1, 0.2, 0.4, 0.2, 0.1)'\), an intuitive, unimodal, and symmetric distribution. This second method uses these probabilities and the corre-

\(^{39}\) Indeed, the literature that works with discrete-time dynamic programming models has used discrete approximations to Gaussian Markov processes at least since Tauchen (1986) without major concerns that the discrete approximations mechanically understate the dispersion of the stochastic process in question.

\(^{40}\) To be specific, my target distribution is the empirical distribution of sales growth realizations purged of heterogeneity due to differences in managers’ subjective expectations. Purging this heterogeneity involves regressing realized sales growth on SBU managers’ ex-ante forecasts and working with the residual from this regression. Residualizing ensures that the variance of my target continuous distribution reflects unpredictable variation in realized sales growth rather than predictable variation that managers have in their own information sets.
sponding quantiles of the empirical distribution (again, disregarding some of the outermost mass \( p \in (0, 1) \)) to select the five support points of the discrete distribution. Namely, pick \( q_i, \ i = 1, 2, 3, 4, 5 \) such that:

\[

d_i = \frac{q_i + q_{i+1}}{2}
\]

where \( F(\cdot) \) now is the CDF of the target distribution ignoring the pre-determined \( p \) mass. I can then use this discretization to construct measures of excess error \( EAFE \) as for the "Tauchen" approach. Table A.2b shows that using this quantile-based approach also does not mechanically generate large excess absolute forecast errors when ignoring modest amounts of tail mass \( p \). For \( p = 0.4 \), the implied excess error is even smaller at 0.058 than for the "Tauchen" approach, effectively ruling out the hypothesis that discretization on its own can generate the large excess errors we find in the SBU data.

### A.8 Additional Evidence of Overextrapolation

In this section I show some additional evidence consistent with my claim that managers responding to the SBU overextrapolate from current conditions when they form beliefs about future sales growth.

#### A.8.1 Breaking down the relationship between forecasts, realizations, and recent sales growth

I confirm that managers appear to underestimate mean reversion of short-term shocks by looking at Figure A.20, in which I repeat the bin-scatter from Figure 7, now plotting forecast and realized sales growth separately on the vertical axis. Managers’ forecasts for sales growth between quarters \( t \) and \( t + 4 \) are essentially flat against the firm’s sales growth between quarters \( t - 1 \) and \( t \) – the quarter just prior to the forecast. By contrast, realized sales growth between \( t \) and \( t + 4 \) correlates negatively with the firm’s lagged performance. This pattern suggests managers forecasts fail to internalize that the current shock decays over time, thus making their errors predictable because this decay is predictable. In this sense, managers overextrapolate from the level of current sales rather than the recent rate of sales growth. This finding is consistent with how I model overextrapolation in Section 3, in which firms receive shocks that shift the level of profitability in a stationary environment.

#### A.8.2 Forecast errors are negatively correlated with past forecast errors

Figure A.21 is a bin-scatter plot of forecast errors on lagged forecast errors, showing a clear negative relationship. The horizontal axis plots twenty quantiles of forecast minus realized sales growth for quarters \( t - 4 \) to \( t \) against the mean forecast minus realized sales growth for \( t \) to \( t + 4 \) on the vertical axis. Managers that fall on the right half of the graph are those who made forecasts on \( t - 4 \) that ended up overestimating the firm’s actual sales growth between \( t - 4 \) and \( t \). Those same managers then subsequently make forecasts on \( t \) for sales growth between \( t \) and \( t + 4 \) and end up underestimating. This pattern is consistent with my finding in Section 2 that managers overextrapolate. Namely, those who receive a negative shock between \( t - 4 \) and \( t \) perceive that negative shock to be particularly persistent and thus end up underestimating as they look forward from \( t \) to \( t + 4 \).

In Table A.3 I show estimates from the regression depicted in Figure A.21, as well as from specifications that add date, sector-by-date, and firm fixed effects. The existence of a negative relationship is highly robust across all specifications, although the coefficient from the fourth column with firm and date fixed effects is significantly larger. This is probably due to the fact that I have a short of the panel in which fixed effects specifications may be upward biased. (Recall that I only have data since late 2014 and I need two years
worth of data of an individual firm to obtain an observation with non-missing current and lagged forecast errors.)

A.8.3 Forecast errors are positively correlated with a second measure of sales growth

Recall that in the SBU questionnaire managers report their firm’s sales growth in the past twelve months (see Figure 2 in the main text). Figure A.22 shows that managers’ forecast errors in the SBU are positively related with their reported sales growth for the twelve months prior. Again, I interpret this figure as evidence of overextrapolation. Managers at firms that receive one or more positive shocks in the year up to \( t \) overestimate the persistence of those shocks and thus their forecasts for sales growth between \( t \) and \( t + 4 \) overestimate the firm’s performance looking forward. Managers at firms that receive one or more negative shocks in the past year, in turn, are too pessimistic about future sales growth.

Table A.4 shows that the relationship between reported past sales growth and forecast errors is robust to controlling for date, sector-by-date, and firm fixed effects. The final column that includes both firm and date fixed effects once again has a larger coefficient, potentially due to biases that are common in dynamic panel regression models. However, the coefficient does not look statistically different from that in the first three columns, so the overall picture is that the relationship between reported past sales growth and forecast errors is robust.

A.9 Managerial Optimism, Overconfidence, and Overextrapolation about Future Employment

Although I focus on biases in managers’ beliefs about their firm’s future sales growth, the SBU also collects subjective probabilities and tracks outcomes for the firm’s level of employment. See Figure A.11 for the SBU’s questions about current and future employment. Here, I document as a robustness check that managers do not appear to be particularly over-optimistic nor pessimistic about their firm’s future employment growth, but they do appear to be overconfident and overextrapolate.

Table A.5 summarizes the results about managers’ optimism/pessimism, overconfidence, and overextrapolation about their firm’s future employment growth. In Panel A, we can see that managers’ appear somewhat pessimistic about their firm’s future employment growth on average. Realized employment growth exceeds its ex-ante forecast by about 0.016 on average, and is statistically significantly different from zero with 95 percent but not 99 percent confidence. Economically speaking, however, this is arguably not a significant deviation from rational expectations, especially given that the standard deviation of realized employment growth over four quarters is 0.175.

Panel B of Table A.5 shows that managers are overconfident about future employment. While the mean absolute forecast error for employment growth is close to 0.11, under managers’ subjective distributions the mean absolute error should only be less than half as big at 0.044. This means there is an excess absolute error of about 0.066.

Turning now to Panel C, we can see that forecast minus realized sales growth for months \( t \) to \( t + 12 \) correlates significantly with firms’ employment growth in months \( t - 2 \) to \( t \) , just prior to managers’ making their forecasts. As with sales growth, the positive relationship between lagged employment growth and forecast errors means that managers at firms performing well when they answer the survey end up overestimating future employment growth, and vice-versa for those at firms performing poorly. I focus here on twelve-month changes in future employment because this is the horizon used for the employment questions in Figure A.11. Similarly I use changes in employment from \( t - 2 \) to \( t \) as an independent variable because respondents get the questionnaire for employment every two months. Neither of these particular choices are crucial to the results. In the second and third columns I include date and firm fixed effects to show that the predictability of forecast errors is not driven by aggregate shocks or by persistent differences across firms.

A.10 Why don’t market forces throw out biased managers?

If managers are truly biased and make systematic mistakes that destroy firm value, we might intuitively expect boards of directors and headhunting firms should realize this and prevent these biased individuals
from taking on managerial positions. In practice, it is not obvious that these other market participants can easily gather the data required to make such assessments.

First, individual point forecasts may be at odds with realizations due to random shocks even if managers have rational expectations. To determine whether an individual manager is biased, you would need to show his or her ex-ante beliefs are systematically inconsistent with realizations, which requires several observed forecasts and realizations. Since firm outcomes are typically reported at relatively low frequencies, namely annually or quarterly, it may take years or decades to obtain enough statistical power to determine if, say, managers’ forecasts are over-optimistic on average.

In my survey data, the volatility of sales growth is such that even after tracking forecasts and realizations for 25 years at a quarterly frequency (yielding 100 observations), one would typically not be able to determine with 95 percent confidence whether a manager who over-estimates her firm’s sales growth by as much as 5 percentage points on average is truly over-optimistic. Given the median CEO tenure is only about 7 years (e.g. see Taylor, 2010), boards typically have a fraction of the data and statistical power I used in this example. Similarly, this small-sample problem may preclude individual managers from figuring out whether their beliefs about a given firm’s risks and prospects are biased or not. By the time they have enough data, they may move to a different firm with potentially different conditions and may thus have to start learning about its profitability all over again.

Second, determining whether managers are biased requires reliable data on their beliefs. If, say, a board of directors routinely asks managers for their own subjective forecasts of the firms’ future performance, it is hard to think how the board could compel them to report their beliefs honestly. For example, the board may not be able to commit to not using those forecasts to judge the managers’ strategy, thus incentivizing managers to misreport. Note this is in contrast with my survey data, in which individual responses are confidential and never reported individually.

Finally, if a board somehow establishes that it will only use managerial forecasts to determine whether managers are biased, this may be an incentive for managers to report honest forecasts, but it could also create incentives for managers to manipulate the firm’s reported or real performance ex-post. Thus, the board may rationally choose to refrain from systematically tracking managerial forecasts accuracy to avoid introducing these additional incentives for managerial misbehavior.
Figure A.1: Sales Questions in the *Survey of Business Uncertainty* prior to September 2016

**Notes:** Sales growth questions in the *Survey of Business Executives* as they appeared prior to September 2016. In months prior to September 2016, the SBE asked for sales growth beliefs in levels rather than growth rates. See Appendix Figure
Figure A.2: Forecast Error Observations from the SBU Belong to Firms From All Sector

Notes: Number of forecast error observations by one-digit sector. Data are from the SBU covering the period 10/2014 to 6/2018, restricting attention to subjective probability distributions. 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 A.3: SBU Respondents Are Larger, Well-Established Firms (Employment)

Notes: Distribution of current employment (winsorized at the top and bottom 5-percent) at the time of forecast for all forecast error observations in the Survey of Business Uncertainty. 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 $t + 4$. $N = 1,574$. 

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Figure A.4: **SBU Respondents Are Larger, Well-Established Firms (Sales)**

![Graph showing quarterly sales distributions](image)

**Notes:** Distribution of current sales ($M$, winsorized at the top and bottom 5-percent) at the time of forecast for all forecast error observations in the *Survey of Business Uncertainty*. 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 A.5: **Firms with Forecast Errors are Older**

![Bar graph showing when firms hired their first paid employee](image)

**Notes:** Number of forecast error observations, sorting firms by the decade in which they hired their first paid employee. 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 $t+4$. Data about when the firm hired its first paid employee comes from a one-off special question included in the January 2017 survey, asking "In what year did your firm hire its first paid employee? If you do not know the precise year please give your best estimate." The respondent then was able to select either an individual year since 2000, or one of "1990-1999", "1980-1989", "1970-1979", or "prior to 1970". $N = 1,414$. 

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Figure A.6: Heterogeneity in Measured 4-Quarter Sales Growth Performance

**Notes:** Distribution of four-quarter sales growth realizations (winsorized at the top and bottom 1 percent) for all forecast error observations in the *Survey of Business Uncertainty*. 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 A.7: **Share of Employment by Firm Size: SBU vs. US Economy**

**Notes:** This figure shows (1) the share of employment across all SBU responses from 10/2014 to 7/2018 made by firms in each firm size category; (2) the share of employment for each firm size category in the US economy in the US Census Bureau’s 2015 Statistics on US Businesses.
Figure A.8: **Share of Employment by Firm Age: SBU vs. US Economy**

**Notes:** This figure shows (1) the share of employment across all SBU responses from 10/2014 to 7/2018 by the firm’s year of birth; (2) the share of employment across firms by year of birth in the US economy according to the US Census Bureau’s 2015 Business Dynamics Statistics.

