Online Appendix for
"The Micro and Macro of Managerial Beliefs"
Not Intended for Publication

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A Data Appendix

This Data Appendix provides additional information about my sample from the Atlanta Fed / Chicago-Booth / Stanford Survey of Business Uncertainty (SBU) and presents additional empirical results to support my analysis of the SBU data. Readers should refer to Altig et al. (2020) and its Online Appendix for more background information about the SBU, its methodology, and basic properties of the data. Recall that the SBU is a monthly panel survey. Unless otherwise noted, results use data from all survey waves between October 2014 and May 2019.

A.1 Representativeness of the SBU

Figures A.1a to A.1e compare my sample of SBU responses with the broader US Economy, replicating similar figures from the Online Appendix of Altig et al. (2020). Each figure shows 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 for 2015. Figure A.1e additionally shows the share of publicly-traded firms and the share of employment in publicly-traded firms in the SBU, respectively at just over 10 and 25 percent. This publicly-traded employment share is not too far from estimates in Davis et al. (2007) that about one-third of employment in the US is in publicly-traded companies.

My assessment is the SBU is broadly representative of the US economy in employment-weighted terms. The survey over-represents larger and older firms. Figure A.1a shows 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.1b. The survey also over-represents sectors like durables manufacturing and finance and insurance, and under-represents health care as we can see in FigureA.1c. Following Altig et al. (2020), I do not reweight the survey to make it resemble the US economy more closely, in part because could require matching it up to confidential US Census data.

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Deviations in the share of employment for particular groups of firms versus the US economy stem partly from the composition of the survey's sampling frame (provided by an affiliate of Dunn & Bradstreet); partly due to deliberate over-sampling of larger firms; and partly because larger firms are more likely to respond. Figure A.2a shows the share of employment by firm size categories for: (1) the US economy; (2) the sampling frame; (3) firms that our recruiters successfully contacted; and (4) SBU responses up to May 2019. While the share of employment among firms with less than 20 employees is smaller than the economy's, the probability with which SBU recruiters successfully contact a firm increases with firm size, which is also evident in Figure A.2b. Larger firms also account for a disproportionate share of SBU responses (relative to their share among those contacted), which is a common finding in voluntary firm surveys. Bloom et al. (2018), for example, obtain a similar result in the University of Nottingham and the Bank of England's Decision Maker Panel, which uses the SBU's methodology to elicit beliefs about own-firm outcomes from British firms.

See Altig et al. (2020) and its Online Appendix for more information on how firms are recruited into the SBU and more descriptive information about the survey's sample. The Online Appendix of Altig et al. (2020), for example, repeats the exercise in Figure A.2a and shows how the sampling frame, contacted firms, and responses differ from the US economy in terms of industry affiliation and region.

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

My empirical analysis focuses on the first and second moments (i.e. expectations and uncertainty) of the five-point subjective distributions provided by firm managers in the SBU and their associated forecast errors. See the main text for a screenshot of the relevant survey questions that elicit subjective distributions for future sales growth and employment. This section provides more detail on how I obtain subjective means (i.e. expectations or forecasts) and subjective mean absolute deviations (my measure of subjective uncertainty) from the raw survey data. The procedure I outline below closely follows the procedures outlined in the Online Appendix of Altig et al. (2020).

The SBU is an unbalanced monthly panel. Respondents receive the sales questionnaire every two to three months.[1] The same applies to the employment questionnaire. Most of my descriptive analysis concerning managerial beliefs in Section 2 of the main text preserves the survey's structure as a monthly panel, but results are similar if I collapse the panel to a quarterly frequency, picking the last response of the calendar quarter. In fact, when I estimate the structural model of managerial decision-making described in Sections 3 and 4 of the main text I first collapse the SBU data to quarterly frequency, keeping only the last response of each calendar quarter. Then, I compute target moments from this quarterly dataset for conformity with the model's quarterly frequency.

A.2.1 Measuring subjective moments

I focus primarily on SBU respondents' beliefs for *sales growth* over the next four quarters. The SBU's raw responses from prior to September 2016 report subjective probability distributions over the dollar *level* of sales looking four quarters ahead. Figure A.3 shows the sales questionnaire for months prior to September 2016. Since September 2016, the sales questions are about growth rates,

[1] Between September 2016 and April 2019, respondents received 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. Starting in May 2019, respondents receive one of the questionnaires about sales, employment, or capital expenditures in a given month, rotating over the three topics quarterly.

as shown in Figure 2 of the main text. The following paragraphs show how I transform the raw survey responses from both questionnaires to obtain data on beliefs about future sales growth rates.

For survey responses prior to September 2016, I first compute the sales growth rate implied by the respondent's reported current sales level in quarter t, s_t, and each of the five potential quarterly sales levels in quarter $t+4$, $s_{j,t+4}$, where $j = 1, 2, 3, 4, 5$ indexes the five support point scenarios.[2] Following the convention in the literature on business dynamics (e.g. see Davis and Haltiwanger, 1992), I measure these five potential growth rates using arc-percentage changes:

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

Survey responses since September 2016 report subjective distributions over sales *growth rates* directly (again, see Figure 2 in the main text). I assume a respondent's support point 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 $x_{j,t+4} = (s_{j,t+4} - s_t)/s_t$. Again, s_t is the reported current sales level and $s_{j,t+4}$ is the implied sales level in quarter $t+4$ under support point scenario $j = 1, 2, 3, 4, 5$. I translate these conventional growth rates into arc-percentage changes for conformity with the pre-September 2016 data (see equation 1), by measuring:

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

I now have, for each survey response in t, a five-point subjective probability distribution for sales growth between quarters t and $t+4$. This distribution consists of a vector of potential growth rates $\{g_{j,t+4}\}_{j=1}^{5}$ and a vector containing their associated subjective probabilities, $\{p_{j,t+4}\}_{j=1}^{5}$. I compute a firm's expectation or forecast for sales growth over the next four quarters as the mean of her subjective distribution, namely by taking the inner product of the potential growth rate and probability vectors. Formally, a respondent's forecast for her firm's sales growth between quarters t and $t+4$, g_{t+4} is:

$$\widetilde{\mathbf{E}}_t[g_{t+4}] \equiv \widetilde{\mathbf{E}}[g_{t+4}|\mathcal{I}_t] = \sum_{j=1}^{5} p_{j,t+4} g_{j,t+4}.$$

The operator $\widetilde{\mathbf{E}}_t[\cdot]$ computes the respondent's subjective expectation on date t when she responded to the survey. I use $\mathcal{I}_t$ to denote the manager's information set at t.

I use the subjective mean absolute deviation from forecast to measure the subjective uncertainty implied by the manager's distribution. This object is the inner product of the probability vector and the vector of absolute deviations from forecast:

$$\begin{aligned}
\widetilde{\mathbf{MAD}}_t[g_{i,t+4}] &\equiv \widetilde{\mathbf{E}}_t\left[\left\|g_{t+4} - \widetilde{\mathbf{E}}_t[g_{t+4}]\right\|\right] \\
&= \sum_{i=1}^{5} \tilde{p}_{j,t+4} \left\| g_{j,t+4} - \sum_{k=1}^{5} \tilde{p}_{k,t+4} g_{k,t+4} \right\|.
\end{aligned}$$

[2]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

This measure of subjective uncertainty is similar but not exactly the same as the one we use in Altig et al. (2020). There, we compute the standard deviation of the subjective distribution. I use the subjective mean absolute deviation because it is the respondent's expected absolute forecast error. Thus, comparing subjective mean absolute deviations with actual absolute forecast errors (as in Fact 2 in Section 2) is an apples-to-apples comparison.

To compute employment growth expectations (i.e. forecasts) and uncertainty, I follow the same procedure as for sales responses prior to September 2016, since the SBU's employment questionnaire asks about current, past, and future employment *levels* (see Appendix Figure A.1 in the main text). Again, this is consistent with the treatment of employment expectations and uncertainty in Altig et al. (2020), except for my use of the mean absolute deviation rather than the standard deviation to measure uncertainty.

A.2.2 Realized growth rates and forecast errors

Sales Growth I measure a respondent 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, s_t, as well its sales as four quarters later, $s_{R,t+4}$:

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

This procedure exploits the SBU's panel dimension and the fact that the survey tracks sales outcomes across time.

Because the SBU asks questions about sales every two or three months, there may be more than one sales growth forecast and more than one reported sales level in the same 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 realized sales growth using sales levels s_t and $s_{R,t+4}$ reported exactly twelve months apart. If there is no data on realized sales $s_{R,t+4}$ 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.

This procedure maximizes the number of observations for realized sales growth rates, namely because I don't require exactly twelve months between beliefs and realizations. It also ensures the recorded sales growth rate (using equation 2) compares sales in quarter $t+4$ with an initial sales level in quarter t when we also observe the subjective distribution for four-quarter horizon sales growth rates.

I then compute forecast errors by taking the difference between a sales growth forecast (i.e. the subjective expectation for sales growth between quarters t and $t+4$) and realized sales growth:

$$ForecastError_{t,t+4} \quad = \quad \widetilde{\mathbf{E}}_t[g_{t+4}] - g_{t+4}.$$

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, I winsorize forecast errors at the 1st and 99th percentiles to limit the influence of outliers but my results are similar without winsorizing.

Employment Growth I follow a similar procedure to compute realized employment growth rate for the 12 months following an employment forecast in t. I also use arc-percentage changes to measure employment growth rates.

Since employment is a stock rather than a flow variable and the questionnaire asks for employment levels looking 12 months ahead (see appendix Figure A.1 in the main text), I record realized employment growth rates based on the firm's employment at t and its employment 12 months later. If the level of employment 12 months after survey t is not available, I use the level of employment recorded 11, 13, 10, or 14 months after t in that order of preference. Again, this procedure aims to maximize the number of observations for which I observe a realized employment growth rate. I do not adjust realized employment growth rates when the initial and final employment levels are not exactly 12 months apart, but results are similar if I, say, multiply realized employment growth by 12/11 when the final employment level is recorded 11 months after the initial.

Cleaning and Reviewing Forecast Errors Following Altig et al. (2020), I review any forecast errors for sales or employment whose magnitude is greater than one. My realized sales and employment growth growth measures are arc-percentage changes bounded by plus and minus two, so forecast-minus-realized sales growth is greater than one in absolute value if, for example, the manager forecasts zero sales growth but sales subsequently drop by two-thirds. The same applies to employment.

During this review, I correct common reporting mistakes that result in the appearance of extreme forecast errors. I use the firm's the history of responses for sales and employment to guide my corrections. For example, some firms use inconsistent units to report sales levels. A firm might report \$5 worth of sales in quarter $t + 4$, having reported sales of \$4,800,000 in quarter t. Clearly, the value in quarter t should be \$5,000,000. Occasionally, firms report annualized rather than quarterly sales figures. For example, the firm above might report \$20,000,000 in sales in quarter $t + 4$, otherwise reporting sales of around \$5,000,000 in quarters t, $t + 1$, $t + 2$, and $t + 3$.