Figure A.9: **Share of Employment by Sector: SBU vs. US Economy**

**Notes:** This figure shows (1) the share of employment across all SBU responses from 10/2014 to 7/2018 made by firms in each sector; (2) the share of employment in each sector of the US economy in the US Census Bureau’s 2015 Statistics on US Businesses. Numbers in parentheses correspond to NAICS two-digit codes for each sector.
Figure A.10: \textbf{Share of Employment by Region: SBU vs. US Economy}

Notes: This figure shows (1) the share of employment across all SBU responses from 10/2014 to 7/2018 made by firms in each region (i.e. Census Division); (2) the share of employment in each region according the US Census Bureau’s 2015 Statistics on US Businesses.
Figure A.11: SBU Questions About Employment

Notes: This figure shows the questions about current employment and beliefs about future employment in the Survey of Business Uncertainty.
Figure A.12: Sales and Employment Growth Forecasts Predict Outcomes

(a) Sales

Notes: This figure shows bin-scatter plots of sales growth and employment growth forecasts on the horizontal axis against realized sales and employment growth. Sales growth forecasts are made in quarter $t$ and forecast sales growth between quarter $t$ and $t+4$. Employment growth forecasts are made in month $m$ and forecast employment growth between $m$ and $m+12$. T-statistics for the underlying regressions are 4.9 and 7.7 for sales and employment, respectively using firm-clustered standard errors. All data are from the SBU with the sample period covering 10/2014 to 6/2018. The plot for sales includes 1,574 forecast error observations from 408 firms, and the employment plot includes 2,143 observations from 460 firms.
Figure A.13: Planned Hiring vs. Sales Growth Forecasts

Notes: This figure shows a bin-scatter plot of planned net hiring (i.e. expectations for employment growth) looking forward a year against the managers'sales growth forecast looking ahead to the next four quarters. All data come from the SBU with the sample period covering 10/2014 to 6/2018. The underlying regression for the figures above includes 3,615 SBU responses from 695 firms.

Figure A.14: Actual Hiring vs. Actual Sales Growth

Notes: This figure shows a bin-scatter plot of actual net hiring (i.e. employment growth) in the year following a forecast against the actual sales growth recorded in the four quarters following the forecast. All data come from the SBU with the sample period covering 10/2014 to 6/2018. The underlying regression for the figures above includes 1,234 SBU responses from 330 firms.
Figure A.15: **Actual Hiring vs. Sales Growth Forecasts**

Notes: This figure shows a bin-scatter plot of actual net hiring (i.e. employment growth) in the year following a forecast against the managers’ sales growth forecast looking ahead over four quarters. All data come from the SBU with the sample period covering 10/2014 to 6/2018. The underlying regression for the figures above includes 1,514 SBU responses from 365 firms.
Figure A.16: Current Hiring vs. Sales Growth Expectations and Uncertainty

(a) Current Hiring vs. Recent Growth

Notes: This figure shows bin-scatter plots of current hiring in quarter $t$ against managers’ sales growth forecasts for quarters $t$ to $t+4$ (top) and the firm’s sales growth between quarters $t-1$ and $t$. All data come from the SBU with the sample period covering 10/2014 to 6/2018.
Figure A.17: Managers are Overconfident About Their Forecasts’ Accuracy

Notes: This figure plots the empirical distribution of absolute forecast errors as well as the distribution of absolute 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 A.18: Managers are Overconfident Across Levels of Subjective Uncertainty

Notes: Bin-scatter plot of realized and subjective absolute forecast errors for sales growth looking four quarters ahead, against ex-ante subjective uncertainty (the standard deviation of respondents' subjective distribution). A respondent's subjective absolute forecast error is the 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 A.19: **Forecast Errors in the SBU vs. IBES**

(a) **Empirical Distributions of Forecast Errors in SBU & IBES**

(b) **Subjective Distribution of Forecast Errors in the SBU vs. Empirical Distribution in IBES**

**Notes:** The top figure shows; (1) the *empirical* distribution of managers’ forecast errors for sales growth looking four quarters ahead from the SBU; (2) the empirical distribution of analyst forecast errors for sales growth four quarters ahead from IBES. The bottom figure shows (1) the *subjective* distribution of managers’ forecast errors for sales growth looking four quarters ahead from the SBU (i.e. the distribution of forecast errors implied by managers’ subjective probabilities); (2) the empirical distribution of analyst forecast errors for sales growth four quarters ahead from IBES. The SBU sample includes 1,574 forecast error observations from 397 firms between 10/2014 and 6/2018. The IBES sample includes 755,685 analyst forecast errors.
Figure A.20: Overextrapolation Arises Because Managers Ignore Mean Reversion

Notes: This figure shows bin-scatters of forecast and realized 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 A.21: Managers Overextrapolate: Forecast Errors Serially Correlated

Notes: This figure shows a bin-scatter plot of forecast minus realized sales growth over quarters $t$ to $t + 4$ on the vertical axis against forecast minus realized sales growth over quarters $t - 4$ to $t$. Data are from the SBU covering 10/2014 to 6/2018. $N = 502$. 

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Figure A.22: **Managers Overextrapolate: Based on Reported Sales Growth**

*Notes:* This figure shows a bin-scatter plot of forecast minus realized sales growth over quarters \( t \) to \( t + 4 \) on the vertical axis against the managers’ reported sales growth for quarters \( t - 4 \) to \( t \). Data are from the SBU covering 10/2014 to 6/2018. \( N = 1,071 \).
Table A.1: **SBU Sample Descriptives: Firms with Forecast Errors**

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</tbody>
</table>

**Notes:** Summary statistics on current employment, current sales, and measured sales growth realizations among all forecast error observations in the *SBU*. An observation here is a survey response in quarter *t* with a well-defined subjective probability distribution for sales growth looking four quarters ahead, and for which I also observe the firm’s realized sales growth between quarters *t* and *t* + 4.

Table A.2: **Discretizing Empirical Distributions**

(a) "Tauchen" (Equidistant-Bins) Approach

<table>
<thead>
<tr>
<th>Mass Excluded (<em>p</em>)</th>
<th>0.01</th>
<th>0.05</th>
<th>0.1</th>
<th>0.2</th>
<th>0.4</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Absolute Fcast. Error</td>
<td>0.024</td>
<td>0.012</td>
<td>0.022</td>
<td>0.042</td>
<td>0.075</td>
<td>0.145</td>
</tr>
</tbody>
</table>

(b) Quantile Approach

<table>
<thead>
<tr>
<th>Mass Excluded (<em>p</em>)</th>
<th>0.01</th>
<th>0.05</th>
<th>0.1</th>
<th>0.2</th>
<th>0.4</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Absolute Fcast. Error</td>
<td>-0.01</td>
<td>0.017</td>
<td>0.031</td>
<td>0.045</td>
<td>0.058</td>
<td>0.145</td>
</tr>
</tbody>
</table>

**Notes:** The above tables show the excess absolute forecast error that would arise from approximating the empirical distribution of realized sales growth between quarters *t* and *t* + 4 under the "Tauchen"-based, and Quantile-based approaches to discretization. Before discretizing, I remove heterogeneity in realized sales growth attributable to differences in subjective first moments, leaving the empirical distribution of realized sales growth for the typical expectation and subjective uncertainty across all 1,574 forecast error observations in the SBU. See Appendix A.7 for a full description of the two discretization approaches.
Table A.3: Managers Overextrapolate: Forecast Errors are Serially Correlated

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast - Realized Sales Growth, quarters t-4 to t</td>
<td>-0.201***</td>
<td>-0.212***</td>
<td>-0.161**</td>
<td>-0.508***</td>
</tr>
<tr>
<td>quarters t to t+4</td>
<td>(0.060)</td>
<td>(0.062)</td>
<td>(0.077)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.020</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Date FE</td>
<td></td>
<td>Y</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Date x Sector FE</td>
<td></td>
<td></td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Firm FE</td>
<td></td>
<td></td>
<td></td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>502</td>
<td>502</td>
<td>428</td>
<td>451</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.042</td>
<td>0.068</td>
<td>0.241</td>
<td>0.495</td>
</tr>
</tbody>
</table>

Notes: Robust standard errors in parentheses, clustered by firm. Data are subjective probability distributions and forecast errors about sales growth looking 4 quarters ahead from the Survey of Business Uncertainty covering all months between October 2014 and June 2018. An observation is a forecast error for a particular firm in a particular month. *** p<0.01, ** p<0.05, * p<0.1

Table A.4: Managers Overextrapolate: Based on Reported Sales Growth

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast - Realized Sales Growth, quarters t to t+4</td>
<td>0.261**</td>
<td>0.267***</td>
<td>0.266**</td>
<td>0.390***</td>
</tr>
<tr>
<td>Reported Sales Growth, 12 months up to t</td>
<td>(0.101)</td>
<td>(0.100)</td>
<td>(0.104)</td>
<td>(0.111)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.018*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Date FE</td>
<td></td>
<td>Y</td>
<td></td>
<td>Y</td>
</tr>
<tr>
<td>Date x Sector FE</td>
<td></td>
<td></td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Firm FE</td>
<td></td>
<td></td>
<td></td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>1,071</td>
<td>1,071</td>
<td>1,062</td>
<td>1,021</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.021</td>
<td>0.039</td>
<td>0.159</td>
<td>0.504</td>
</tr>
</tbody>
</table>

Notes: Robust standard errors in parentheses, clustered by firm. Data are subjective probability distributions and forecast errors about sales growth looking 4 quarters ahead from the Survey of Business Executives covering all months between October 2014 and February 2018. An observation is a forecast error for a particular firm in a particular month. *** p<0.01, ** p<0.05, * p<0.1

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Table A.5: Beliefs Biases About Future Employment Growth

| Panel A. Optimism | Employment Growth | Forecast Error |  |  |  |
|-------------------|-------------------|----------------|---|---|
|                   | Forecast | Realized | Forecast - Realized |  |  |  |
| Mean              | 0.009   | 0.025   | -0.016  |  |  |  |
| SE                | (0.004) | (0.006) | (0.005) |  |  |  |
| Obs.              | 2,143   | 2,143   | 2,143   |  |  |  |
| Firms             | 460     | 460     | 460     |  |  |  |

| Panel B. Overconfidence | Absolute Forecast Error | Excess Error |  |  |  |
|-------------------------|-------------------------|--------------|---|---|
|                         | Empirical | Subjective | Empirical - Subjective |  |  |  |
| Mean                    | 0.111    | 0.044     | 0.066    |  |  |  |
| SE                      | (0.005)  | (0.003)   | (0.004)  |  |  |  |
| Obs.                    | 2,143    | 2,143     | 2,143    |  |  |  |
| Firms                   | 460      | 460       | 460      |  |  |  |

| Panel C. Overextrapolation | Forecast - Realized Emp. Growth, months $t$ to $t + 12$ |  |  |  |
|----------------------------|----------------------------------------------------------|---|---|
| Emp. Growth, months $t - 2$ to $t$ | 0.356 | 0.357 | 0.470 |
| (0.065)                       | (0.066) | (0.047) |  |  |  |
| Constant                     | -0.026  |          |          | (0.007) |  |  |
| Date FE                      | Y       |          |          |  |  |  |
| Firm FE                      | Y       |          |          |  |  |  |
| Obs.                         | 1,088   | 1,088    | 1,035    |  |  |  |
| Firms                        | 299     | 299      | 246      |  |  |  |
| R-squared                    | 0.070   | 0.071    | 0.545    |  |  |  |
B Model Appendix

B.1 An Alternative Way of Writing Down Managers’ Optimization Problem and True Firm Value

Equations 4 and 5 in the main text express managers’ problem and the firm’s true value recursively. Although I use these recursive forms to compute managers’ policy functions, subjective valuations of the firm, and the firm’s true value, the same objects can be represented as a sequence problem that may be more intuitive to some readers.

Since managers are risk-neutral and own a share \( \theta \in (0, 1] \) of the firm, their objective is to maximize the net present value of the firm’s cash flows, discounted at the equilibrium risk-free rate. Managers take as given the full path of current and future risk-free rates \( \{r_{t+1}\}_{t=0}^{\infty} \) and wages \( \{w_t\}_{t=0}^{\infty} \), which are deterministic.