These examples show how, in many cases, it is easy to see that an extreme forecast error is the result of a reporting mistake. In other cases, there may be no obvious mistake. I flag forecast errors significantly larger one in absolute value where there is no obvious mistake, and exclude them from forecast error analyses in the main text and this Online Appendix. In all cases, I document any corrections or exclusions from forecast error analyses, noting the reason for the edit or exclusion.

A.3 Additional evidence that my empirical measures of overprecision are unlikely to be driven by measurement error

The key statistic I use to measure the degree of managerial overprecision is the mean excess absolute forecast error: the difference between the average absolute forecast error in the SBU and the average subjective mean absolute deviation computed from managers' subjective distributions.

SBU respondents report sales levels themselves, so realized sales growth between quarter t (when we record the manager's beliefs) and quarter $t+4$ (the forecast horizon) is almost certainly measured with error. For example, managers may report their firm's current sales level using round numbers before final accounts are ready. SBU respondents also don't have strong incentives to be accurate, so they may report approximate sales levels reported in t and $t+4$. Measurement error could, thus, increase the average absolute forecast error I observe in the data, driving a wedge between it and the average subjective mean absolute deviation. In a worst case scenario, this wedge could be fully responsible for the average excess absolute forecast error I see in the data and which I interpret as managerial overprecision.

To get a handle on how much measurement error in reported sales matters, I compare the magnitude of forecast errors in the SBU with the magnitude of errors made by professional analysts forecasting publicly traded firm's sales four quarters ahead (the same forecast horizon as the SBU). Figure A.4a shows the distribution of forecast errors in the SBU as well as the distribution of errors made by professional analysts in IBES. In the latter case, I take realized sales values from official financials reported in Compustat.[3] We should expect sales data in Compustat to have significantly less measurement error than there might be in the SBU. In particular, Compustat sales levels should not be contaminated by the sorts of rounding, inattention, and approximation issues we might expect in the SBU reported sales data.

Looking at Figure A.4a, it seems SBU managers do make slightly larger forecast errors than do analysts in IBES. This may be due partly to greater measurement error in the SBU, but we can also expect SBU firms to be more volatile and therefore have larger forecast errors. Firms in IBES are some of the larger publicly-traded firms in the US. Since firm-level volatility declines with firm size (see, for example Davis et al., 2007), it is not surprising that sales of IBES firms are more predictable than sales of firms my SBU sample of smaller, primarily privately-held firms.

Figure A.4b suggests that it is managers' subjective distributions that look implausible rather than the distribution of forecast errors in the SBU. The figure compares the distribution of SBU forecast errors implied by manager beliefs as reported in the SBU, against the distribution of empirical forecast errors in IBES. I compute the subjective distribution of errors as in Figure 1a of the main text, assuming realizations are drawn independently from each manager's subjective distribution. Looking at the figure, this subjective distribution of errors in the SBU looks implausibly concentrated around zero. Professional forecasters make much larger errors, and measurement error is also unlikely to be a major driver of those errors. Thus, the discrepancy between the magnitude of subjective and actual forecast errors in the SBU is not likely to be the result of measurement error.

A.4 Is overprecision mechanically related to the SBU's use of five-point subjective probability distributions?

The SBU elicits managerial beliefs using a five-point discrete distributions. (For example see Figure A.3 for questions about future sales levels.) Realized sales, employment, and their respective growth

[3] Owing to the structure and variables available in IBES I construct forecast errors for this exercise somewhat differently from the main analyses in the paper. IBES reports forecasts and realizations of the *level* of sales. For comparability, I construct the implied forecasts for the growth rate of sales (looking four quarters ahead) in IBES by computing the growth rate implied by the current sales level and the analyst forecast for the future level. In the SBU, I construct an analogous forecast error, computing 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 rates. Throughout, I compute growth rates using arc-percentage changes.

rates are essentially continuous outcomes, however. This discrepancy raises the concern that my key measures of overprecision—excess absolute forecast errors—may be mechanically large because discrete approximations simply have a hard time capturing continuous distributions.

I demonstrate these concerns are unfounded by computing discrete, five-point approximations of the (continuous) distribution of realized sales growth rates that do not mechanically generate large excess absolute forecast errors when realizations are drawn from the underlying continuous distribution.[4] I use two methods to approximate the target distribution. 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 target distribution[5] to disregard. Then, I pick five equidistant support points $q_i, \quad i = 1,2,3,4,5$ where q_1 and q_5 are the $\frac{p}{2}$th and $(1-\frac{p}{2})$th quantiles of the target distribution. Finally, I assign probabilities to the five support points based on the cumulative distribution $F(\cdot)$ of the target distribution:

$$
\begin{aligned}
p_1 &= F\left(\frac{q_1+q_2}{2}\right) \\
p_2 &= F\left(\frac{q_2+q_3}{2}\right) - F\left(\frac{q_1+q_2}{2}\right) \\
&\dots \\
p_5 &= 1 - F\left(\frac{q_4+q_5}{2}\right).
\end{aligned}
$$

Once I have this approximate discrete distribution I use it to construct the forecast $E = \sum_{i=1}^{5} p_i q_i$ and mean absolute deviation $MAD = \sum_{i=1}^{5} p_i \|q_i - E\|$ implied by the discrete approximation. Then I find the mean absolute forecast error implied by the discrete approximation's forecast and outcomes from the target distribution, $MAFE = \sum_{n=1}^{N} \frac{1}{N} \|E - g_n\|$. Here, n indexes observations of the empirical sales growth (g_n) distribution I am targeting. Finally, I compute the excess absolute forecast error generated by my discrete approximation, $EAFE = MAFE - MAD$, the same measure of overprecision I use in the main text.

Table A.1a shows how this excess error changes when I discretize and 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 points 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 second method to approximate the continuous realized growth rate distribution. The mean probability vector SBU respondents assign is approximately $(p_1, p_2, p_3, p_4, p_5)' = (0.1, 0.2, 0.4, 0.2, 0.1)'$, implying a unimodal distribution. I then use the corresponding quantiles of the target 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 $q_i, \quad i = 1,2,3,4,5$ such

[4] 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.

[5] 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.

that:

$$
\begin{aligned}
p_1 &= F\left(\frac{q_1+q_2}{2}\right)\\
p_2 &= F\left(\frac{q_2+q_3}{2}\right) - F\left(\frac{q_1+q_2}{2}\right)\\
&\ldots\\
p_5 &= 1 - F\left(\frac{q_4+q_5}{2}\right)
\end{aligned}
$$

where $F(\cdot)$ now is the CDF of the target distribution truncated at its $\frac{p}{2}$th and $(1-\frac{p}{2})$th quantiles. I then use this discrete approximation to construct measures of excess error $EAFE$ as for the "Tauchen" approach above. Table A.1b 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. Thus, using reasonable methods to discretize the target distribution have a hard time generating the large excess absolute errors that characterize the SBU data.

Where does managerial overprecision come from, then? Looking at Figure 1a in the main text, we can see that managers' subjective distributions overestimate the probability of near-zero forecast errors. 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 their forecasts by about 10 to 15 percentage points, which is actually very much within the realm of normal (the standard deviation of actual forecast errors is close to 0.26). These patterns suggest managers place the five support points of their subjective distributions too close together, and that is the proximate cause of their overprecision.

Altig et al. (2020) also show that if we interpret respondent distributions as a continuous distribution with five bins, each centered around one of the support point scenarios, the implied subjective expectations and uncertainty are nearly identical to the ones we obtain from the discrete distributions in the SBU. This is additional evidence that the discrete nature of the SBU does not mechanically generate overprecision.

A.5 Additional Evidence on Overextrapolation

This section provides additional evidence that managers responding to the SBU overextrapolate from current conditions when they form beliefs about future sales growth.

A.5.1 Breaking down the relationship between forecasts, realizations, and recent sales growth

Figure A.5a shows that managers appear to underestimate mean reversion of short-term shocks. The figure shows two bin-scatter plots, for forecast and realized sales growth for quarters t to $t+4$ separately on the vertical axis, against lagged sales growth from $t-1$ to t on the horizontal axis. Managerial forecasts for sales growth from t to $t+4$ are essentially flat against the firm's lagged sales growth from $t-1$ to t. By contrast, realized sales growth for t to $t+4$ correlates negatively with the firm's lagged sales growth. This pattern suggests managerial forecasts fail to internalize mean reversion in the current shock to sales growth, making forecast errors predictable because this decay is predictable. Managers, thus, appear to overextrapolate from shocks to sales *levels* rather than from growth rates. This result justifies my choice of a stationary, mean-reverting process for firm-level shocks and managerial beliefs that underestimate the rate of mean reversion (overestimate the persistence).

One concern with Figure A.5a is that it heightens concerns that my measure of overextrapolation may be driven by transitory measurement error in reported sales levels, which would mechanically generate the negative correlation between lagged sales growth from quarters $t-1$ to t and realized sales growth between t and $t+4$. I address this concern below in Figure A.5c and in the main text, where I incorporate measurement error in my estimation of the structural model and find that measurement error alone cannot explain why lagged sales growth for $t-1$ to t has predictive power for forecast errors for sales growth in t to $t+4$.

A.5.2 Forecast errors are negatively correlated with past forecast errors

Figure A.5b shows 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 made forecasts in $t-4$ that ended up *overestimating* the firm's actual sales growth between $t-4$ and t. Those same managers subsequently make forecasts in t for sales growth between t and $t+4$ and end up *underestimating.* This pattern is consistent with my finding in the main text 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.2, I show estimates from the regression depicted in Figure A.5b, as well as from specifications that weight by employment, or include date, sector-by-date, and firm fixed effects. The negative relationship is robust across all specifications, although the coefficient in columns (5) and (6) with firm and date fixed effects are materially larger. This is probably because I am working with a short panel (covering October 2014 to May 2019) so the dynamic panel specification in that column may be upward biased (e.g. see Arellano and Bover, 1995).

Altig et al. (2020) also report that forecast revisions across survey waves predict future forecast errors in ways that are consistent with overextrapolation.

A.5.3 Forecast errors are positively correlated with a second measure of lagged sales growth

Figure A.5c shows that managerial forecast errors in the SBU are positively related with reported sales growth for the twelve months prior. In contrast with other tests for overextrapolation, this figure uses a past sales growth measure based on the SBU's look-back question from Figure 2 in the main text. This result is particularly useful because this look-back measure of past sales growth is unlikely to be mechanically contaminated by transitory measurement error in sales levels.[6] Indeed, these reported past sales growth data have a lower dispersion than quarter-on-quarter measured sales sales growth. The positive relationship in Figure A.5c suggests transitory measurement error is not the primary driver of my tests for overextrapolation.

Table A.3 shows that the relationship between reported past sales growth and forecast errors is

[6] I restrict attention to survey waves after September 2016 in which the look-back question is phrased in terms of growth rates. Prior to September 2016, the look-back question referred to levels, so a measure of past sales growth based on the look-back question and the current sales question could be contaminated by the sort of transitory measurement error that could generate the appearance of overextrapolation.

robust to controlling for date, sector-by-date, and firm fixed effects, or weighting by employment. The final two columns includes both firm and date fixed effects and find larger slope coefficients, again, potentially due to biases that are common in dynamic panel regression models. The overall picture, however, is that the relationship between reported past sales growth and forecast errors is robust.

A.5.4 Overextrapolation does not explain away managerial overprecision

Since overextrapolation documents a bias in manager forecast errors conditional on past sales growth (or past forecast errors), it mechanically generates larger absolute forecast errors than managers expect ex-ante. Thus, overextrapolation could be driving the large discrepancy in subjective and empirical absolute errors that I take as evidence of overprecision.

To test this hypothesis, Figure A.5d shows a bin-scatter plot with the absolute value of lagged sales growth, from quarter $t-1$ to t on the horizontal axis, and the excess absolute forecast errors (i.e. empirical absolute errors minus subjective mean absolute deviations) on the vertical axis. The figure shows a positive relationship, consistent with the previous paragraph. But firms with near-zero recent past sales growth still appear overprecise. The microdata regression estimates a highly significant, positive constant term of 0.117 with a standard error of 0.024. Thus, while overextrapolation does amplify the discrepancy between empirical and subjective absolute errors, it is by no means the driving factor.

A.6 Managerial Optimism, Overprecision, and Overextrapolation about Future Employment

Although I focus on biases in managerial beliefs about future own-firm sales growth in the main text, Facts 1 to 3 are similar for beliefs about future employment. Thus, Facts 1 to 3 appear to be robust features of managerial beliefs rather than spurious results that are only present in the SBU's sales data.

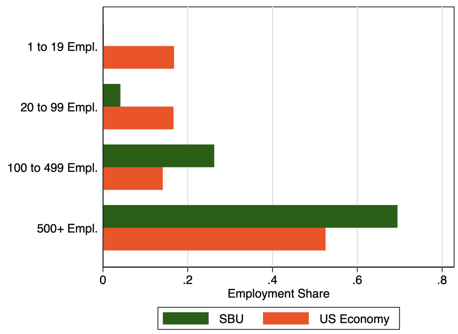
Table A.4 summarizes these results about managerial optimism/pessimism, overprecision, and overextrapolation about own-firm future employment growth. In Panel A, we can see that managers' appear somewhat pessimistic about their firm's future employment growth on average. Realized employment growth exceeds its ex-ante forecast by about 0.016 on average. The difference between forecast and realized is statistically significantly different from zero with 99 percent confidence, using firm-clustered and double clustered standard errors by firm and date.

As with sales, this apparent pessimism is not very robust, and arguably not economically significant. First, the magnitude of the difference between forecast and realized employment growth is comparable to the analogous measure for sales growth (about -0.013). The estimate is also small relative to the standard deviation of employment growth forecast errors, which is 0.16. Weighting by employment, the magnitude of the point estimate goes down by about 50 percent and stops being statistically significant. Taking a closer look and computing the mean forecast-minus-realized employment growth for ten deciles of the employment distribution, it is clear that the negative point estimate is driven by the smallest firms, who as of mid-2019 are likely benefitting from better than expected macroeconomic conditions. The same patterns are true for my analysis of sales growth forecast errors in the main text.

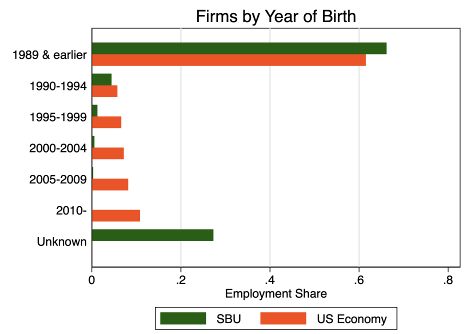
Panel B of Table A.4 shows that managers are overprecise about future employment growth rates. While the mean absolute forecast error for employment growth is close to 0.10, managers' subjective distributions would imply a mean absolute error should about 30 percent as large. This means there is an excess absolute error of about 0.071.

Turning now to Panel C, we can see that forecast minus realized employment growth for months t to $t+12$ correlates significantly with firms' employment growth in months $t-2$ to t. 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.

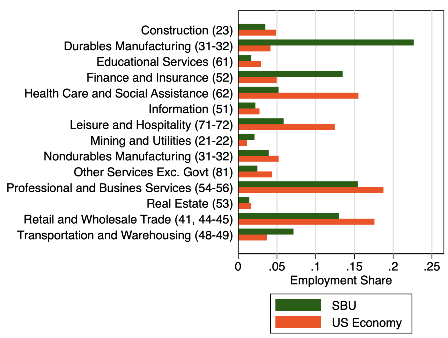
Figure A.1: **SBU Representativeness**



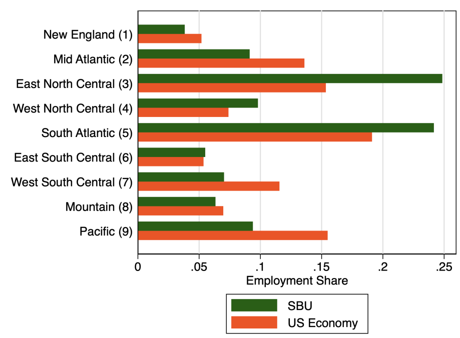
(a) **Share of Employment by Firm Size: SBU vs. US Economy**



(b) **Share of Employment by Firm Age: SBU vs. US Economy**

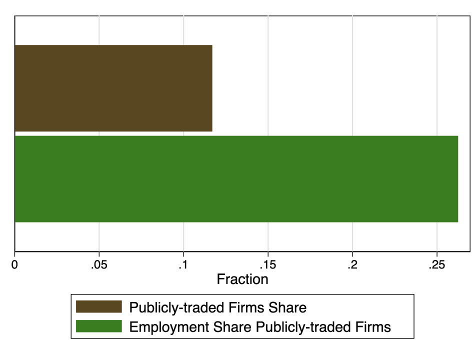


(c) **Share of Employment by Sector: SBU vs. US Economy**



(d) **Share of Employment by Region: SBU vs. US Economy**

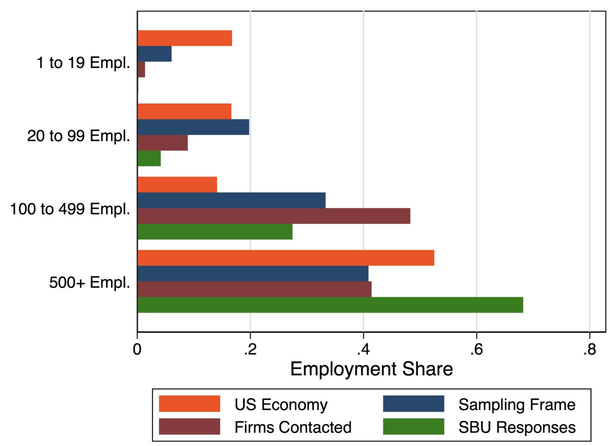
(e) **Share of Firms and Employment by Whether Publicly-traded**



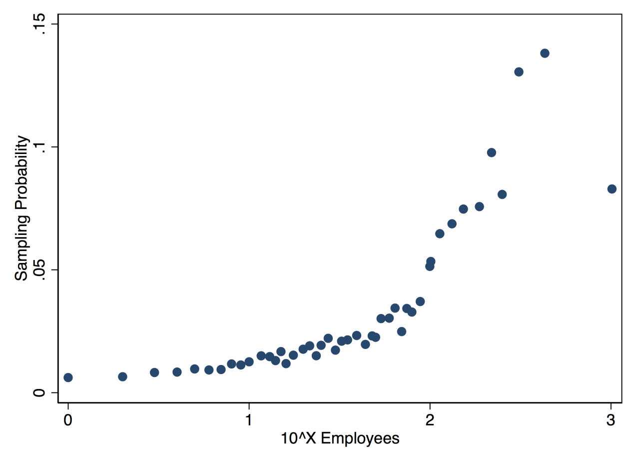
Notes: The above figures showthe share of employment across all SBU responses from 10/2014 to 7/2018 and in the US economy based on the US Census Bureau's 2015 Statistics on US Businesses or Business Dynamics Statistics for firms by: *(top left)* size category, *(top right)* year of birth (i.e. year the firm hired its first paid employee), *(middle left)* sector, and *(middle right)* Census Division. The *bottom* figure shows: (1) the share of firms in the SBU that reported their shares being listed on a stock exchange or traded in over-the-counter markets during the January-February 2019 special questions on firm ownership; (2) the share of employment across all SBU responses from 10/2014 to 5/2019 made by firms who reported their shares being listed on a stock exchange or traded in over-the-counter markets.

Figure A.2: **SBU Sampling Patterns**

(a) **Share of Employment in the SBU's Sampling Frame, Contacted Firms, and SBU Responses vs. the US Economy**

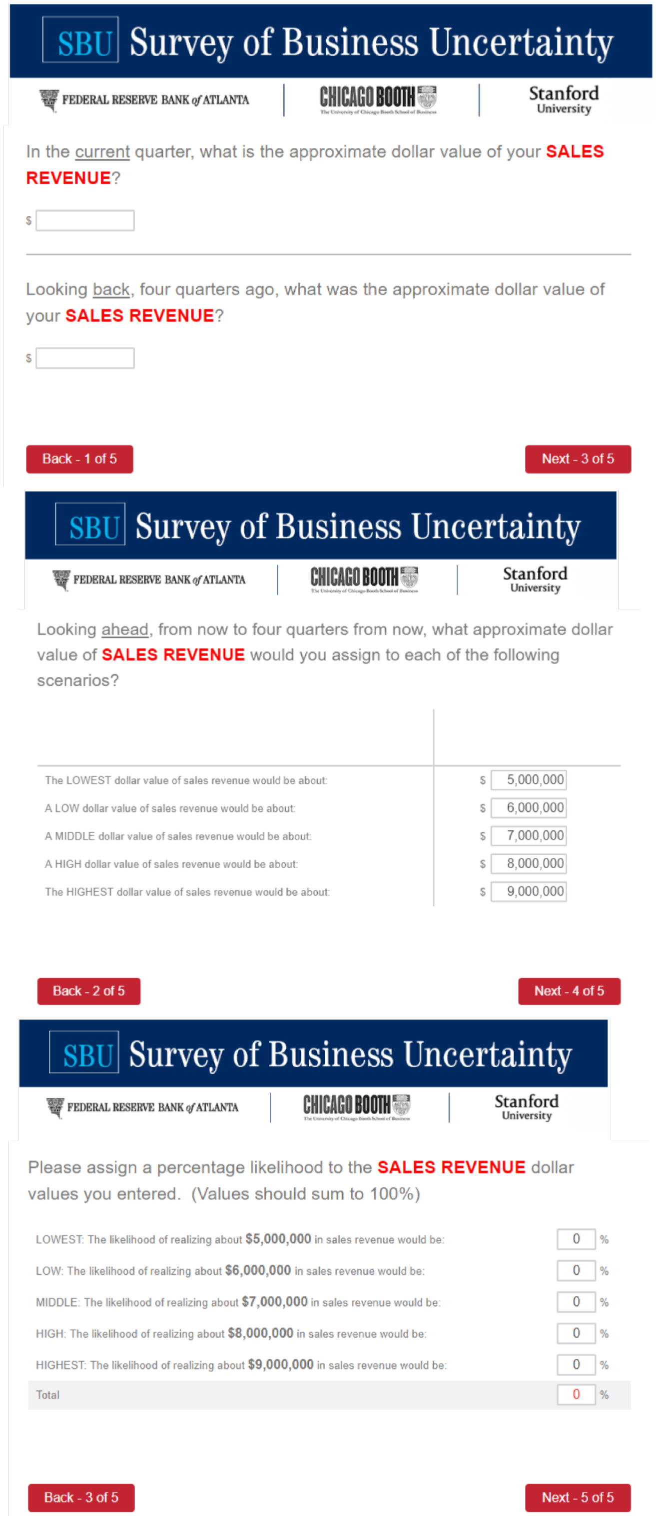


(b) **Sampling Probability Increases with Firm Size**



Notes: The left figure shows the share of employment accounted for by firms in each of the size categories listed on the vertical axis, respectively in (1) The US economy, based on the Census' 2015 Statististics on US Businesses; (2) the SBU's sampling frame; (3) the sample of firms that the SBU recruiting team successfully made contact with; (4) the sample of all SBU responses from 10/2014 to 5/2019. The right figure shows a bin-scatter of the empirical probability of being successfully contacted by the SBU's recruiting team in each of 100 employment quantiles of the SBU Sampling Frame.