However, they forecast their firms’ future business conditions \( z_{t+k} \) for \( k > 0 \) under their own subjective beliefs. The following sequence problem thus represents managers’ problem, given some initial business conditions \( z_0 \) and labor \( n_0 \):

\[
\tilde{V}(z_0, n_0) = \max_{\{n_{t+1}\}_{t=0}} \tilde{E}_0 \left[ \sum_{t=0}^{\infty} \frac{\pi(z_t, n_t, n_{t+1}; w_t)}{R_t} \right]
\]

where \( R_t \) is the (non-stochastic) composite discount factor used to value period-\( t \) cash flows in period 0:

\[
R_t = \Pi_{s=0}^{t}(1 + r_{s+1})
\]

and, again, operator \( \tilde{E}[:\cdot] \) denotes the managers’ subjective expectations based on her stochastic process from equation 3 in the main text. Looking at this formulation, it is clear that the share of the firm actually owned by the manager \( \theta \) is irrelevant for their optimal policy.

From standard dynamic programming results (e.g. see Stokey et al., 1989) we know that managers’ hiring policy on date \( t \) can be written solely as a function of current business conditions and labor: \( n_{t+1} = \kappa(z_t, n_t) \). Taking as given a manager’s policy function \( \kappa(\cdot) \), the objective, expected net present value of the firm’s cash flows is:

\[
V(z_0, n_0) = E_0 \left[ \sum_{t=0}^{\infty} \frac{\pi(z_t, n_t, \kappa(z_t, n_t); w_t)}{R_t} \right]
\]

where I have substituted in the manager’s policy\(^{41}\). In contrast with the managers’ valuation, computing the true value of the firm requires forecasting future cash flows based on the unbiased expectation \( E[:\cdot] \).

Implicit in both the managers’ subjective and the true value of the firm is the capacity to forecast future prices \( w_t \) and \( R_t \) perfectly. This in practice follows from my assumption that there is no aggregate risk both in the baseline model from Section 3 and the investment-based model in B.5. Then, an equilibrium includes a deterministic sequence of prices that I assume model agents know with certainty.

B.2 Definition of Aggregate Quantities

Here I define aggregate quantities in my model economy from Section 3 in the main text. Below I use \( \Phi(z, n) \) to denote the measure of firms in the economy with business conditions \( z \) and labor \( n \).

Aggregate output or GDP in my model economy is the sum of value added across all firms less spending

\(^{41}\) I use the dynamic programming result here for simplicity of exposition. In practice, we could denote \( \{n_{t+1}\}_{t=0}^{\infty} \) to be the manager’s optimal policy and let it be a function of the entire history of shocks and expectations of future shocks.
on adjustment costs:

\[
Y = \int_{\mathbb{Z} \times \mathbb{N}} \left[ zn^\alpha - \lambda \left( \frac{\kappa(z,n) - (1-q)n}{n} \right)^2 \right] \Phi(z,n) \, \Phi(z,n) = \hat{Y} - AC.
\]

Here I use \( \hat{Y} \) to denote gross output (before subtracting adjustment costs) and \( AC \) total spending on adjustment costs. This definition of GDP is crucial for parts of my analysis about the aggregate implications of beliefs biases in Section 5.2 of the main text. I justify subtracting adjustment costs from GDP because resources spent in this way do not constitute income for any agents in the economy and instead are essentially intermediate business expenses that subtract from profits and thus value added.

Recall that managers in the model are risk neutral and own a share \( \theta = \in (0,1] \). They consume \( \theta \) times the firm’s current cash flow \( \pi(\cdot) \), while the rest of the firm’s cash flow goes to the representative household. As stated in the main text, the household then receives capital income \( \theta \Pi \) where

\[
\Pi = \int_{\mathbb{Z} \times \mathbb{N}} \pi(z,n,\kappa(z,n);w) \Phi(z,n) \,
\]

and \( \kappa(z,n) \) is the hiring policy of a manager at a firm with state \((z,n)\).

It follows that aggregate output must be equal to the household’s consumption plus the managers’ consumption, or equivalently the sum of labor and capital income:

\[
Y = C + \theta \Pi = wN + \Pi
\]

**B.3 Firm Value Welfare Change and Formulas**

To compute the change in firm value from replacing a biased manager for a counterfactual manager who is unbiased (or less biased), I first compute each of their policy functions \( \kappa(\cdot) \) and \( \kappa^c(\cdot) \) respectively. Based on those policy functions, I find the true net present value of cash flows generated by their respective policies, \( V(\cdot) \) and \( V^c(\cdot) \), by solving the functional equation in 5 in the main text. See Appendix C.3 for more details about computing true firm value. The average percent change in firm value obtained from replacing a biased manager is then:

\[
E[\Delta V] \% = 100 \cdot \int_{\mathbb{Z} \times \mathbb{N}} \left[ \frac{V^c(z,n)}{V(z,n)} - 1 \right] \Phi(z,n).
\]

The consumption-equivalent difference in welfare between my baseline economy with consumption \( C \) and aggregate labor \( N \) and a counterfactual economy with \( C^c \) and \( N^c \), both in their long-run stationary general equilibrium is \( 100 \times \xi \), where \( \xi \) satisfies:

\[
\sum_{t=0}^{\infty} \beta^t \left[ \frac{C(1+\xi)^{1-\gamma}}{1-\gamma} - \chi \frac{N^{1+\eta}}{1+\eta} \right] = \sum_{t=0}^{\infty} \beta^t \left[ \frac{C^c(1-\gamma)}{1-\gamma} - \chi \frac{N^c^{1+\eta}}{1+\eta} \right]
\]

which has a simple closed form solution:

\[
\xi = \left[ \frac{C^c(1-\gamma) - \chi (1+\eta) [N^c^{1+\eta} - N^{1+\eta}]}{C} \right]^{1-\gamma} - 1.
\]
B.4 Capital and Intermediate Goods in my Baseline Model

My baseline setup in Section 3 assumes sales are a function of just labor. By omitting capital, I’m implicitly assuming the firm has a fixed stock of physical and intangible capital and that changes in that capital stock are part of the firm’s profitability shock. Given capital moves relatively slowly and my model has a quarterly frequency this assumption seems fairly reasonable.

My sales function in Section 3 also abstract from intermediate goods that may be used in product. Implicitly, you could imagine that the firm consumes some of the final good in the economy as an intermediate in production. To the extent the underlying production function for gross output has the same Cobb-Douglas assumption I assume in my baseline setup, including intermediates that the firm optimizes statically, then you would get a value-added production function of the form I assume in Section 3.

B.5 Investment Model

B.5.1 Technology

As in Section 3, there is a continuum of firms with access to a decreasing returns to scale revenue production function using capital $k$, labor $n$ and a Hick-neutral shock $\hat{z}:

\hat{y}(\hat{z}_t, k_t, n_t) = \hat{A}\hat{z}_t k_t^\alpha n_t^\nu.

The constant $\hat{A}$ is a scaling factor.

The firm hires labor statically in a spot market and pays the equilibrium wage $w_t$. After making its optimal labor choice, the firm receives earnings or operating income (= revenue minus wage bill) that depends on the capital stock it had entering the period and the equilibrium wage:

$y(z_t, k_t; w_t) = A(w_t)z_t k_t^\alpha$

where $y(\cdot)$ now denotes earnings as opposed to revenue, $z_t = \hat{z}_t^{1/(1-\nu)}$ is a renormalization of the firm’s shock, and $\alpha = \hat{\alpha}/(1-\nu)$. The function $A(\cdot)$ is decreasing, so higher wages result in lower earnings for the same amount of capital.

The firm’s capital stock follows a standard law of motion, so that the amount of capital in place for quarter $t+1$ depends on the previous quarter’s capital less depreciation plus investment:

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

Investment is subject to adjustment costs, which I assume to have a two components: (1) smooth quadratic costs in the gross investment rate, and (2) partial irreversibility that means re-sold capital is sold at a discount. The total cost of obtaining capital $k_{t+1}$ next quarter starting from capital $k_t$ is then:

$AC(k_t, k_{t+1}) = \begin{bmatrix}
    k_{t+1} - (1-\delta)k_t \\
    -\lambda_1[k_{t+1} - k_t(1-\delta)] \cdot 1(k_{t+1} < k_t(1-\delta)) \\
    +\lambda_q k_t \left( \frac{k_{t+1} - (1-\delta)k_t}{k_t} \right)^2
  \end{bmatrix}$

The first term represents the cost of acquiring new capital, the second implies a loss of $\lambda_1 \in [0,1]$ for any capital that is re-sold, and $\lambda_q$ scales the firm’s quadratic adjustment costs. Following the consensus in the literature (e.g. see Cooper and Haltiwanger (2006), Bloom (2009), and Winberry (2015)) that capital adjustment typically involves both convex and non-convex costs, I include one type of each. As in the main, labor-based model from Section 3, the magnitude and form of adjustment costs matters for the quantitative implications of biases in my model.

The firm’s cash flow in period $t$ equals earnings (itself revenue minus labor costs) less capital adjustment costs.
costs:

\[ \pi(z_t, k_t, k_{t+1}; w_t) = y(z_t, k_t; w_t) - AC(k_t, k_{t+1}) \]

### B.5.2 Subjective and Objective Shock Processes

As before, shocks to the firm’s earnings follow a Gaussian autoregressive process in logs:

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

but the manager running the firm may have incorrect beliefs about the mean, persistence, and standard deviation of innovations to \( \log(z_t) \). She believes:

\[ \log(z_{t+1}) = \tilde{\mu} + \tilde{\rho} \log(z_t) + \tilde{\sigma} \varepsilon_{t+1}. \]

### B.5.3 Manager’s Decision Problem and True Firm Value

Also as in the baseline model from Section 3, I assume each manager running a firm in the economy is compensated with a share \( \theta \in (0, 1] \) of her firm’s equity and therefore aims to maximize the net present value of her firm’s cash flows (discounted at the equilibrium risk-free rate). This optimization requires the manager to forecast future shocks \( z \), which she does under her subjective beliefs. The manager’s recursive problem is therefore:

\[ \tilde{V}(z_t, k_t; w_t, r_{t+1}) = \max_{k_t > 0} \pi(z_t, k_t, k_{t+1}; w_t) + \frac{1}{1 + r_{t+1}} \tilde{\mathbb{E}}[\tilde{V}(z_{t+1}, k_{t+1}; w_{t+1}, r_{t+2})] \quad (10) \]

where \( \tilde{\mathbb{E}}[\cdot] \) denotes the manager’s expectations under her subjective beliefs.

Given a manager’s policy \( k_{t+1} = \kappa(z_t, k_t; w_t, r_{t+1}) \), the true net present value of the firm’s cash flows \( V(\cdot) \) (without a tilde) is:

\[ V(z_t, k_t; w_t, r_{t+1}) = \pi(z_t, k_t, \kappa(z_t, k_t); w_t) + \frac{1}{1 + r_{t+1}} \mathbb{E}[V(z_{t+1}, \kappa(z_t, k_t); w_{t+1}; r_{t+2})] \]

where \( \mathbb{E}[\cdot] \) takes expectations according to the objective stochastic process for \( z_{t+1} \).

### B.5.4 Household and Equilibrium

Again, there is an aggregate household that consumes, supplies labor, and owns the remaining \((1 - \theta)\) equity in the firms in the economy. The household’s problem is identical to that of Section 3.5.

A stationary equilibrium in this specification of the model is then a set of prices \( \{w, r\} \), consumption, labor supply and saving choices by the household \( C, N^S, B \), subjective firm valuations \( \tilde{V}(z_t, k_t; w, r) \) made by managers, and a stationary distribution \( \phi : Z \times \mathcal{N} \to [0, 1] \) such that:

1. \( \tilde{V}(z_t, k_t; w, r) \) solves each managers’ problem in (10).

2. The household optimally chooses steady-state consumption \( C \), labor supply \( N^S \), and savings \( B = 0 \) (in zero-net-supply by assumption).

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

\[ \phi(z', k') = \int_{Z \times K} \phi(z, k) \cdot Pr(z' | z) \cdot 1(k' = \kappa(z, k; w, r)) dz dk \]
4. The labor market clears:
\[
N^S = N^D = \int_{z,k} n(z,k;w)\phi(z,k)dzdk
\]

C Simulation Appendix

C.1 Model Solution Details

Here I provide some additional details regarding the algorithm I use to solve for managers’ dynamic hiring problem in equation 4 of the main text. I solve for managers’ value and policy functions over a discretized \((z,n)\) state space employing policy function iteration. I choose grids of size \((z,n) = (21,100)\) since the managers’ dynamic program is standard and, by contemporary standards, not computationally intensive with only two state variables. As is standard for numerical dynamic programming I make my grid for possible labor choices \(n\) linear in log-space and make the end-points of the grid far out enough so that under the stationary distribution of the estimated model \(\phi(z,n)\) there is near zero probability of ending up in the highest and lowest grid points, i.e. so \(\max_z\{\phi(z,n_1),\phi(z,n_{100})\} < 10^{-5}\).