Figure A.3: **Sales Questions in the *Survey of Business Uncertainty* prior to September 2016**



SBU Survey of Business Uncertainty

FEDERAL RESERVE BANK of ATLANTA | CHICAGO BOOTH | Stanford University

In the current quarter, what is the approximate dollar value of your **SALES REVENUE**?

$

Looking back, four quarters ago, what was the approximate dollar value of your **SALES REVENUE**?

$

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SBU Survey of Business Uncertainty

FEDERAL RESERVE BANK of ATLANTA | CHICAGO BOOTH | Stanford University

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

The LOWEST dollar value of sales revenue would be about:	$ 5,000,000
A LOW dollar value of sales revenue would be about:	$ 6,000,000
A MIDDLE dollar value of sales revenue would be about:	$ 7,000,000
A HIGH dollar value of sales revenue would be about:	$ 8,000,000
The HIGHEST dollar value of sales revenue would be about:	$ 9,000,000

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SBU Survey of Business Uncertainty

FEDERAL RESERVE BANK of ATLANTA | CHICAGO BOOTH | Stanford University

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

LOWEST: The likelihood of realizing about **$5,000,000** in sales revenue would be:	0 %
LOW: The likelihood of realizing about **$6,000,000** in sales revenue would be:	0 %
MIDDLE: The likelihood of realizing about **$7,000,000** in sales revenue would be:	0 %
HIGH: The likelihood of realizing about **$8,000,000** in sales revenue would be:	0 %
HIGHEST: The likelihood of realizing about **$9,000,000** in sales revenue would be:	0 %
Total	0 %

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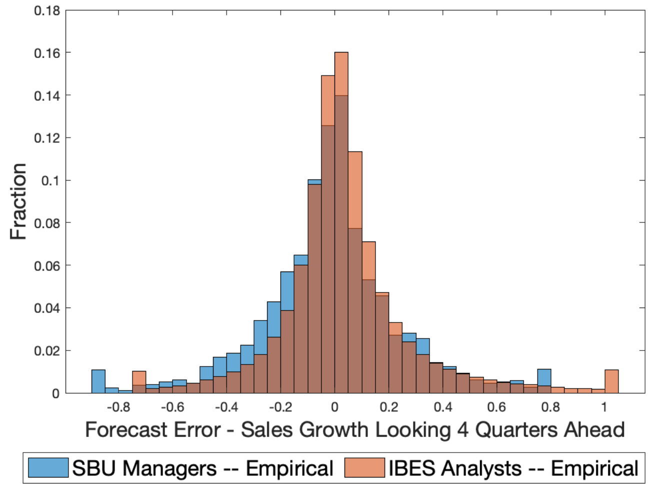
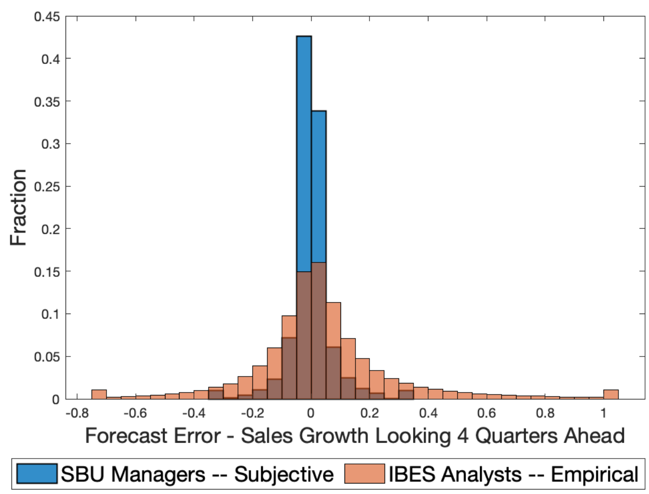
Notes: Sales growth questions in the *Survey of Business Executives* as they appeared prior to September 2016. In months prior to September 2016, the SBU asked for sales growth beliefs in levels rather than growth rates. See Appendix Figure

Figure A.4: **Forecast Errors in the SBU vs. IBES**

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



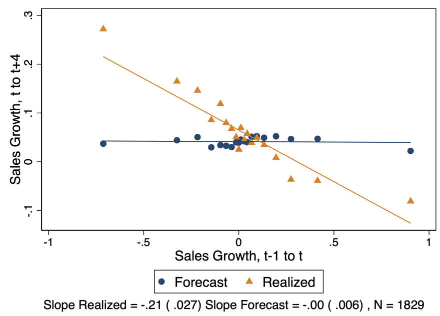
(b) **Subjective Distribution of Forecast Errors in the SBU vs. Empirical Distribution in IBES**



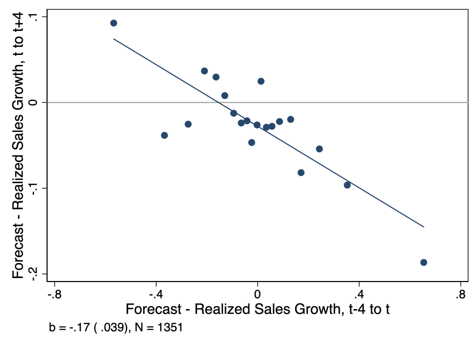
Notes: The top figure shows; (1) the *empirical* distribution of managers' forecast errors for sales growth looking four quarters ahead from the SBU; (2) the empirical distribution of analyst forecast errors for sales growth four quarters ahead from IBES. The bottom figure shows (1) the *subjective* 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 2,580 forecast error observations from 446 firms between 10/2014 and 5/2019. The IBES sample includes 755,685 analyst forecast errors.

Figure A.5: **Additional Evidence on Overextrapolation**

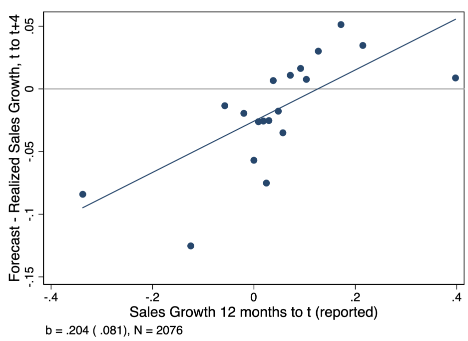
(a) **Managers Ignore Mean Reversion**



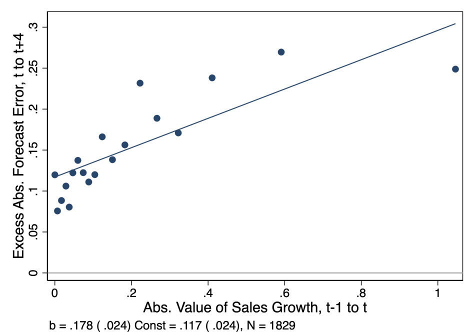
(b) **Serial Correlation in Forecast Errors**



(c) **Overextrapolation from Reported Sales Growth**



(d) **Overprecision or overextrapolation?**



Notes: *(Top left)* 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. 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 $t+4$. *(Top right)* 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. *(Bottom left)* 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. *(Bottom right)* This figure shows a bin-scatter plot of excess absolute forecast errors (absolute forecast error minus subjective uncertainty) for sales growth over quarters t to $t+4$ on the vertical axis against the absolute value of sales growth from quarters $t-1$ to t.Data are from the *SBU* and the sample period includes all months between 10/2014 to 5/2019, except the bottom figure which restricts attention to 9/2016 and later when we asked the look-back past sales growth question in terms of growth rates.

Table A.1: **Discretizing Empirical Distributions**

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

Mass Excluded (p)	0.01	0.05	0.1	0.2	0.4	Data
Excess Absolute Fcast. Error	0.030	0.022	0.027	0.043	0.077	0.148

(b) **Quantile Approach**

Mass Excluded (p)	0.01	0.05	0.1	0.2	0.4	Data
Excess Absolute Fcast. Error	-0.0153	0.015	0.031	0.0446	0.058	0.148

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 dierences in subjective first moments, leaving the empirical distribution of realized sales growth for the typical expectation and subjective uncertainty across all 2,580 forecast error observations in the SBU covering the 10/2014 to 5/2019 sample period. See section A.4 of the Online Appendix for a full description of the two discretization approaches.

Table A.2: **Managers Overextrapolate: Forecast Errors are Serially Correlated**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	**Forecast - Realized Sales Growth, quarters t to $t+4$**					
Forecast - Realized Sales Growth,	-0.179***	-0.159**	-0.182***	-0.185***	-0.309***	-0.317***
quarters $t-4$ to t	(0.067)	(0.067)	(0.040)	(0.045)	(0.042)	(0.052)
(0.052)						
Constant						
Date FE			Y		Y	Y
Date x Sector FE				Y		
Firm FE					Y	Y
Employment-weighted		Y				Y
Observations	1,351	1,332	1,351	1,257	1,316	1,298
R-squared	0.032	0.027	0.052	0.232	0.348	0.499
Within R-squared			0.033	0.033	0.089	0.121

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 May 2019. 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.3: **Managers Overextrapolate: Based on Reported Sales Growth**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	**Forecast - Realized Sales Growth, quarters t to t+4**					
Reported Sales Growth,	0.205**	0.197*	0.216***	0.216***	0.375***	0.509***
12 months up to t	(0.081)	(0.112)	(0.082)	(0.073)	(0.063)	(0.087)
Date FE			Y		Y	Y
Date x Sector FE				Y		
Firm FE					Y	Y
Employment-weighted		Y				Y
Observations	2,076	2,074	2,076	2,048	2,015	2,013
R-squared	0.012	0.008	0.0297	0.171	0.333	0.413
Within R-squared			0.013	0.013	0.035	0.060

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 May 2019. 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: **Beliefs about Future Employment Growth**

	(1)	(2)	(3)
	Panel A. Optimism		
	Employment Growth		**Forecast Error**
	Forecast	Realized	Forecast - Realized
Mean	0.010	0.024	-0.015
Firm-clustered SE	(0.003)	(0.005)	(0.004)
Firm and date-clustered SE	(0.003)	(0.005)	(0.004)
Obs.	3,095	3,095	3,095
Firms	510	510	510
	Panel B. Overconfidence		
	Absolute Forecast Error		**Excess Error**
	Empirical	Subjective	Empirical - Subjective
Mean	0.044	0.107	0.063
Firm-clustered SE	(0.003)	(0.005)	(0.004)
Firm and date-clustered SE	(0.003)	(0.005)	(0.004)
Obs.	3,095	3,095	3,095
Firms	510	510	510
	Panel C. Overextrapolation		
Dependent Variable	**Forecast - Realized Emp. Growth, months t to $t+12$**		
Emp. Growth, months. $t-2$ to t	0.237	0.238	0.352
	(0.051)	(0.052)	(0.053)
Date FE		Y	Y
Firm FE			Y
Obs.	2,165	2,165	2,104
Firms	376	376	315
R-squared	0.039	0.050	0.398
Within R-squared		0.039	0.107

Notes: Panel A *(top)* reports the mean employment growth forecast for the next 12 months, the mean employment growth realization, and the mean employment growth forecast error (equal to forecast minus realized). Panel B *(middle)* reports the mean empirical absolute forecast error, mean subjective absolute forecast error (i.e. the mean subjective absolute deviation) and the mean excess absolute forecast error (empirical minus subjective error). Panel C *(bottom)* reports the coefficient form a regression of forecast minus realized employment growth for months t to $t+12$ on the firm's lagged employment growth between months $t-2$ to t. Data are from the SBU at include all survey waves between 10/2014 and 5/2019.

B Model Appendix

B.1 Definition of Aggregate Quantities

Here I provide formal definitions for aggregate quantities in the model economy from Section 3 of the main text. 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 on adjustment costs:

$$\begin{aligned} Y &= \int_{\mathcal{Z}\times\mathcal{N}} \left[zn^{\alpha} - \lambda \left(\frac{\kappa(z,n) - (1-q)n}{n} \right)^2 n \right] \mathrm{d}\Phi(z,n) \\ &= \hat{Y} - AC. \end{aligned}$$

$\hat{Y}$ denotes gross output (before subtracting adjustment costs) and AC denotes total spending on adjustment costs. This definition of GDP is crucial for my analysis about the aggregate implications of biases in managerial beliefs, as described in Section 3 of the main text. I subtract adjustment costs from GDP assuming those resources do not constitute income for any agents in the economy and instead are intermediate business expenses that diminish profits and value added.

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

$$\begin{aligned} \Pi &= \int_{\mathcal{Z}\times\mathcal{N}} \pi(z,n,\kappa(z,n);w)\mathrm{d}\Phi(z,n) \\ &= \int_{\mathcal{Z}\times\mathcal{N}} \left[zn^{\alpha} - wn - \lambda \left(\frac{\kappa(z,n) - (1-q)n}{n} \right)^2 n \right] \mathrm{d}\Phi(z,n) \end{aligned}$$

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 all labor and capital income in the economy:

$$\begin{aligned} Y &= C + \theta\Pi \\ &= wN + \Pi \end{aligned}$$

B.2 Firm Value and Welfare Change Formulas

To compute the change in the net present value of cash flows a firm would obtain from hiring a counterfactual manager who has rational expectations (or more generally, another beliefs process) I use the following steps.

First, I solve for the original and replacement manager's respective policy functions, $\kappa(\cdot)$ and $\kappa^c(\cdot)$ (see Section C below). I use those policy functions to compute the objective net present value of cash flows generated by each manager, $V(\cdot)$ and $V^c(\cdot)$. (See Appendix C.3 for more details on this computation.) The average percent change in firm value (holding all else equal) obtained from replacing the original manager for the counterfactual manager is then:

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

The operator $\mathbb{E}[\cdot]$ computes expectations with respect to the model's stationary distribution $\Phi(z,n)$.

The percent difference in welfare (in consumption units) between my baseline economy with stationary equilibrium consumption and aggregate labor C and N, and a counterfactual economy with consumption and labor C_c and N_c, is given by $100 \times \xi$, where ξ satisfies:

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

The above equation has a closed form solution for ξ:

$$\xi \quad = \quad \frac{\left[C_c^{1-\gamma} - \chi \frac{1-\gamma}{1+\eta}[N_c^{1+\eta} - N^{1+\eta}]\right]^{1-\gamma}}{C} - 1.$$

In practice, my welfare counterfactuals solve for ξ numerically, but I have verified that the numerical solution is accurate in comparison with the above closed form solution.

B.3 Capital and Intermediate Goods in my Baseline Model

My baseline model assumes sales are a function of only labor, ignoring capital and intermediates. I focus on employment rather than investment dynamics because the quality of employment data in the SBU being much higher than the quality of investment data. Nearly 90 percent of SBU firms are privately-held and the survey responses are anonymized for confidentiality. Thus, even with a de-anonymized version of the data, it would be nearly impossible to obtain financials and investment data, since the US does not have a comprehensive database of private businesses' financial statements. Section 6 of the main text considers an extended model with both capital and labor that I calibrate using some of my estimated parameters and investment moments reported in the literature.

Given my estimate of the returns to scale in the firm's production function is between 0.8 and 0.9 and my estimate that there are nontrivial adjustment costs, readers may want to interpret my setup without physical capital as follows. Suppose the true underlying model has two factors of production—labor and capital. Suppose capital investment is subject to adjustment costs and one-period time-to-build, under uncertainty about the next period's firm-level profitability shock z_{t+1}. Firms choose labor statically, based on their current capital k_t and shock z_t. Estimating my one-factor model on the data tracking labor dynamics will largely track movements in physical capital subject to capital adjustment costs.

My specification for firm revenue abstracts from intermediate goods that may also be a factor of production. This assumption can be weakened to allow firms to consume some of the final good in the economy as an intermediate. If the underlying production function for *gross output* is Cobb-Douglas, and the firm's choice of intermediate inputs is static, then the value-added production function would also be Cobb-Douglas and proportional to the gross output production function. Such a setup would be consistent and isomorphic with my baseline assumption that ignores intermediates.

C Simulation Appendix

C.1 Model Solution Details

Here I provide some additional details about the algorithm and computational choices I use to solve managers' dynamic hiring problem from the model in main text.

I solve for managers' value and policy functions over a discretized (z, n) state space employing value function iteration, aided by Howard's improvement algorithm. I choose grids of size $(z, n) = (21, 100)$ since 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 zero probability of ending up in the highest and lowest grid points, i.e. so $\max_z\{\phi(z, n_1), \phi(z, n_{100})\} < 10^{-5}$. For my baseline estimation of the model I set the lowest and highest grid points at $n_1 = 0.05$ and $n_{100} = 5$.

C.1.1 Discretizing the subjective and objective driving processes

I approximate both the objective and subjective stochastic processes for $\log(z_t)$ using two discrete Markov chains whose support is a common set of grid points, implementing the Tauchen (1986) algorithm. I use a relatively dense grid (21 points) to ensure to obtain accurate approximations of the conditional first and second moments of both the subjective beliefs process and objective stochastic processes on the same grid. (See Section 3 in the main text for the specification of the two processes.) Representing the two stochastic processes on the same discrete grid is computationally convenient and implies managers are only wrong about the probability of a given event happening, but they are correct about the set of events that may happen.

I center the grid for $\log(z_t)$ around zero since the objective stochastic process is mean zero (a normalization) and the subjective stochastic processes is approximately mean zero (which follows from Fact 1 in the main text). Given vector of conditional volatilities and persistence parameters for the two processes $\{\sigma, \tilde{\sigma}, \rho, \tilde{\rho}\}$, I set the highest and lowest grid points at $\pm 2.575 * \sqrt{\frac{\hat{\sigma}^2}{1-\hat{\rho}^2}}$ where $\hat{\sigma} = \max\{\sigma, \tilde{\sigma}\}$ and $\hat{\rho} = \max\{\rho, \tilde{\rho}\}$. The grid thus covers 99 percent of the support of a mean zero Gaussian AR(1) process whose unconditional standard deviation is the largest possible given some combination of one the conditional volatilities σ and $\tilde{\sigma}$ and one of the persistences ρ and $\tilde{\rho}$.

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

Given some value of the stationary equilibrium wage w and risk-free rate r, I solve for managers' optimal subjective valuation of the business in numerically using standard techniques. Specifically, I use value function iteration aided by Howard's improvement algorithm over a discretized (z, n). The only noteworthy detail for this procedure is I use managers' subjective beliefs process (instead of the true stochastic process) to compute manager expectations 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 solves the optimization problem below, taking as given my guess for $\tilde{V}_0(\cdot)$ and prices w and r:

$$\kappa_0(z_t, n_t) = \arg\max_{n_{t+1}} \pi(z_t, n_t, n_{t+1}; w) + \frac{1}{1+r}\tilde{\mathbf{E}}[\tilde{V}_0(z_{t+1}, n_{t+1}; w, r)]. \tag{3}$$

See Section 3 of the main text for the definition of the cash flow function $\pi(z_t, n_t, n_{t+1}; w)$. The $\tilde{\mathbf{E}}[\cdot]$ operator takes expectations with respect to the managers' subjective stochastic process for future firm-level shocks z_{t+1}.

Then, I implement Howard's improvement algorithm. First, I apply the Bellman operator that implements the policy $\kappa_0(\cdot)$ for a fixed number T of periods. So for $\tau = 1, 2, ..., T$,

$$\tilde{V}_\tau(z_t, n_t; w, r) = \pi(z_t, n_t, \kappa(z_t, n_t); w, r) + \frac{1}{1+r}\tilde{\mathbf{E}}[V_{\tau-1}(z_{t+1}, \kappa(z_t, n_t); w, r)] \tag{4}$$

Then, I obtain a new guess for the optimal policy function $\kappa_1(\cdot)$ by applying the maximization in (3) using $\tilde{V}_T(\cdot)$ in place of $\tilde{V}_0(\cdot)$ for my guess for the manager's subjective valuation of the firm.

If the distance between the previous and current guesses of the policy function is under some pre-specified tolerance, then $\kappa_1(\cdot)$ is the manager's optimal policy. That is, if

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

If the maximum distance between $\kappa_0(\cdot)$ and $\kappa_1(\cdot)$ exceeds ε, I instead treat $\kappa_1(\cdot)$ as a new guess of the policy function and once again apply Howard's improvement algorithm in 4 to obtain a new guess for the policy function.

In practice I set $\varepsilon = 10^{-20}$ and $T = 300$. Once I know the optimal policy, it is straightforward to iterate on it to obtain a solution for the managers' subjective valuation of the firm $\tilde{V}(\cdot)$, namely by applying the procedure in equation 4 using the optimal policy $\kappa_1(\cdot)$.

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

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

To start, I guess that the stationary distribution is uniform across the discrete grid of states (z, n), calling this initial guess $\phi_0(z, n)$. Thus, for any pair of grid points (z_j, n_k), $\phi_0(z_j, n_k) = (z \cdot n)^{-1}$, $j \in \{1, 2, ..., 21\}$ and $k \in \{1, 2, ..., 100\}$.