C.1.1 Discretizing the subjective and objective driving processes

I approximate both the objective and subjective stochastic processes for \(\log(z_t)\) on a single set of grid points using the algorithm of Tauchen (1986). My choice of 21 grid points for \(\log(z)\) is dense enough to achieve an accurate approximation of the conditional first and second moments of both the subjective and objective AR(1) processes on the same grid. Representing the two stochastic processes on the same discrete grid is computationally convenient and seems a reasonable choice so that managers are only wrong about the probability of a given event happening, but they are correct about the set of event that may potentially happen. In practice, I pick the set of potential grid points to be symmetric around zero (given both the true and subjective stochastic processes are approximately mean zero in the model). For any given set of \(\sigma, \tilde{\sigma}, \rho,\) and \(\tilde{\rho}\), the highest and lowest grid points for \(\log(z_t)\) are at
\[
\pm 2.575 \times \sqrt{\frac{\hat{\sigma}^2}{1-\hat{\rho}^2}}\text{ where } \hat{\sigma} = \max\{\sigma, \tilde{\sigma}\} \text{ and } \hat{\rho} = \max\{\rho, \tilde{\rho}\} \text{ so that the grid covers 99 percent of the support of a Gaussian AR(1) process with mean zero and the largest unconditional standard deviation possible given the parameters fed into the model.}
\]

C.1.2 Computing managers’ optimal policies and subjective firm valuations

Given some value of the stationary equilibrium wage \(w\), 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 via policy function iteration (i.e. value function iteration aided by Howard’s improvement algorithm). The only noteworthy detail for this procedure is 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 (subjective) value.

Starting with a guess for the managers’ subjective valuation of the firm \(\tilde{V}_0(z_t, n_t; w, r)\) I solve for the policy \(n_{t+1} = \kappa_0(z_t, n_t)\) that maximizes the RHS of the functional equation in 4 taking as given my guess for \(\tilde{V}(\cdot)\) and prices \(w\) and \(r\):
\[
\kappa_0(z_t, n_t) = \arg\max_{n_{t+1}} \pi(z_t, n_t, n_{t+1}; w) + \frac{1}{1+r} \tilde{E}[\tilde{V}_0(z_{t+1}, n_{t+1}; w, r)].
\]

Again, note here that the \(\tilde{E}[\cdot]\) operator takes expectations with respect to the managers’ subjective distribution for future idiosyncratic shocks.

Then I implement Howard’s improvement algorithm by first applying the Bellman operator that imple-
ments the policy \( \kappa_0(\cdot) \) for a fixed number \( T \) of periods. So for \( \tau = 1, 2, \ldots, T \):

\[
\hat{V}_\tau(z_t, n_t; w, r) = \pi(z_t, n_t, \kappa(z_t, n_t); w, r) + \frac{1}{1 + r} \mathbb{E}[V_{\tau-1}(z_{t+1}, n_{t+1}; w, r)]
\]  

(12)

and finally find a new guess for the optimal policy function \( \kappa_1(\cdot) \) by applying the maximization in 11 using guess \( \hat{V}_\tau(\cdot) \) as the continuation value. Then if the distance between the previous and current guesses of the policy function is under some pre-specified tolerance I have found the firm’s optimal policy, that is if:

\[
\max_{z, n} \| \kappa_1(z, n) - \kappa_0(z, n) \| < \varepsilon.
\]

In practice I pick \( \varepsilon = 10^{-20} \) and \( T = 300 \). Then it is straightforward to iterate again on the solution to the optimal policy to obtain the ultimate guess for the managers’ subjective valuation of the firm \( \hat{V}(\cdot) \) by applying the procedure in equation 12.

If the maximum distance exceeds \( \varepsilon \) I instead treat \( \kappa_1(\cdot) \) as a new guess of the policy function and re-apply Howard’s improvement algorithm in 12 to obtain a new guess for the policy function.

### C.1.3 Computing the stationary distribution of firms across the state space

After solving for managers’ policy function \( \kappa(z, n) \) I compute the stationary distribution of firms across the discretized state space \( \phi(z, n) \) numerically. Specifically, I exploit the Markovian structure of the model and employ non-stochastic simulation based on Young (2010).

To start, I make a guess that the stationary distribution is uniform across the discrete grid of states \((z, n)\), calling this initial guess \( \phi_0(z, n) \). Then, I obtain a new guess \( \phi_1(z, n) \) by moving the mass at each point in the state space forward in time according the dynamics of the model. This involves distributing a fraction of the mass currently at point \((z_j, n_k)\) to point \((z_p, \kappa(z_j, n_k))\) according to the objective transition probability \( Pr(z_{t+1} = z_p | z_t = z_n) \). Note that this procedure acknowledges that labor \( n \) moves endogenously under managers’ potentially-biased policy function but productivity moves according to its true stochastic process from equation 1.

After moving all of the mass forward I have obtained \( \phi_1(z, n) \). I then compute the maximum distance between this new guess and the previous one, 

\[
d = \max_{z, n} \| \phi_1(z, n) - \phi_0(z, n) \|
\]

If \( d \) is under a pre-specified tolerance I deem \( \phi_1(z, k) \) to be the stationary distribution \( \phi(z, k) \). Otherwise, I repeat the procedure iteratively until the distance between \( \phi_{\tau+1}(z, k) \) and \( \phi_{\tau}(z, k) \) is less than the tolerance.

### C.1.4 Computing labor market equilibrium

Given any guess for the wage \( w \) I can compute managers’ optimal policies \( \kappa(z, n) \) and the stationary distribution of firms \( \phi(z, n) \). Using the stationary distribution \( \phi(\cdot; w) \) I can then test whether the labor market is in equilibrium. First, I compute the household’s consumption \( C = w N^D + \Pi \), where \( N^D = \int_{z \times N} n \cdot \phi(z, n; w) dz dn \) is aggregate labor demand and \( \Pi \) is the household’s total capital income (see equation 6) under the current guess for the manager’s policies and the wage. 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. I thus obtain excess labor demand \( N^D - N^S \), which equals zero in equilibrium.

To compute the equilibrium of the economy I therefore write a function that computes the economy’s excess labor demand given some wage, namely by solving for managers’ optimization problem, for the stationary distribution and then labor demand and supply given the guess for the wage. I employ a standard nonlinear one-dimensional solver in Matlab to find a wage \( w \) for which excess labor demand is close to zero.
C.1.5 Computing moments for the population of firms in the economy

Given I compute the equilibrium stationary distribution of firms $\phi(z, n)$ numerically it is straightforward to use this object to compute population moments for the firms in the model. This procedure avoids drawing random numbers and thus introducing any simulation error.

For illustration, consider any outcome $X(z, n)$ that is a function of the state space in the model. The mean value of $X(z, n)$ is then $E[X(z, n)] = \sum_{z,n} X(z, n) \cdot \phi(z, n)$ where $E[\cdot]$ takes the expectation with respect to the stationary distribution of firms in the model’s equilibrium. For moments of dynamic variables, like the firms’ sales growth that depend say on a firm’s shock next period $z_{t+1}$ in addition to the current state $(z_t, n_t)$ I use the dynamic distribution $\hat{\phi}(z, n, z') = \phi(z, n) \cdot Pr(z_{t+1} = z' | z_t = z)$ and again computes moments using these weights to average across potential values of the random variable.

C.2 Computing Managers’ Beliefs About Sales Growth Between Quarters $t$ and $t + 4$

Relative to the typical dynamic model of firms in heterogeneous-agent macro and corporate finance, my baseline model from Section 3 is actually pretty simple and computationally tractable to solve. Given some parameters, solving for equilibrium typically takes about 10 to 15 seconds on my quad-core 3.6 GHz 2017 iMac with 32GB of RAM.

What is more computationally intensive is obtaining managers’ beliefs about sales growth between quarter $t$ and $t + 4$, which are necessary for obtaining moments in the model about managers’ forecast errors that I use to discipline my estimates of managers’ subjective stochastic process, namely $\{\mu, \sigma, \rho\}$. Specifically, sales in period $t + 4$ are a function of the firm’s idiosyncratic shock and the firm’s labor force in period $t + 4$:

$$\hat{y}_{t+4} = z_{t+4}n_{t+4}^\alpha.$$

From the standpoint of quarter $t$ and the firm’s current state $(z_t, n_t)$, this object is a random variable depending on all possible paths of shocks between $t$ and $t + 4$, $\zeta = \{z_{t+1}, z_{t+2}, z_{t+3}, z_{t+4}\}$, particularly because

$$n_{t+4} = \kappa(z_{t+3}, n_{t+3})$$
$$= \kappa(z_{t+3}, \kappa(z_{t+2}, n_{t+2}))$$
$$= \kappa(z_{t+3}, \kappa(z_{t+2}, \kappa(z_{t+1}, n_{t+1}))))$$
$$= \kappa(z_{t+3}, \kappa(z_{t+2}, \kappa(z_{t+1}, \kappa(z_t, n_t))))).$$

So conditional on $(z_t, n_t)$ $\hat{y}_{t+4}$ is a four-dimensional object that occurs with a given probability depending on a possible path of shocks $Pr(\zeta|z_t)$. To compute a managers’ forecast for future sales growth as well as an unbiased forecast thus involves computing two separate expectations with respect to two distinct four-dimensional discrete probability mass functions (depending on whether we forecast with the objective or subjective stochastic process for shocks to $z$). Since my grid for potential $z$-shock values has 21 points, computing a forecast for sales growth between $t$ and $t + 4$ for a given point in the state space $(z_t, n_t)$ involves a summation with $21^4 = 194,481$ terms.

In order to keep memory requirements tractable, I thus apply the law iterated expectations liberally to compute forecast error moments in the model. To begin, I store the conditional subjective and objective expectation for sales growth between $t$ and $t + 4$

$$E[\Delta y_{t,t+4}(z_t, n_t)] = \sum_\zeta Pr(\zeta | z_t) \Delta y_{t,t+4}(z_t, n_t, \zeta)$$
$$E[\Delta y_{t,t+4}(z_t, n_t)] = \sum_\zeta Pr(\zeta | z_t) \Delta y_{t,t+4}(z_t, n_t, \zeta)$$
where $\hat{P}_r(\zeta|z)$ and $Pr(\zeta|z)$ denote the subjective and objective probability measures with respect to shocks that might occur between $t$ and $t+4$ conditional on $z_t = z$.

Then I obtain forecast error moments in the population of firms by averaging across firm’s stationary distribution $\phi(z, n)$. For example:

$$E[ForecastError_{t,t+4}] = E \left[ \hat{E}[\Delta y_{t+1}|z_t, s_t] - \Delta y_{t,t+4} \right]$$

$$= E \left[ \hat{E}[\Delta y_{t+1}(z, n)] - E[\Delta y_{t,t+4}(z, n)] \right]$$

$$= \sum_{z,n} \phi(z, n) \cdot \left[ \hat{E}[\Delta y_{t+1}(z, n)] - E[\Delta y_{t,t+4}(z, n)] \right]$$

where the $E[\cdot]$ operator takes expectations across the state space after conditioning on $(z, n)$ rather than across future shocks. Recall that this moment is particularly useful for pinning down the extent of managerial optimism about shocks to $\log(z_t)$, namely $\bar{\mu} - \mu$.