I obtain a new guess for the stationary distribution $\phi_1(z, n)$ by moving the mass at each point (z, n) in the state space forward according the dynamics of the model. All firms with profitability z_j and labor n_k on date t choose labor $\kappa(z_j, n_k)$ for period $t+1$. But their profitability in $t+1$ is a random variable with the following distribution: $Pr(z_{t+1}|z_t = z_j)$, which depends on the objective stochastic process for z. Following these dynamics, a fraction of the mass at that is at point (z_j, n_k) in period t ends up at point $(z_p, \kappa(z_j, n_k))$ in $t+1$, for $p = 1, 2, ..., 21$. The mass that moves to this point is equal to $\phi(z_j, n_k) \cdot Pr(z_{t+1} = z_p|z_t = z_j)$, where the first factor is the mass originally at (z_j, n_k) and second term captures the stochastic movement of profitability between t and $t+1$. I repeat this procedure for each point in the state space.

After moving all of the mass forward from period t to $t+1$ I have obtained a new distribution of firms across the state space $\phi_1(z,n)$. I then compute the distance between this new distribution function 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. In practice, I use a tolerance of 10^{-20}, so I only obtain convergence of stationary distribution once the distribution is virtually identical to the previous one.

C.1.4 Computing the 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 $C = wN^D + (1-\theta)\Pi$, where $N^D = \int_{\mathcal{Z}\times\mathcal{N}} n \cdot \phi(z,n;w)\mathrm{d}z\mathrm{d}n$ is aggregate labor demand and $(1-\theta)\Pi$ is the household's total capital income under the current guess for the manager's policies and the wage. (Recall that the household owns a share $1-\theta$ of firm equity, with the remaining share owned by managers). Then I find the household's desired labor supply N^s given C and w according to its intra-temporal labor-leisure tradeoff (see Section 3 of the main text). I thus obtain excess labor demand $N^D - N^S$, which must be zero in equilibrium. I employ a standard nonlinear one-dimensional solver in Matlab to find a wage w for which excess labor demand is near zero.

C.1.5 Computing moments for the population of firms in the economy

Since 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 that add simulation error to model-implied moments.

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 $\mathbb{E}[X(z,n)] \equiv \sum_{z,n} X(z,n)\cdot\phi(z,n)$ where $\mathbb{E}[\cdot]$ 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 first compute the dynamic distribution $\tilde{\phi}(z,n,z') = \phi(z,n)\cdot Pr(z_{t+1} = z'|z_t = z)$. Then, I compute the moment as a weighted average of the outcomes, with the weights given now by the dynamic distribution: $\mathbb{E}[X(z,n,z')] \equiv \sum_{z,n} X(z,n,z')\cdot\tilde{\phi}(z,n,z')$.

C.2 Computing Managerial Beliefs About Sales and Employment Growth Between Quarters t and $t+4$

Relative to the typical dynamic model of firms in heterogeneous-agent macro and corporate finance, my model is simple and computationally tractable. 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.

Obtaining managerial beliefs about sales and employment growth between quarters t and $t+4$, however, is more computationally intensive. These beliefs are necessary to obtain model moments about managerial forecasts, subjective uncertainty, and forecast errors, which are key to estimating the managers' subjective stochastic process, namely $\{\tilde{\mu}, \tilde{\sigma}, \tilde{\rho}\}$. Specifically, sales in period $t+4$ are a function of the firm's idiosyncratic shock and the firm's labor 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 $t+4$, $\zeta = \{z_{t+1}, z_{t+2}, z_{t+3}, z_{t+4}\}$, since

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

So *conditional on* (z_t, n_t), $\hat{y}_{t+4}$ is a random variable that occurs with a given probability $Pr(\zeta|z_t)$, which is a four-dimensional probability mass function since ζ has four dimensions. Computing a managers' forecast for future sales growth, as well as an objective forecast, is therefore computationally expensive because it needs to consider all possible shock paths between t and $t+4$. 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.

To lower the amount of memory required for the above computations, I exploit the law of iterated expectations to compute beliefs and forecast error moments in the model. To begin, I store the conditional subjective and objective expectation for sales growth between t and $t+4$ conditional on (z_t, n_t) in memory:

$$\begin{aligned} \tilde{\mathbf{E}}[\Delta y_{t,t+4}(z_t, n_t)] &= \sum_{\zeta} \widetilde{Pr}(\zeta|z_t) \Delta y_{t,t+4}(z_t, n_t, \zeta) \\ \mathbf{E}[\Delta y_{t,t+4}(z_t, n_t)] &= \sum_{\zeta} Pr(\zeta|z_t) \Delta y_{t,t+4}(z_t, n_t, \zeta) \end{aligned}$$

where $\tilde{Pr}(\zeta|z)$ 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:

$$\begin{aligned} \mathbf{E}[ForecastError_{t,t+4}] &= \mathbf{E}\left[\tilde{\mathbf{E}}[\Delta y_{t,t+4}] - \Delta y_{t,t+4}\right] \\ &= \mathbb{E}\left[\tilde{\mathbf{E}}[\Delta y_{t,t+4}(z,n)] - \mathbf{E}[\Delta y_{t,t+4}(z,n)]\right] \\ &= \sum_{z,n} \phi(z,n) \cdot \left[\tilde{\mathbf{E}}[\Delta y_{t,t+4}(z,n)] - \mathbf{E}[\Delta y_{t,t+4}(z,n)]\right] \end{aligned}$$

where the $\mathbb{E}[\cdot]$ operator takes expectations across the state space after conditioning on (z, n) rather than across future shocks.

I use a similar procedure to obtain managers' subjective mean absolute deviations from their forecast. First, I obtain the subjective mean absolute deviation conditional on (z_t, n_t) and store it in memory:

$$\begin{aligned}
\widetilde{\mathbf{MAD}}(z_t,n_t) &= \tilde{\mathbf{E}}\left[\|\Delta y_{t,t+4}(z_t,n_t) - \tilde{\mathbf{E}}[\Delta y_{t,t+4}(z_t,n_t)]\|\right] \\
&= \sum_{\zeta} \widetilde{Pr}(\zeta|z_t)\cdot\left[\|\Delta y_{t,t+4}(z_t,n_t,\zeta) - \tilde{\mathbf{E}}[\Delta y_{t,t+4}(z_t,n_t)]\|\right]
\end{aligned}$$

Then I do the same for objective absolute forecast error conditional on (z_t, n_t):

$$\begin{aligned}
\mathbf{E}[AbsForecastError_{t,t+4}(z_t,n_t)] &= \mathbf{E}\left[\|\Delta y_{t,t+4}(z_t,n_t) - \tilde{\mathbf{E}}[\Delta y_{t,t+4}]\|\right] \\
&= \sum Pr(\zeta|z_t)\cdot\left[\|\Delta y_{t,t+4}(z_t,n_t,\zeta) - \tilde{\mathbf{E}}[\Delta y_{t,t+4}(z_t,n_t,\zeta)]\|\right].
\end{aligned}$$

Applying the law of iterated expectations, I compute the mean excess absolute forecast error in the model:

$$\begin{aligned}
\mathbf{E}[ExcessAbsForecastError_{t,t+4}] &= \mathbf{E}\left[AbsForecastError_{t,t+4} - \widetilde{\mathbf{MAD}}\right] \\
&= \mathbb{E}\left[\mathbf{E}[AbsForecastError_{t,t+4}(z_t,n_t)] - \widetilde{\mathbf{MAD}}(z_t,n_t)\right] \\
&= \sum_{z,n}\phi(z,n)\cdot\left[\mathbf{E}[AbsForecastError_{t,t+4}(z,n)] - \widetilde{\mathbf{MAD}}(z,n)\right]
\end{aligned}$$

where again $\mathbb{E}[\cdot]$ takes the expectation across the stationary distribution after conditioning at each point in the state space. Recall that the excess absolute forecast error is my crucial target for disciplining the relative magnitude of managers' subjective uncertainty about shocks to $\log(z_t)$, $\tilde{\sigma}$, relative to the true volatility of those shocks σ.

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

$$Cov(\Delta y_t, ForecastError_{t,t+4}) = \mathbb{E}\left[\begin{array}{c} (\Delta y_t(z_t,n_t) - \mathbb{E}[\Delta y_t(z_t,n_t)])\cdot \\ \left(\begin{array}{c} ForecastError_{t,t+4}(z_t,n_t) \\ -\mathbb{E}[ForecastError_{t,t+4}(z_t,n_t)] \end{array}\right)\end{array}\right]. \tag{5}$$

Although seemingly straightforward, computing this moment is slightly more complicated as Δy_t is really a function of (z_{t-1}, n_{t-1}, z_t) so I need to take the expectation $\mathbb{E}[\cdot]$ using the distribution $\tilde{\phi}(z,n,z') = \phi(z,n)\cdot Pr(z_{t+1} = z'|z_t = z)$. Applying the law of iterated expectations here crucially relies on Δy_t being deterministic conditional on (z_{t-1}, n_{t-1}, z_t) which greatly reduces the number of computations required as we can then separately compute the two terms inside the outermost brackets in equation 5.

I follow a similar procedure to obtain moments related to managerial expectations and uncertainty about employment growth over the next year. I make the timing assumption that the firm's reported employment in the SBU on date t corresponds to the end-of-period labor n_{t+1}, Thus, I compute expectations and uncertainty about employment growth between $t+1$ and $t+5$, Δn_{t+5}, which *conditional on* today's state (z_t, n_t) is a function of a five-dimensional tuple of shocks: $(z_{t+1}, z_{t+2}, z_{t+3}, z_{t+4}, z_{t+5})$, since $n_{t+5} = \kappa(z_{t+5}, n_{t+4})$, where $\kappa(\cdot)$ again is the manager's policy function.

C.3 Computing Objective Firm Value

I compute objective firm values numerically using standard dynamic programming results (e.g. see Stokey et al., 1989). Let the operator $T(\cdot)$ take as an argument a function $f : \mathcal{Z} \times \mathcal{N} \to \mathbb{R}$ and be defined as follows:

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

Again, $\mathbf{E}[\cdot]$ is the expectations operation with respect to the *objective* stochastic process for z_t, as given in the main text. Under standard conditions, $T(\cdot)$ is a contraction mapping. So, starting from a guess $V^0(\cdot)$ for the firm's objective value, I update the guess by letting $V^1(z_t, n_t) = T(V^0(z_t, n_t))$ and iterate until the sup norm between $V^m(\cdot)$ and $V^{m+1}(\cdot)$ is under a pre-specified tolerance (in practice 10^{-20}). This procedure is computationally inexpensive (and arguably trivial), yet it crucially helps me compare managers' subjective valuations of their own firms $\tilde{V}(\cdot)$ against the true value $V(\cdot)$ delivered by managers' policies, as well as the objective value delivered by biased versus unbiased managers.

C.4 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 the SBU is a monthly survey in which panel members answer questions about sales and employment every other month for most of my sample period (covering October 2014 to May 2019). For conformity with the quarterly frequency of my structural model, I collapse the data to quarterly frequency. For each calendar quarter I pick the *last* value reported for each variable. Whenever I compute growth rates, I use arc-percentage changes, 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: $\Delta y_t = \frac{y_t - y_{t-1}}{\frac{y_t + y_{t-1}}{2}}$
- Sales growth between quarter t and $t+4$: $\Delta y_{t+4} = \frac{y_{t+4} - y_t}{\frac{y_{t+4} + y_t}{2}}$
- Net hiring in period t (equivalently, current hiring): $\Delta n_{t+1} = \frac{n_{t+1} - n_t}{\frac{n_{t+1} + n_t}{2}}$. Here I make the timing assumption that the firm's employment level in reported in quarter t is n_{t+1}. Thus, labor used to produce in quarter t, n_t, is the amount reported in quarter $t-1$. This assumption captures real-world lags in recruiting, interviewing and training new employees.
- Net hiring (i.e. employment growth) between quarters t and $t+4$: $\Delta n_{t+5} = \frac{n_{t+5} - n_{t+1}}{\frac{n_{t+5} + n_{t+1}}{2}}$, again respecting the timing convention whereby the firm's current reported employment is n_{t+1}.
- The manager's forecast for sales growth between t and $t+4$, $\tilde{\mathbf{E}}[\Delta y_{t+4}]$, and her subjective mean absolute deviation, $\widetilde{\mathbf{MAD}}[\Delta y_{t+4}]$, measured according to the description in Appendix A.2.
- The firm's forecast error for sales growth between t and $t+4$: $ForecastEror_{t,t+4} = \tilde{\mathbf{E}}[\Delta y_{t+4}] - \Delta y_{t+4}$, with forecasts and realizations measured following the description in Appendix A.2.

- The firm's excess absolute forecast error for sales growth between t and $t+4$:

$$ExcessAbsForecastError_{t,t+4} = \|ForecastEror_{t,t+4}\| - \widetilde{\mathbf{MAD}}[\Delta y_{t+4}];$$

  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.

- Planned hiring (i.e. expected employment growth) for the next 12 months is given by: $\tilde{\mathbf{E}}[\Delta n_{t+5}]$, measured according to the description in Appendix A.2.

- Uncertainty about future hiring (i.e. employment growth) is given by $\widetilde{\mathbf{MAD}}[\Delta n_{t+5}]$.

C.4.2 Computing target moments and the weighting matrix

My estimation targets a vector of nineteen data moments $m(X)$. Table C.1 below reproduces their values, their standard errors and also shows how many firm-quarter observations I use to compute each moment. To maximize the sample size for each moment, I use all firm-quarter observations for which I observe the necessary variables to estimate that moment. This means I don't hold constant the sample used to compute different data moments.

Two of my target moments are means, namely the mean forecast error and mean excess absolute forecast error. I compute these in the data as simple arithmetic means. However, the other 17 moments are variances or covariances. Since variability of sales, employment, forecasts, and subjective uncertainty in the data may reflect persistent differences across firms and aggregate shocks, I compute my target variance and covariance moments using only 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. Then I compute the target variance or covariance using the residuals from those regressions.[7]

As I described in Section 4 of the main text, I use the optimal weighting matrix in my econometric minimization procedure, namely an inverse of the firm-clustered variance-covariance matrix of targeted moments given by:

$$\Omega = \mathbf{E}\left[(m(X) - \mathbf{E}[m(X)]) \cdot (m(X) - \mathbf{E}[m(X)])'\right].$$

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 reports my estimate $\hat{\Omega}$. I justify this choice of weighting matrix given its good small sample performance shown when used in similar simulation-based estimators in Bazdresch et al. (2017). When I estimate $\hat{\Omega}$, I also take into account that different pairs of moments may have different underlying samples and numbers of observations.

[7] 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 residualizing.

C.4.3 Minimizing the econometric objective and computing standard errors

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

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

Recall that I set $W = \hat{\Omega}^{-1}$, the inverse of my estimate of the covariance matrix of data 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 $\hat{\vartheta}$ is asymptotically normally distributed with variance Σ :

$$\sqrt{n}(\hat{\vartheta} - \vartheta) \quad \rightarrow \quad \mathcal{N}(0, \Sigma)$$

where

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

In practice, I use an estimate of the asymptotic variance $\hat{\Omega}$ in place of Ω and obtain numerical derivatives for $\widehat{\frac{\partial m(\vartheta)}{\partial \vartheta}}$ evaluated at the estimated $\hat{\vartheta}$. I compute the latter using two-sided derivates with step size equal to 2.5 percent of each element $\hat{\vartheta}$ in my baseline calculation:

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

The matrix $M = (n_1^{-1}, ..., n_{19}^{-1})' \cdot (n_1^{-1}, ...n_{19}^{-1})$, where n_i is the number of observations I use to compute moment $i = 1, ..., 19$ in the SBU data. The square root of the diagonal of $\hat{\Sigma}$ contains the standard errors of the elements in $\hat{\vartheta}$.

C.4.4 Sensitivity of estimated parameters to moments

Figures C.1 to C.3 show the sensitivity of estimated parameters to moments in the three specifications of the model, which I compute following Andrews, Gentzkow, and Shapiro (2017). We can see that certain pairs of parameters (e.g. α and λ, σ and $\tilde{\sigma}$, and ρ and $\tilde{\rho}$ in the convex only specification) are sensitive to similar sets of moments, but the sensitivities differ quantitatively within pairs.

One important feature of Figures C.1 to C.3 is that they clearly shows how both technological parameters and managerial beliefs are sensitive to forecast error and beliefs moments as well as moments concerning sales and employment dynamics with no beliefs. So the beliefs data also help me identify the technology parameters, and, similarly, sales and employment dynamics help me identify beliefs parameters.

C.5 Robustness of quantitative results to key calibrated and estimated parameters

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 parameters all affect the quantitative results in counterfactuals. To address these concerns, in Tables C.3 and C.4 I report how sensitive my key counterfactual outcomes are to changes in the adjustment costs parameters λ and F, the exogenous labor separation rate q, and the returns to scale α. The table focuses on the convex adjustment costs specification while the second uses hybrid (convex + fixed) adjustment costs. The first columns of each sub-table replicate the baseline results from Tables 8 and 9 in the main text, using my baseline estimates and calibration.

The columns labels "High" and "Low" adjustment costs in Tables C.3a and C.3b compute my main results with adjustment costs parameter that are λ triple and one-third my estimated value. Tables C.3a and C.3b instead increase or decrease λ and F by fifty percent since there are two sources of adjustment costs. 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. Accordingly, higher adjustment costs can lead to higher firm value and welfare when managers have rational expectations. However, higher adjustment costs also means rational and biased managers both react less, so their hiring policies might be more similar.

I also consider how changing the exogenous worker separation rate q changes the results. I calibrate this parameter because my target moments for employment concern *net* rather than gross hiring (I observe changes in employment, not gross hires and fires). Changing q, thus, does not change my model-implied moments and means that is not easy to identify and estimate q with my current estimation approach. The third column of tables C.3 and C.4 uses $q = 0.026$ (consistent with a 10 percent annual attrition rate) rather than $q = 0.083$ (30 percent annual attrition, following Shimer, 2005). At higher separation rates managers get to re-optimize a larger fraction of their firm's workforce each quarter, so other things equal hiring mistakes are less costly. This logic explains why we obtain higher firm value costs in the fourth column of Table C.3a. However, in Table C.3b I find smaller costs of biases with the lower separation rate, likely due to general equilibrium price effects.

The incentive to reach a target firm size, conditional on beliefs and adjustment costs, depends crucially on the returns to scale parameter, α. I estimate α to be between 0.8 and 0.9 in my preferred model specifications, which is consistent with typical estimates of revenue returns to scale in macroeconomics, but also consider consider how my quantitative results change if I impose smaller returns to scale of $\alpha = 0.65$. At both the micro and macro levels, managerial biases are less costly with lower returns to scale, since steeper declines in the marginal product of labor diminishes managerial motives to overreact to shocks. See Hsieh and Klenow (2009) for a similar discussion, whereby increasing revenue returns to scale leads to larger gains from eliminating misallocation in India and China.

C.6 Consumer Welfare and Managerial Biases if Prices Remain Constant

Table C.5 shows the difference in consumer welfare, aggregate output, labor demand, and labor productivity between a counterfactual economy with rational managers, and my baseline economy with biased managers, but wages in both economies are consistent with the equilibrium of the baseline economy. For brevity, I focus on the model specification with only convex adjustment costs. As in the main text, both economies also have the same interest rate because that is pinned down by the household's discount factor β that is the same in both economies.

Table C.5 makes it clear why I need to consider general equilibrium forces in my analysis of the aggregate impact of managerial biases in the main text. Managers who have rational expectations demand some 25 percent more labor from the household than do biased managers if we hold wages constant, presumably since their firms are also more profitable. Since firms are larger, aggregate output also rises by about 20 percent, and labor productivity drops by over 4 percent. Since consumers supply more labor at the same wage, their labor-leisure tradeoff is distorted and consumer welfare drops by 6 to 8 percent depending on how much of the extra profits associated with rational expectations belong to the consumers versus the managers (i.e. θ). Clearly, the quantities in Table C.5 are implausible. Without the discipline of general equilibrium, it does not make sense to compute a counterfactual comparing long-run welfare across economies with biased versus rational managers.

C.7 Managerial Biases Interact with Other Public Policies

This section expands on my argument in the main text that managerial beliefs matter for the impact of public policies. I show that the cost of managerial overprecision 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 when managers have non-rational rather than rational expectations.

I extend my baseline model with convex adjustment costs to allow for labor income and payroll taxes, respectively τ_n and τ_p, rebating the tax revenue to consumers via a lump sum transfer T_t. The following equations show the firm's cash flow function, the representative consumer's budget constraint, and the government's (balanced) budget with these taxes:

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

In Figure C.4 I show that the results from my main macro counterfactual, where I compare economies with biased and unbiased managers, depend on the level of labor income and payroll taxes in place. Each point in the figure compares consumer welfare in an economy in which managers have rational expectations relative to an economy in which managers use my estimated (non-rational) beliefs process, as a function of the tax rates. For each point in the figure, I calibrate the household's disutility of labor χ targeting a steady-state quantity of labor N equal to $1/3$ in the equilibrium with biased managers and taxes. Then I compute the equilibrium of an economy where managers have rational expectations and record the difference in welfare. From the figure, it is clear that larger distortionary taxes of either kind increase the welfare implications of non-rational managerial beliefs.

Figure C.5 shows the results from a related exercise, which examines how the welfare costs of distortionary labor income taxes depend on managerial beliefs. Each point in the figure considers an economy with labor income taxes τ_n according to the horizontal axis. The vertical axis shows how much higher consumer welfare would be in the stationary equilibrium with no taxes, $\tau_n = 0$. As with Figure C.4, I re-calibrate the household's disutility of labor χ 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 managers have rational expectations or not, holding the rest of the parameters fixed at their estimated values. Taxes are less costly in terms of consumer welfare when managers have rational expectations.

The the intuition for why taxes amplify the cost of managerial biases in Figure C.4 and why managerial biases amplify the costs of distortionary taxes in Figure C.5 is related to the envelope theorem. When the representative household's consumption and leisure are near their (undistorted) optimal levels, distorting the consumption-leisure tradeoff has second order welfare effects that are relatively small. When consumption and leisure are distorted to begin with, second order effects from further distortions like taxes or non-rational managerial beliefs become larger. These results provide additional motivation for why policy-makers should care about pervasive sources of inefficiency like overprecision and overextrapolation in managerial beliefs, even if it may be difficult to design policies that change beliefs directly.