I use a similar procedure to obtain managers’ the subjective mean absolute deviations from their forecast:

$$\bar{MAD}(z_t, n_t) = \hat{E} \left[ \|\Delta y_{t+1}(z_t, n_t) - \hat{E}[\Delta y_{t+1}(z_t, n_t)]\| \right]$$

$$= \sum_{z,n} \hat{P}_r(\zeta|z_t) \cdot \left[ \|\Delta y_{t+1}(z_t, n_t, \zeta) - \hat{E}[\Delta y_{t+1}(z_t, n_t)]\| \right]$$

and the objective absolute forecast error conditional on $(z_t, n_t)$:

$$E[AbsForecastError_{t,t+4}(z_t, n_t)] = E \left[ \|\Delta y_{t+1}(z_t, n_t) - \hat{E}[\Delta y_{t+1}]\| \right]$$

$$= \sum_{\zeta} Pr(\zeta|z_t) \cdot \left[ \|\Delta y_{t+1}(z_t, n_t, \zeta) - \hat{E}[\Delta y_{t+1}(z_t, n_t)]\| \right]$$

. Then applying the law of iterated expectations again I ultimately use to compute the mean excess absolute forecast error in the model:

$$E[ExcessAbsForecastError_{t,t+4}] = E \left[ E[AbsForecastError_{t,t+4}(z_t, n_t)] - \bar{MAD}(z_t, n_t) \right]$$

$$= \sum_{z,n} \phi(z, n) \cdot \left[ E[AbsForecastError_{t,t+4}(z, n)] - \bar{MAD}(z, n) \right]$$

Recall that this moment is my crucial target for disciplining the relative magnitude of managers’ subjective uncertainty about shocks to $\log(z_t)$, $\bar{\sigma}$, relative to the true volatility of those shocks $\sigma$.

I also apply the law of iterated expectations in a similar fashion to compute the final forecast error moment I require for estimation and which helps pin down managers’ perception of shock persistence $\tilde{\rho}$ relative to the true persistence $\rho$. Namely I compute the covariance between sales growth between $t-1$ and $t$ and the forecast error for sales growth between $t$ and $t + 4$:

$$Cov(\Delta y_t, ForecastError_{t,t+4}) = E \left[ \frac{(\Delta y_t(z_t, n_t) - E[\Delta y_{t+1}(z_t, n_t)]) \cdot \hat{E}[ForecastError_{t,t+4}(z_t, n_t)] - E[ForecastError_{t,t+4}(z_t, n_t)]}{\hat{E}[ForecastError_{t,t+4}(z_t, n_t)]} \right]. \tag{13}$$

Although seemingly straightforward, computing this moment is slightly more complicated as $\Delta y_t$ is really a function of $(z_{t-1}, n_{t-1}, z_t)$ so I need to take the expectation $E[\cdot]$ using the distribution $\hat{\phi}(z, n, z') = \phi(z, n) \cdot Pr(z_{t+1} = z'| z_t = z)$. Applying the law of iterated expectations here crucially relies on $\Delta y_t$ being deterministic conditional on $(z_{t-1}, n_{t-1}, z_t)$ which greatly simplifies the number of computations required as we can then separately compute the two terms inside the outermost brackets in equation 13.
C.3 Computing True Firm Value

I compute true firm values by solving the functional equation in \(5\) numerically using standard dynamic programming results (e.g. see Stokey et al., 1989). Note that the following operator is a contraction for any function \(f(\cdot)\) whose domain is the state space of the economy:

\[
T(f(z_t, n_t)) = \pi(z_t, n_t, \kappa(z_t, n_t); w) + E[f(z_{t+1}, \kappa(z_t, n_t))],
\]

where crucially \(E[\cdot]\) is the expectations operation with respect to the true stochastic process for \(z_t\), as given in \(1\) in the main text. Thus, starting from a guess \(V^0(\cdot)\) for \(V(\cdot)\) or \(V^c(\cdot)\), I update the guess by letting \(V^1(z_t, n_t) = T(V^0(z_t, n_t))\) and iterating until the sup norm between \(V^m(\cdot)\) and \(V^{m+1}\) is under a pre-specified tolerance. This is computationally inexpensive (and arguably trivial), yet it crucially helps me compare managers’ subjective valuations of their own firms \(\hat{V}(\cdot)\) against the true value \(V(\cdot)\) delivered by managers’ policies.

C.4 GMM Estimation Details

C.4.1 SBU variable definitions

Here I define the specific variables from the SBU that I employ in my structural estimation of the model. Note that although the SBU is a monthly survey in which panel members answer questions about sales and employment every other month, for conformity with my quarterly model I collapse my data to quarterly frequency. In particular, for each quarter I pick the last value reported within a given quarter. I measure all growth rates variables by taking the difference across periods and dividing that by the average, following the long tradition in the literature on business dynamics.

The variables I use in my estimation procedure are the following:

- Sales growth between quarters \(t - 1\) and \(t\): \(\Delta y_t = \frac{y_t - y_{t-1}}{y_t + y_{t-1}}\)
- Sales growth between quarter \(t\) and \(t + 4\): \(\Delta y_{t+4} = \frac{y_{t+4} - y_{t}}{y_{t+4} + y_{t}}\)
- Net hiring in period \(t\): \(\Delta n_{t+1} = \frac{n_{t+1} - n_t}{n_{t+1} + n_t}\). Here I take the firm’s employment level in its last response in quarter \(t\) to be \(n_{t+1}\). This treatment is consistent with my one-period lag in between hiring and production in the model and captures real-world lags in recruiting, interviewing and training new employees.
- The firm’s forecast error between \(t\) and \(t + 4\): \(\text{ForecastError}_{t,t+4} = \hat{E}[\Delta y_{t+4}'] - \Delta y_{t+4}'\), with forecasts and realizations measured following the description in Appendix A.2.
- The firm’s excess absolute forecast error between \(t\) and \(t + 4\): \(\text{ExcessAbsForecastError}_{t,t+4} = \|\text{ForecastError}_{t,t+4}'\| - \text{MAD}[\Delta y_{t+4}']\), that is the difference between the manager’s realized absolute forecast error and her ex-ante subjective mean absolute deviation: where I again compute the latter according to the description in Appendix A.2.

C.4.2 Computing target moments and the weighting matrix

My estimation targets a vector of eight moments \(m(X)\) described in Section 4.2 of the main text. Table C.1 below reproduces their values, their standard errors and also shows how many firm-quarter observations I use to compute each moment. Since the SBU is a relatively small dataset and I need firms to keep responding to the survey for a year in order to record a forecast error observation, I compute each moment using all firm-quarter observations for which I observe the necessary variables. This means my moments are ultimately not based on the same set of observations, which I take into account when I compute the variance-covariance matrix of moments that I use to construct the moment-weighting matrix of my econometric objective function.
Two of my target moments are means, namely the mean forecast error and mean excess absolute forecast error. I compute this as simple arithmetic means. However, the other six moments are covariances. Since variability of sales, employment, and forecast errors in the data may reflect persistent differences across firms and aggregate shocks, I compute my target variance and covariance moments based only on within-firm variation after controlling for aggregate shocks. That is, I first regress each of the variables that go into one of my variance or covariance targets on a full set of firm and date fixed effects and then compute the target moment on the residuals from those regressions.42

As I described in Section 4.2 of the main text, I use the GMM optimal weighting matrix in my econometric minimization procedure, which for my purposes consists of the inverse of the firm-clustered variance-covariance matrix of targeted moments \( \Omega = E[m(X)m(X)'] \). This treatment of heteroskedasticity accounts for within-firm correlation across observations. I estimate this variance-covariance matrix using the influence function approach from Erickson and Whited (2002). Table C.2 shows my estimate \( \hat{\Omega} \). I justify this choice of weighting matrix given the good small sample performance shown for similar simulation-based estimators in Bazdresch et al. (2017).

C.4.3 Minimizing the econometric objective and computing standard errors

My structural estimation procedure aims to find the vector of parameters \( \theta \) that minimizes the weighted distance between model and data moments, as described briefly in the main text:

\[
\min_{\theta} [m(\theta) - m(X)]' W [m(\theta) - m(X)] .
\]

Recall that I set \( W = \hat{\Omega}^{-1} \), the inverse of the covariance matrix of moments. I conduct this minimization using a standard simulated annealing algorithm that uses randomization to find the minimum of the econometric objective.

Following standard results, as sample sizes go to infinity, the vector of estimated parameters \( \hat{\theta} \) is asymptotically normally distributed with variance \( \Sigma \):

\[
\sqrt{n}(\hat{\theta} - \theta) \to \mathcal{N}(0, \Sigma)
\]

where

\[
\Sigma = \left[ \frac{\partial m(\theta)}{\partial \theta'} W \frac{\partial m(\theta)}{\partial \theta} \right]^{-1} \frac{\partial m(\theta)}{\partial \theta'} W \Omega W \frac{\partial m(\theta)}{\partial \theta} \left[ \frac{\partial m(\theta)}{\partial \theta'} W \frac{\partial m(\theta)}{\partial \theta} \right]^{-1}.
\]

In practice, I compute an estimate of the asymptotic variance of by plugging in \( \hat{\Omega} \) in place of \( \Omega \) and obtaining numerical derivatives for \( \frac{\partial m(\theta)}{\partial \theta} \) evaluated at the estimated \( \hat{\theta} \). I compute the latter using two-sided derivates with step size equal to 2 percent of each element \( \hat{\theta} \) in my baseline calculation:

\[
\hat{\Sigma} = \left[ \frac{\partial m(\hat{\theta})}{\partial \theta'} W \frac{\partial m(\hat{\theta})}{\partial \theta} \right]^{-1} \frac{\partial m(\hat{\theta})}{\partial \theta'} W M \hat{\Omega} W \frac{\partial m(\hat{\theta})}{\partial \theta} \left[ \frac{\partial m(\hat{\theta})}{\partial \theta'} W \frac{\partial m(\hat{\theta})}{\partial \theta} \right]^{-1}.
\]

The matrix \( M = (n_1^{-1}, ..., n_8^{-1})' \cdot (n_1^{-1}, ..., n_8^{-1}) \) where \( n_i \) is the number of observations I use to compute moment \( i = 1, ..., 8 \) in the SBU data. The square root of the diagonal of \( \hat{\Sigma} \) contains the standard errors of the elements in \( \hat{\theta} \).

\footnote{For a couple of moments, specifically those relating sales growth in \( t - 1 \) and \( t \) to forecast errors and sales growth between \( t \) and \( t + 4 \), removing variation due to firm and date fixed effects may introduce dynamic panel complications that could result in biased estimates of those covariances. However, none of these affected moments change by economically significant amounts after the residualizing, so I am not too worried of potential biases due to this dynamic panel structure.}
C.4.4 Sensitivity of estimated parameters to moments

Figure C.1 shows the sensitivity of estimated parameters to moments, which I compute based on Andrews, Gentzkow, and Shapiro (2017). We can see that although moments in the right hand and left hand columns are sensitive to similar sets of moments qualitatively, there are quantitatively significant differences in the sensitivity of moments to parameters across columns. For example, the decreasing returns parameter $\alpha$ and the adjustment costs parameter $\lambda$ are both positively sensitive to the variance of net hiring $\text{Var}(\Delta n_{t+1})$ and the variance of sales growth $\text{Var}(\Delta y_t)$, but $\alpha$ is relatively more sensitive to the second and $\lambda$ the first.

One important feature of Figure C.1 is that it clearly shows how both technological parameters and managers’ subjective beliefs are sensitive to forecast error moments as well as moments concerning sales and employment dynamics with no beliefs. So forecast error moments are also helping me identify the technology parameters and vice versa for moments about firms’ sales and employment dynamics helping me identify technological parameters. Going back to the example with the decreasing returns and adjustment costs parameters $\alpha$ and $\lambda$, both are highly sensitive to the "overextrapolation" moment, the covariance between recent sales growth and the forecast error looking four quarters ahead $\text{Cov}(\text{FE}_{t+4}, \Delta y_t)$, although this sensitivity is stronger for $\alpha$ than $\lambda$.

C.5 The Role of General Equilibrium Price Effects

Table C.3 explores how changes in the equilibrium wage – the key price in this economy – fit into the headline results about welfare and reallocation from Tables 9 and 10 in the main text. Looking at the top row of Table C.3, it is now clear that an economy without overconfidence ($\bar{\sigma} = \sigma$ only) has higher wages and total labor input in equilibrium, which increase the representative consumer’s labor income and – especially – consumption. We see the opposite general equilibrium effects looking at the economy in the second row, which has overconfident managers that don’t overextrapolate ($\bar{\rho} = \rho$ only). Consumer welfare gains are large here despite lower wages, a modest increase in consumption, and higher profits. In the bottom two rows we that equilibrium wages and the household’s labor and consumption choices differ significantly despite the two economies looking similar in terms of reallocation and gains in consumer welfare in Table 10.

Another interesting result from Table C.3 is that total profits, and therefore managers’ total consumption, declines in three of the four counterfactuals, including the case in which managers are fully unbiased ($\bar{\rho} = \rho$, $\bar{\sigma} = \sigma$, and $\bar{\mu} = \mu$). In all cases the change in profits goes hand in hand with a change in the wage and therefore firms’ operating costs. This result might seem unsettling to the extent that the removing biases does not necessary result in a Pareto improvement. That said, the 4.4 percent reduction in total profits amounts to a reduction in total managerial consumption equal to 0.11 percent of GDP. By comparison, the extra 0.99 consumption-equivalent the household accrues amounts to about 0.96 percent of GDP, almost nine times as much.

The final column of Table C.3 shows the difference in aggregate output (= total revenue less spending on adjustment costs) relative to the baseline biased economy in each of the four counterfactual economies. Although output increases in all cases because my counterfactual economies all reduce the amount of unnecessary spending on adjustment costs, the relative ranking intuitively corresponds to changes in the total amount of labor employed, displayed in the second column. The top row ($\bar{\sigma} = \sigma$) sees the second largest increase in output despite having the smallest increase in welfare. These results justify my focus on the impact of biases for consumer welfare rather than GDP. Note this is in contrast with much of the misallocation literature, which considers models in which GDP of TFP are equal to welfare (e.g., Hsieh and Klenow, 2009, explicitly say TFP and welfare are one and the same in their model).

C.6 Managerial Biases Interact with Other Public Policies

In this section, I show that the cost of managerial overconfidence and overextrapolation is higher when consumers and firms in my model economy are subject to distortionary payroll and labor income taxes. Similarly, I show that the welfare costs of distortionary taxation are higher in an economy with biased managers, relative to an economy in which managers have rational expectations.

I modify the representative consumer’s budget constraint by introducing labor income taxes $\tau_n$ and rebating the tax revenue using a lump sum transfer $T_t$, while also taxing firms’ wage bill by $\tau_p$. The
following equations show firm’s cash flow, the household’s budget constraint, and the government’s budget balance condition in this setup:

\[
\begin{align*}
\pi(z_t, n_t, n_{t+1}; w_t) &= z_t n_t^\alpha - (1 + \tau_p) w_t n_t - AC(n_t, n_{t+1}) \\
C_t + B_{t+1} &= (1 - \tau_n) w_t N_t + (1 + r_t) B_t + \Pi_t + T_t \\
T_t &= (\tau_n + \tau_p) w_t N_t.
\end{align*}
\]

In Figure C.2 I show how the results from my main macro counterfactual experiment depend on the combination of the labor income and payroll taxes in place in the economy. Namely, each point in the figure compares consumer welfare in an economy with rational managers and taxes relative to an economy in which managers are overconfident and overextrapolate to the extent that I estimate in Section 4.2 of the main text. For each point in the figure, I re-calibrate the household’s disutility of labor \(\chi\) targeting a steady-state quantity of labor \(N\) equal to 1/3 in the equilibrium with biased managers and taxes. The broad lesson from this exercise is that larger distortionary taxes of either kind increase the cost of having biased managers.

Figure C.3 shows the results from a related exercise, looking at how the welfare costs of distortionary income taxes depend on whether managers are biased. Each point in the figure takes an economy with labor income taxes \(\tau_n\) according to its position along the horizontal axis and plots on the vertical axis how much higher consumer welfare would be in the stationary equilibrium with no taxes, \(\tau_n = 0\). As with Figure C.2, I re-calibrate the household’s disutility of labor \(\chi\) targeting \(N = 1/3\) in the "initial" equilibrium with taxes. The two lines in the figure correspond to the welfare costs of the distortionary tax if the economy has biased managers versus not, holding the rest of the parameters fixed at their estimated values. With biased managers, taxes are more costly in terms of consumer welfare.

The intuition for why taxes amplify the cost of managerial biases in Figure C.2 and why managerial biases amplify the costs of distortionary taxes in Figure C.3 is related to the envelope theorem. Namely, when the representative consumer’s consumption and leisure are close to their (undistorted) optimal levels, changing other parameters of her utility maximization problem has second order welfare effects that are relatively small. When consumption and leisure are distorted, the second order effects from changing further distortions like taxes or managerial biases become larger. I view these results as further motivation for why policy-makers should care about pervasive sources of inefficiency like managerial overconfidence and overextrapolation, even if it may be difficult to design policies that change the nature of managerial biases themselves.

C.7 Investment Model Solution and Estimation

C.7.1 Solution

I solve the model of investment dynamics under possibly incorrect subjective beliefs using the same techniques I outline in Section 4 and earlier portions of Appendix C for the baseline specification. Solving this version of the model with static labor choices is actually simpler because the equilibrium wage does not enter into managers’ dynamic investment decision. So I impose the normalization that the function scaling firm revenues \(A(w) = 1\) under the equilibrium wage \(w\). This means I do not need to solve for the economy’s equilibrium wage to compute the stationary distribution of firms across the state space, \(\phi(z, k)\) and hence to compute any moments from that distribution I might need for estimation.

C.7.2 Estimation

As with the baseline model, I pick a set of parameters – mainly concerning the household– and estimate the main parameters that govern hiring and firing decisions by minimizing the weighted distance between a set of model and data moments. Table C.4 shows the externally-calibrated parameters for the labor-based model specification. I estimate seven parameters, namely the earnings elasticity of capital, \(\alpha\), the magnitude of partial irreversibility \(\lambda_i\) and quadratic adjustment costs \(\lambda_{q}\), the subjective and objective persistences of the firm-level shock process \(\rho\) and \(\tilde{\rho}\), as well as the subjective and objective standard deviation of shock
innovations, $\sigma$ and $\delta$. Finally, I estimate the subjective mean of firm level shocks, $\hat{\mu}$ (having normalized the true mean $\mu$ to zero).

I estimate the model of investment dynamics by matching the three forecast error moments from the SBU as well as moments that capture the dynamics of investment and output in Compustat data. I use data from two different sources because I do not have reliable data on capital expenditures and capital stocks in the SBU. To mitigate concerns that my two data sources are not conformable, I restrict attention in this baseline estimation to a sample of Compustat firms with less than 7500 employees, the 99th percentile for employment in the SBU. However, I acknowledge that this may not fully address concerns that a sample of public firms may not be representative of my SBU sample or of the US economy (see for example Davis et al., 2007). Since my estimation targets two disjoint sets of moments I choose as weighting matrix the unique elements of the covariance matrix of net investment, the log-sales-to-capital ratio, and sales growth, compute my moments on the mean-zero residuals from those regressions. Specifically, I consider the six

$$
\begin{align*}
\tilde{\sigma} & = \frac{\tilde{\mu} - \mu}{\tilde{\sigma}} \\
\rho & = \frac{\tilde{\rho}}{\tilde{\sigma}} \\
\tilde{\rho} & = \frac{\rho}{\tilde{\sigma}}
\end{align*}
$$

I estimate the model of investment dynamics by matching the three forecast error moments from the baseline estimates of Section 4.2 for the baseline labor dynamics model. Managers underestimate the mean shock innovation by $\hat{\mu} = 0.0005$ (relative to $\mu = 0$), which amounts to about 2 basis points of the true standard deviation of those innovations. However they are severely overconfident, with $\delta = 0.110$, a bit more than half the true standard deviation of innovations, $\sigma = 0.202$. Additionally, they believe the persistence of shocks to be $\hat{\rho} = 0.977$, significantly larger than $\rho = 0.859$. This discrepancy leads managers in the model to believe shocks have a half life of about 30 quarters when the true half life is only about 4.5. Thus, managers appear to overextrapolate more severely in this exercise than they do under the baseline results from Section 4.2. I obtain moments about the joint within-firm dynamics of output and capital from Compustat Quarterly covering all years between 1990 and 2017. I choose this long sample in order to minimize issues related to estimating moments on a short panel. Since the firms in my SBU sample are much smaller than my Compustat sample, so SBU moments would receive little weight in the econometric minimization procedure if I did not adjust.

Tables C.5a and C.5b show my targeted data moments, their model counterparts, and my parameter estimates. Quantitatively, the parameters of the subjective and objective stochastic process are respectively similar to the results from the baseline estimates of Section 4.2. I choose this weight on Compustat and SBU moments. Adjusting the weight matrix is important in this case because the SBU sample is much smaller than my Compustat sample, so SBU moments would receive little weight in the econometric minimization procedure if I did not adjust.

I restrict attention to firms incorporated and headquartered in the United States, exclude financials and utilities (SIC 4900 & 6000-6999) as is standard in studies of investment, and drop firms with negative sales, net property, plant, and equipment, short term or long-term debt. Additionally, I drop all firm-quarters with employment over 7500 – the 99th percentile of employment in my SBU sample – to focus on firms that are similar in size to the firms in the SBU. Because my model is tailored toward capturing investment dynamics at firms making day-to-day decisions, I also exclude firms whose sales or net property, plant, and equipment change by a factor of three or more either upward or downward. I acknowledge that this procedure is a crude and simple way of choosing firms in Compustat that are not too different from my SBU sample, given the constraint that I do not have high-quality investment data in the SBU.

The variables from compustat that I consider are net investment ($= \text{the growth rate of net property, plant, and equipment between quarter } t-1 \text{ and } t$), the log-capital-output ratio ($= \log(\text{sales}/\text{lagged net property, plant, and equipment})$) and sales growth between quarter $t$ and $t+1$. Following the usual convention, I assume that the amount of capital available for production in quarter $t$ is the end-of-period amount reported in quarter $t-1$. In order to isolate within-firm variation and exclude cross-firm heterogeneity that is not a part of my model, I regress each of these variables on a full set of firm and date fixed effects and then compute my moments on the mean-zero residuals from those regressions. Specifically, I consider the six unique elements of the covariance matrix of net investment, the log-sales-to-capital ratio, and sales growth, as well as the autocorrelation of the log-sales-to-capital ratio. I compute these moments and their variance-covariance matrix using simple GMM and then use these estimates as an input into my structural estimation procedure.

\footnote{I compute the autocorrelation of the log-sales-to-capital ratio as the OLS coefficient from a regression of the residualized log-sales-to-capital ratio on its lag. It is well known that this sort of dynamic panel regression may be inconsistent when estimated via OLS in this way, especially for highly correlated series, so I also compute the autocorrelation using the consistent estimator proposed in Han and Phillips (2010). Both estimators give essentially the same autocorrelation of 0.8, so I proceed with the OLS-based moment.}
Table C.1: Target Moments For Estimation

<table>
<thead>
<tr>
<th>Moment</th>
<th>Value</th>
<th>Standard Error</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean(Forecast Error)</td>
<td>-0.013</td>
<td>0.008</td>
<td>1,256</td>
</tr>
<tr>
<td>Mean(Excess Absolute Forecast Error)</td>
<td>0.143</td>
<td>0.007</td>
<td>1,256</td>
</tr>
<tr>
<td>Cov(Forecast Error_{t+4}, Sales Growth_{t-1,t})</td>
<td>0.011</td>
<td>0.003</td>
<td>680</td>
</tr>
<tr>
<td>Var(Sales Growth)</td>
<td>0.060</td>
<td>0.004</td>
<td>2,195</td>
</tr>
<tr>
<td>Var(Net Hiring)</td>
<td>0.019</td>
<td>0.003</td>
<td>2,313</td>
</tr>
<tr>
<td>Cov(Net Hiring, Sales Growth)</td>
<td>0.003</td>
<td>0.001</td>
<td>1,858</td>
</tr>
<tr>
<td>Cov(Sales Growth_{t+4}, Sales Growth_{t-1,t})</td>
<td>-0.012</td>
<td>0.003</td>
<td>691</td>
</tr>
<tr>
<td>Cov(Sales Growth_{t+4}, Net Hiring_{t+1})</td>
<td>-0.002</td>
<td>0.001</td>
<td>686</td>
</tr>
</tbody>
</table>

Notes: This table shows the values of the eight target moments I use in my baseline estimation of the model in Sections 3 and 4.2 of the main text, reproduced from Table 6a. Here I additionally report the standard errors of each of the target moments and the number of firm-quarter observations from the SBU I use to compute each moment.

Figure C.1: Sensitivity of Estimated Parameters to Moments

Notes: This figure shows Andrews-Gentzkow-Shapiro (2017) sensitivities for each of the parameters in the baseline model with respect to targeted moments. Each bar corresponds to the coefficient from a theoretical local regression of parameters on moments, with units expressed in terms of standard deviations.
### Table C.2: Variance-Covariance Matrix of Moments

<table>
<thead>
<tr>
<th>Moment</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Mean(Forecast Error)</td>
<td>6.16E-05</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2) Mean(Excess Absolute Forecast Error)</td>
<td>-5.78E-06</td>
<td>4.45E-05</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3) Cov(Forecast Error\textsubscript{t,t+4}, Sales Growth\textsubscript{t-1,t})</td>
<td>1.81E-06</td>
<td>3.93E-06</td>
<td>6.28E-06</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4) Var(Sales Growth)</td>
<td>6.67E-07</td>
<td>1.11E-05</td>
<td>1.28E-06</td>
<td>1.89E-05</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(5) Var(Net Hiring)</td>
<td>-6.06E-07</td>
<td>1.23E-06</td>
<td>1.75E-07</td>
<td>2.84E-06</td>
<td>6.01E-06</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(6) Cov(Net Hiring, Sales Growth)</td>
<td>6.53E-07</td>
<td>-3.98E-07</td>
<td>-5.80E-08</td>
<td>9.25E-07</td>
<td>1.04E-06</td>
<td>1.37E-06</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(7) Cov(Sales Growth\textsubscript{t,t+4}, Sales Growth\textsubscript{t-1,t})</td>
<td>-1.73E-06</td>
<td>-4.52E-06</td>
<td>-5.81E-06</td>
<td>-1.86E-06</td>
<td>-7.98E-08</td>
<td>3.19E-08</td>
<td>7.12E-06</td>
<td></td>
</tr>
<tr>
<td>(8) Cov(Sales Growth\textsubscript{t,t+4}, Net Hiring\textsubscript{t,t+1})</td>
<td>2.32E-07</td>
<td>8.47E-07</td>
<td>-6.25E-08</td>
<td>-3.14E-07</td>
<td>-6.37E-07</td>
<td>-3.84E-07</td>
<td>1.51E-07</td>
<td>1.36E-06</td>
</tr>
</tbody>
</table>

**Notes:** This table shows my estimate of the variance-covariance of the vector of moments targeted in estimation, namely those in Table C.1. I estimate this variance-covariance matrix using the influence function approach from Erickson and Whited (2002).
Table C.3: Impact of Individual Biases: GE Price Effects

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>Δ C. Welfare</th>
<th>ΔN %</th>
<th>Δw %</th>
<th>ΔΠ %</th>
<th>ΔC %</th>
<th>ΔY %</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \tilde{\sigma} = \sigma ) only</td>
<td>0.40</td>
<td>1.1</td>
<td>4.1</td>
<td>-3.7</td>
<td>0.9</td>
<td>0.8</td>
</tr>
<tr>
<td>( \tilde{\rho} = \rho ) only</td>
<td>0.68</td>
<td>-0.7</td>
<td>-0.6</td>
<td>2.0</td>
<td>0.3</td>
<td>0.4</td>
</tr>
<tr>
<td>( \tilde{\rho} = \rho ) and ( \tilde{\sigma} = \sigma )</td>
<td>0.91</td>
<td>0.4</td>
<td>4.7</td>
<td>-3.0</td>
<td>1.1</td>
<td>1.0</td>
</tr>
<tr>
<td>( \tilde{\rho} = \rho, \tilde{\sigma} = \sigma, ) and ( \tilde{\mu} = \mu )</td>
<td>0.99</td>
<td>1.4</td>
<td>6.1</td>
<td>-4.4</td>
<td>1.7</td>
<td>1.6</td>
</tr>
</tbody>
</table>

Notes: This table shows the difference in aggregate consumer welfare, labor, wages, total firm profits, consumption and GDP between an economy whose managers lack one or more of overconfidence (\( \tilde{\sigma} = \sigma \)), overextrapolation (\( \tilde{\rho} = \rho \)), or pessimism (\( \tilde{\mu} = \mu \)) and my baseline economy with biased managers. Each of the economies is at its stationary general equilibrium.

Figure C.2: Taxes Amplify Welfare Impact of Managerial Biases

Notes: This figure shows the welfare change of moving to an economy with rational managers as a function of the payroll and labor income taxes of the baseline economy. For each point in the figure, I re-calibrate the household’s disutility of labor so as to attain aggregate labor \( N = 1/3 \) in the baseline equilibrium with the combination of taxes in the figure.
Figure C.3: Managerial Biases Amplify Welfare Impact of Taxes

Notes: This figure shows the welfare change of removing labor income taxes, starting from an economy with tax $\tau_n$ and no payroll taxes ($\tau_p = 0$). Each line shows this welfare change depending on whether managers are biased or have rational expectations.
Table C.4: Externally-Calibrated Parameters: Investment Model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
<th>Target/Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta$</td>
<td>0.026</td>
<td>Quarterly depreciation</td>
<td>NIPA 10% annual</td>
</tr>
<tr>
<td>$\mu$</td>
<td>0</td>
<td>Mean $\log(z)$</td>
<td>Normalization</td>
</tr>
<tr>
<td>$\hat{\alpha}$</td>
<td>0.275</td>
<td>Revenue elasticity of capital</td>
<td>2/3 labor share in physical output</td>
</tr>
<tr>
<td>$\hat{\nu}$</td>
<td>0.551</td>
<td>Revenue elasticity of labor</td>
<td>2/3 labor share in physical output</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>2</td>
<td>Inverse EIS</td>
<td>Hall (2009)</td>
</tr>
<tr>
<td>$\eta$</td>
<td>2</td>
<td>Inverse Frisch Elasticity of Lab. Supply</td>
<td>Chetty et al. (2011)</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.96^{1/4}</td>
<td>Household Discount Factor</td>
<td>Annual Interest Rate of 4%</td>
</tr>
<tr>
<td>$\chi$</td>
<td>0.114</td>
<td>Disutility of work</td>
<td>Steady-state Labor $N^* = 1/3$</td>
</tr>
<tr>
<td>$\theta$</td>
<td>0.05</td>
<td>Managers’ share of equity</td>
<td>Nikolov and Whited (2014)</td>
</tr>
</tbody>
</table>

Note: I set the values for $\hat{\alpha}$ and $\hat{\nu}$, the coefficients on the revenue production function assuming a coefficient of 2/3 in physical output and returns to scale of 0.81 as implied by my estimate of the returns to scale for revenue $\alpha$ in Table C.5b.
Table C.5: Structural Estimation of Investment Model

(a) Data and Model Moments: Investment Model

<table>
<thead>
<tr>
<th>Moment</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean(Forecast Error)</td>
<td>-0.014</td>
<td>-0.014</td>
</tr>
<tr>
<td>Mean(Excess Absolute Forecast Error)</td>
<td>0.144</td>
<td>0.144</td>
</tr>
<tr>
<td>Cov(Forecast Error&lt;sub&gt;t,t+4&lt;/sub&gt;,Sales Growth&lt;sub&gt;t-1,t&lt;/sub&gt;)</td>
<td>0.011</td>
<td>0.012</td>
</tr>
<tr>
<td>Var(Net Investment)</td>
<td>0.020</td>
<td>0.010</td>
</tr>
<tr>
<td>Var(Sales Growth)</td>
<td>0.055</td>
<td>0.044</td>
</tr>
<tr>
<td>Cov(Sales Growth,Net Investment)</td>
<td>0.003</td>
<td>0.002</td>
</tr>
<tr>
<td>Cov(Sales Growth&lt;sub&gt;t,t+4&lt;/sub&gt;,Sales Growth&lt;sub&gt;t-1,t&lt;/sub&gt;)</td>
<td>-0.010</td>
<td>0.006</td>
</tr>
<tr>
<td>Cov(Sales Growth&lt;sub&gt;t,t+4&lt;/sub&gt;,Net Investment&lt;sub&gt;t&lt;/sub&gt;)</td>
<td>0.004</td>
<td>0.002</td>
</tr>
<tr>
<td>Autocorr(log(Sales/Lagged Capital))</td>
<td>0.803</td>
<td>0.733</td>
</tr>
</tbody>
</table>

(b) Estimated Parameters: Investment Model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Explanation</th>
<th>Estimate (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>α</td>
<td>Earnings curvature</td>
<td>0.596 (0.003)</td>
</tr>
<tr>
<td>λ&lt;sub&gt;q&lt;/sub&gt;</td>
<td>Quadratic adjustment cost</td>
<td>0.088 (0.003)</td>
</tr>
<tr>
<td>λ&lt;sub&gt;i&lt;/sub&gt;</td>
<td>&lt;i&gt;k&lt;/i&gt;-resale loss</td>
<td>0.091 (0.001)</td>
</tr>
<tr>
<td>ρ</td>
<td>True shock persistence</td>
<td>0.864 (0.0009)</td>
</tr>
<tr>
<td>̂ρ</td>
<td>Subjective shock persistence</td>
<td>0.960 (0.0009)</td>
</tr>
<tr>
<td>σ</td>
<td>True shock volatility</td>
<td>0.200 (0.0002)</td>
</tr>
<tr>
<td>̂σ</td>
<td>Subjective shock volatility</td>
<td>0.100 (0.0002)</td>
</tr>
<tr>
<td>̂μ</td>
<td>Subjective shock mean</td>
<td>-0.001 (0.000007)</td>
</tr>
</tbody>
</table>

Notes: This table shows the results from my estimation of the investment model from Appendix B.5, with the estimation described in Appendix C.7.2. Sub-table C.5a (top) shows my target moments in the data and the corresponding model moments after choosing the vectors of parameters that minimize the weighted distance between model and data moments. I compute the top three forecast error moments from SBU data with (the sample period covering 10/2014 to 6/2018. All of my variance and covariance based moments are computed after purging variation attributable to firm and date fixed effects. The investment and sales moments come from a sample of Compustat firms with less than 7500 employees, from a sample covering all years from 1990 to 2017. I compute model moments numerically using the stationary distribution of firms across the (z, k) state space. Sub-table C.5b (bottom) shows the values and standard errors of the estimated parameters. Note that I normalize the true mean of the stochastic process for log(z) to μ = 0. The weighting matrix is the firm-level clustered covariance matrix of the moments, adjusted to place equal weight on Compustat and SBU moments. I perform the numerical optimization using simulated annealing.
D Heterogeneity in Managerial Oversight, Misbehavior, and Bias

My paper undoubtedly connects to the large literature on agency conflicts between managers and shareholders, although conflicts are not the focus my analysis and contributions. Indeed, my analysis takes as given that biased managers operate the firms in my model, abstracting from the micro-foundations of how 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. By abstracting from explicit agency conflicts, I also potentially ignore how the interaction between biased managers and shareholders or board members may ultimately shape the dynamic decisions that I observe in the data.

To address some of these concerns, in this Appendix I ask how my model captures the behavior of firms in which managers may be subject to stronger or weaker oversight, in which managers appear better or worse-behaved, or simply more biased based on alternative proxies. To consider differences in oversight, I re-estimate versions of my model splitting the SBU sample by median employment, arguing that small firms in my data are more likely to be owner operated and thus managers less subject to external oversight. I also estimate versions my investment-based model from Appendix C.7 on subsamples of Compustat firms with good versus bad governance, namely firms with above or below median management entrenchment based on the index from Bebchuk et al. (2008).4445 To explore managerial empire-building tendencies, I also re-estimate my Compustat-investment model on subsamples of firms with mergers and acquisitions (i.e. for which AQGQ>0) in the eight calendar quarters prior to the current date, versus those for which AQGQ is zero or missing over the same period. Finally, I consider how my model captures the behavior of managers that have previously been identified as being biased. I compare estimates of my investment model based on subsamples of firms that Malmendier and Tate (2015) identify as having "overconfident" CEOs versus not based on CEO stock option exercise behavior. If a CEO exercises any vested stock options within one year of the expiration and the options were at least 40 percent in the money 12 months prior to expiration, Malmendier and Tate (2015) identify this CEO as "overconfident".

Since the SBU data are confidential and I cannot as of now match them to Compustat, for the exercises that focus on public firms data I target the three beliefs moments from the SBU and investment and output moments taken from the relevant subsample of Compustat. Any differences in the estimated parameters and so forth thus ultimately come from differences in firm-level behavior across the subsamples. If we conjecture that managerial beliefs are less rational in firms with more severe agency conflicts or more badly-behaved managers, we may also expect differences in estimated parameters across subsamples would be more extreme if we could obtain subsample-specific beliefs moments.

Tables D.1 and D.2 shows the results from my estimation across subsamples of firms. Tables D.1a and D.2a show the data and model moments for each estimation. Looking at the data moments on their own, it appears that subsamples with less oversight, empire-building and "overconfident" managers have more erratic or overreactive investment behavior based on the volatility of investment and its covariance with contemporaneous sales growth.

Looking now at Tables D.1b and D.2b, I argue my estimates of model parameters differ in expected ways across sub-samples. In particular, I find the behavior of firms where there appears to be less oversight is consistent with their managers being more biased in the sense of there being a larger gap between \( \tilde{\rho} \)

---

44 This E-index takes a value between one and six depending on how many governance provisions associated with entrenched management are in place at a particular firm in a particular year. The governance provisions considered include poison pills, golden parachute arrangements, staggered boards, supermajority requirements for mergers, and provisions that make it difficult for shareholders to amend the firm’s charter or by-laws.

45 The index is not time-invariant but about 80 percent of the variation is across firms, so I construct my "good" and "bad" governance subsamples by first averaging the firm’s index score across years and then splitting the sample by the median score.

46 Note that this meaning of overconfident is conceptually distinct from the precise meaning in my paper. Malmendier and Tate (2015) use the word "overconfident" to describe CEOs who appear to believe their firm’s future performance is inherently better than it appears currently. I use "overconfident" to describe managers who underestimate the volatility of future business conditions, that is managers who feel less uncertain about the firm’s future performance than they should be. What Malmendier and Tate (2015) term overconfident is more similar to the concept of "over-optimism" in my work.
and $\rho$ and a smaller $\tilde{\sigma}/\sigma$ ratio. Other parameters also behave in intuitive ways. In the case of firms with weak governance, managers also face somewhat weaker adjustment frictions, especially in the form of partial irreversibility, possibly because they need to devote less managerial time and fewer resources negotiating with the board and shareholders about their plans and strategies. By contrast, firms that recently engaged in M&A activity have similar or perhaps slightly higher adjustment costs. This result could be an indication that managers with empire-building tendencies are especially willing to spend on investment projects and M&A despite those actions being relatively costly. Finally, firms with "overconfident" CEOs according to Malmendier and Tate (2015) also face somewhat smaller adjustment costs and behave in ways consistent with them being significantly more biased than firms with CEOs who do not appear "overconfident".

Finally, looking at Table D.3, I ask whether more badly-behaved managers destroy a larger share of firm value than those who appear to be better behaved or subject to less severe agency conflicts. I find mixed results. Public firms with highly entrenched management could increase firm value by 3.3 percent if they hired a rational manager, less than the 4.1 percent for firms with less entrenched management. This result owes to the lower magnitude of adjustment costs in highly-entrenched firms, and also to smaller shocks experienced by these firms ($\sigma = 0.158$ relative to $\sigma = 0.187$ at firms with and low entrenchment). Managers at firms with high entrenchment and poor governance destroy relatively less value because their overreactions are less costly, and because they have fewer opportunities to overreact since the firm is less volatile to begin with. Looking instead at firms conducting versus not conducting M&A in recent quarters, moving to a rational manager increases firm value by 3.3 percent for acquirors and just a bit less, 2.8 percent for non-acquirors. This result is consistent with firms with a taste for acquisitions behaving in a way consistent with more severe overconfidence and overextrapolation. Finally, for firms with "overconfident" CEOs according to Malmendier and Tate (2015), replacing those CEOs with others who have rational expectations would increase the value of the firm by 3.7 percent, more than the 3.3 percent in the subsample for which CEOs don't appear "overconfident." This is despite firms with "overconfident" CEOs being significantly less volatile and facing smaller adjustment costs. From this analysis, it is clear that simply having a CEO who is more biased does not automatically imply she destroys more firm value. The magnitude of other parameters that help explain the behavior of this biased and potentially badly-behaved CEO also matter, which depends on the type of bad behavior considered and how any particular model captures the behavior.
Table D.1: **Sample Split Estimation Results: Large vs. Small SBU Firms**

(a) **Model and Data Moments for Small vs. Large SBU Firms**

<table>
<thead>
<tr>
<th>Moment</th>
<th>Small Data</th>
<th>Model</th>
<th>Large Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean(Forecast Error)</td>
<td>-0.020</td>
<td>-0.015</td>
<td>-0.006</td>
<td>-0.005</td>
</tr>
<tr>
<td>Mean(Excess Absolute Forecast Error)</td>
<td>0.165</td>
<td>0.158</td>
<td>0.126</td>
<td>0.114</td>
</tr>
<tr>
<td>Cov(Forecast Error(<em>{t,t+4}), Sales Growth(</em>{t-1,t}))</td>
<td>0.015</td>
<td>0.009</td>
<td>0.009</td>
<td>0.004</td>
</tr>
<tr>
<td>Var(Sales Growth)</td>
<td>0.075</td>
<td>0.060</td>
<td>0.051</td>
<td>0.038</td>
</tr>
<tr>
<td>Var(Net Hiring)</td>
<td>0.026</td>
<td>0.001</td>
<td>0.014</td>
<td>0.002</td>
</tr>
<tr>
<td>Cov(Net Hiring, Sales Growth)</td>
<td>0.004</td>
<td>0.004</td>
<td>0.001</td>
<td>0.004</td>
</tr>
<tr>
<td>Cov(Sales Growth(<em>{t,t+4}),Sales Growth(</em>{t-1,t}))</td>
<td>-0.017</td>
<td>-0.018</td>
<td>-0.011</td>
<td>-0.005</td>
</tr>
<tr>
<td>Cov(Sales Growth(<em>{t,t+4}), Net Hiring(</em>{t,t+1}))</td>
<td>-0.002</td>
<td>-0.004</td>
<td>-0.001</td>
<td>-0.002</td>
</tr>
</tbody>
</table>

(b) **Parameter Estimates for Large vs. Small SBU Firms**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Small</th>
<th>Large</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\alpha)</td>
<td>0.611 (0.089)</td>
<td>0.588 (0.113)</td>
</tr>
<tr>
<td>(\lambda)</td>
<td>28.707 (1.423)</td>
<td>24.084 (2.368)</td>
</tr>
<tr>
<td>(\rho)</td>
<td>0.752 (0.008)</td>
<td>0.864 (0.011)</td>
</tr>
<tr>
<td>(\tilde{\rho})</td>
<td>0.889 (0.007)</td>
<td>0.924 (0.013)</td>
</tr>
<tr>
<td>(\sigma)</td>
<td>0.232 (0.001)</td>
<td>0.190 (0.001)</td>
</tr>
<tr>
<td>(\tilde{\sigma})</td>
<td>0.086 (0.002)</td>
<td>0.099 (0.002)</td>
</tr>
<tr>
<td>(\tilde{\mu})</td>
<td>-0.004 (0.0001)</td>
<td>-0.001 (0.0001)</td>
</tr>
</tbody>
</table>

**Notes:** This table shows the results from my structural estimation of the model from Section 3 splitting the sample by median employment. Sub-table D.1a *(top)* shows my target moments in the data and the corresponding model moments for each sub-sample 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 D.1b *(bottom)* shows the values and standard errors of the parameters that minimize the weighted distance between model and data moments for each of the subsamples. 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 D.2: Sample Split Estimation Results: Compustat

(a) Model and Data Moments for Sample-Split Estimations

<table>
<thead>
<tr>
<th>Moment</th>
<th>Entrenchment</th>
<th>Acquisitions</th>
<th>&quot;Overconfident&quot; CEO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High</td>
<td>Low</td>
<td>Yes</td>
</tr>
<tr>
<td>Mean(Forecast Error)</td>
<td>-0.014</td>
<td>-0.014</td>
<td>-0.014</td>
</tr>
<tr>
<td>Mean(Excess Absolute Forecast Error)</td>
<td>0.144</td>
<td>0.144</td>
<td>0.144</td>
</tr>
<tr>
<td>Cov(Forecast Error_t,t+4,Sales Growth_{t-1,t})</td>
<td>0.011</td>
<td>0.011</td>
<td>0.011</td>
</tr>
<tr>
<td>Var(Net Investment)</td>
<td>0.010</td>
<td>0.004</td>
<td>0.012</td>
</tr>
<tr>
<td>Var(Sales Growth)</td>
<td>0.026</td>
<td>0.028</td>
<td>0.035</td>
</tr>
<tr>
<td>Cov(Sales Growth,Net Investment)</td>
<td>0.002</td>
<td>-0.000</td>
<td>0.002</td>
</tr>
<tr>
<td>Cov(Sales Growth_{t+4},Sales Growth_{t-1,t})</td>
<td>-0.001</td>
<td>-0.002</td>
<td>-0.001</td>
</tr>
<tr>
<td>Cov(Sales Growth_{t+4},Net Investment_{t})</td>
<td>0.002</td>
<td>-0.002</td>
<td>0.003</td>
</tr>
<tr>
<td>Autocorr(log(Sales/Lagged Capital))</td>
<td>0.839</td>
<td>0.698</td>
<td>0.859</td>
</tr>
</tbody>
</table>

(b) Parameter Estimates for Compustat Sample-Split Estimations

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Entrenchment</th>
<th>Acquisitions</th>
<th>&quot;Overconfident&quot; CEO</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>High</td>
<td>Low</td>
<td>Yes</td>
</tr>
<tr>
<td>α</td>
<td>0.601 (0.014)</td>
<td>0.591 (0.011)</td>
<td>0.601 (0.049)</td>
</tr>
<tr>
<td>λ_q</td>
<td>0.154 (0.010)</td>
<td>0.121 (0.002)</td>
<td>0.089 (0.093)</td>
</tr>
<tr>
<td>λ_i</td>
<td>0.103 (0.006)</td>
<td>0.131 (0.003)</td>
<td>0.128 (0.006)</td>
</tr>
<tr>
<td>ρ</td>
<td>0.805 (0.003)</td>
<td>0.863 (0.003)</td>
<td>0.831 (0.012)</td>
</tr>
<tr>
<td>ρ̃</td>
<td>0.965 (0.006)</td>
<td>0.969 (0.001)</td>
<td>0.959 (0.008)</td>
</tr>
<tr>
<td>σ</td>
<td>0.158 (0.001)</td>
<td>0.187 (0.0003)</td>
<td>0.182 (0.001)</td>
</tr>
<tr>
<td>σ̃</td>
<td>0.062 (0.003)</td>
<td>0.089 (0.0006)</td>
<td>0.079 (0.002)</td>
</tr>
<tr>
<td>μ̃</td>
<td>-0.002 (0.0001)</td>
<td>-0.002 (0.0001)</td>
<td>-0.001 (0.0004)</td>
</tr>
</tbody>
</table>

Notes: Table D.2a (top) shows data and model moments from separate estimations of the capital-based model specification for subsamples of Compustat rms with highly-entrenched vs. not highly-entrenched management Bebchuk et al. (2008), a subsample of firms with positive acquisitions (AQCQ) in the past eight quarters versus not, and "overconfident" or "longholder"CEOs versus not according to Malmendier and Tate (2015). Table D.2b (bottom) shows parameter estimates for the capital-based model specification for the same subsamples of Compustat firms.
Table D.3: Change in Firm Value from Hiring Unbiased Manager: Sample Splits

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>∆ True Firm Value (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Size</td>
</tr>
<tr>
<td></td>
<td>SBU</td>
</tr>
<tr>
<td>ρ = ρ, σ = σ, and µ = µ</td>
<td>2.0</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table shows percent change in firm value from replacing a biased manager with an unbiased one based on the model estimates for subsamples of SBU firms that are small versus large (i.e. below versus above median employment in the SBU), as well as subsamples of Compustat with highly-entrenched versus not highly-entrenched management Bebchuk et al. (2008), a subsample of firms with positive acquisitions (AQCQ) in the past eight quarters versus not, and "overconfident" or "longholder" CEOs versus not according to Malmendier and Tate (2015).