Table C.1: **Target Moments For Estimation**

Empirical fact/feature	**Moment**	**Value**	**Std. Error**	N
1	Mean(Forecast Error$_{t,t+4}$)	-1.592E-02	6.584E-03	1947
2	Mean(Excess Absolute Forecast Error$_{t,t+4}$)	1.475E-01	6.378E-03	1947
3	Cov(Forecast Error$_{t,t+4}$, Sales Growth$_{t-1,t}$)	1.356E-02	2.047E-03	1245
0	Cov(Sales Growth Forecast$_{t,t+4}$, Hiring Plans$_{t,t+4}$)	6.715E-04	2.220E-04	4037
0	Cov(Sales Growth Uncertainty$_{t,t+4}$,Hiring Uncertainty$_{t,t+4}$)	2.892E-04	1.453E-04	4044
0	Cov(Net Hiring$_t$, Sales Growth Forecast$_{t,t+4}$)	2.782E-04	1.673E-04	2935
0	Cov(Net Hiring$_t$, Sales Growth Uncertainty$_{t,t+4}$)	-3.702E-04	3.210E-04	2937
0	Cov(Sales Growth Forecast$_{t,t+4}$, Realized Sales Growth$_{t,t+4}$)	1.678E-03	5.896E-04	1844
0	Cov(Hiring Plans$_{t,t+4}$, Realized Employment Growth$_{t,t+4}$)	2.209E-03	6.864E-04	2113
0	Cov(Sales Growth Uncertainty$_{t,t+4}$, Sales Abs. Forecast Error$_{t,t+4}$)	3.356E-04	1.649E-04	1837
0	Cov(Hiring Uncertainty$_{t,t+4}$, Hiring Abs. Forecast Error$_{t,t+4}$)	2.788E-04	1.202E-04	2104
0	Var(Sales Growth Forecast$_{t,t+4}$)	3.569E-03	3.769E-04	3535
0	Var(Hiring Plans$_{t,t+4}$)	3.572E-03	4.510E-04	4037
0	Var(Sales Growth Uncertainty$_{t,t+4}$)	1.459E-03	7.147E-04	4117
0	Var(Hiring Uncertainty$_{t,t+4}$)	1.146E-03	2.876E-04	4044
Dynamics	Var(Sales Growth$_{t-1,t}$)	5.943E-02	4.013E-03	3026
Dynamics	Var(Net Hiring$_t$)	1.757E-02	1.885E-03	3175
Dynamics	Cov(Net Hiring$_t$, Sales Growth$_{t-1,t}$)	2.139E-03	9.662E-04	2655
Dynamics	Cov(Sales Growth$_{t,t+4}$,Sales Growth$_{t-1,t}$)	-1.375E-02	2.134E-03	1260

Notes: This table shows the values of the target moments I use in my baseline estimation of the dynamic model with biased managers described the main text. 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.

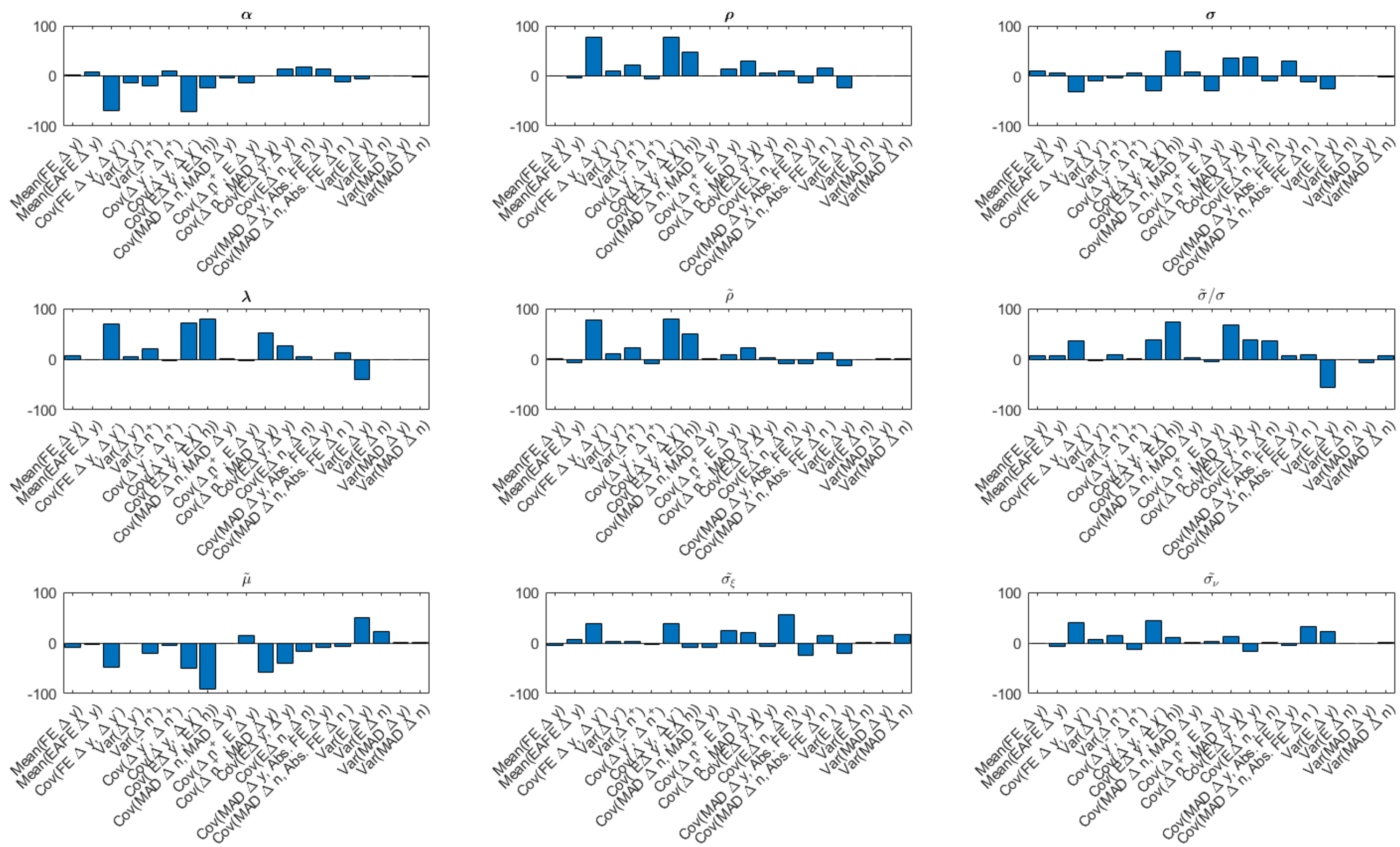
Table C.2: **Variance-Covariance Matrix of Moments**

Moment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mean(Forecast Error$_{t,t+4}$)	4.33E-05									
Mean(Excess Absolute Forecast Error$_{t,t+4}$)	-4.27E-06	4.07E-05								
Cov(Forecast Error$_{t,t+4}$, Sales Growth$_{t-1,t}$)	-3.27E-07	4.97E-06	4.19E-06							
Cov(Sales Growth Forecast$_{t,t+4}$, Hiring Plans$_{t,t+4}$)	-1.57E-06	1.14E-05	1.69E-06	1.61E-05						
Cov(Sales Growth Uncertainty$_{t,t+4}$,Hiring Uncertainty$_{t,t+4}$)	-5.83E-07	2.21E-06	1.88E-07	2.30E-06	3.55E-06					
Cov(Net Hiring$_t$, Sales Growth Forecast$_{t,t+4}$)	4.41E-07	1.43E-07	9.58E-08	1.42E-07	2.73E-07	9.33E-07				
Cov(Net Hiring$_t$, Sales Growth Uncertainty$_{t,t+4}$)	8.19E-07	-4.99E-06	-4.00E-06	-1.78E-06	-1.13E-07	-6.05E-08	4.55E-06			
Cov(Sales Growth Forecast$_{t,t+4}$, Realized Sales Growth$_{t,t+4}$)	-1.19E-07	2.19E-07	5.63E-08	1.68E-07	4.28E-08	3.69E-08	-1.16E-07	4.93E-08		
Cov(Hiring Plans$_{t,t+4}$, Realized Employment Growth$_{t,t+4}$)	4.35E-09	5.80E-09	1.96E-08	2.41E-08	1.83E-08	1.19E-08	-1.84E-08	9.13E-09	2.11E-08	
Cov(Sales Growth Uncertainty$_{t,t+4}$, Sales Abs. Forecast Error$_{t,t+4}$)	-1.53E-08	1.73E-07	-7.13E-09	9.90E-09	8.69E-08	2.72E-08	-4.05E-11	1.10E-08	2.52E-09	2.80E-08
Cov(Hiring Uncertainty$_{t,t+4}$, Hiring Abs. Forecast Error$_{t,t+4}$)	1.52E-07	-2.61E-07	-1.35E-07	-2.63E-07	-1.13E-07	-6.96E-08	1.71E-07	-6.01E-08	-1.48E-08	-1.91E-08
Var(Sales Growth Forecast$_{t,t+4}$)	-1.26E-07	4.77E-07	2.23E-08	3.01E-07	1.26E-07	-5.95E-09	-1.49E-07	5.81E-08	6.21E-09	2.74E-08
Var(Hiring Plans$_{t,t+4}$)	1.01E-07	6.99E-07	1.12E-07	5.80E-07	2.39E-07	1.10E-07	-2.72E-07	1.26E-07	2.06E-08	3.71E-08
Var(Sales Growth Uncertainty$_{t,t+4}$)	-1.35E-08	4.77E-08	8.89E-08	1.05E-07	9.09E-08	5.59E-08	-4.62E-08	4.07E-09	4.01E-09	9.00E-10
Var(Hiring Uncertainty$_{t,t+4}$)	-1.23E-08	5.90E-08	3.82E-08	4.18E-08	2.92E-08	1.33E-08	-1.57E-08	-1.17E-10	8.01E-09	-3.17E-10
Var(Sales Growth$_{t-1,t}$)	-3.10E-07	7.05E-07	1.15E-07	3.68E-07	1.33E-07	7.31E-08	-1.82E-07	6.23E-08	1.08E-08	1.95E-08
Var(Net Hiring$_t$)	-2.12E-07	7.82E-07	1.62E-07	5.86E-07	2.97E-07	1.15E-07	-2.40E-07	7.41E-08	1.74E-08	1.82E-08
Cov(Net Hiring$_t$, Sales Growth$_{t-1,t}$)	-4.26E-07	6.12E-07	2.07E-07	5.68E-07	1.50E-07	1.10E-07	-4.28E-07	1.44E-07	4.26E-08	3.77E-08
Cov(Sales Growth$_{t,t+4}$,Sales Growth$_{t-1,t}$)	-1.35E-07	7.66E-08	8.23E-08	1.48E-07	1.71E-07	7.12E-08	-6.38E-08	9.15E-09	2.31E-08	7.96E-09

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).

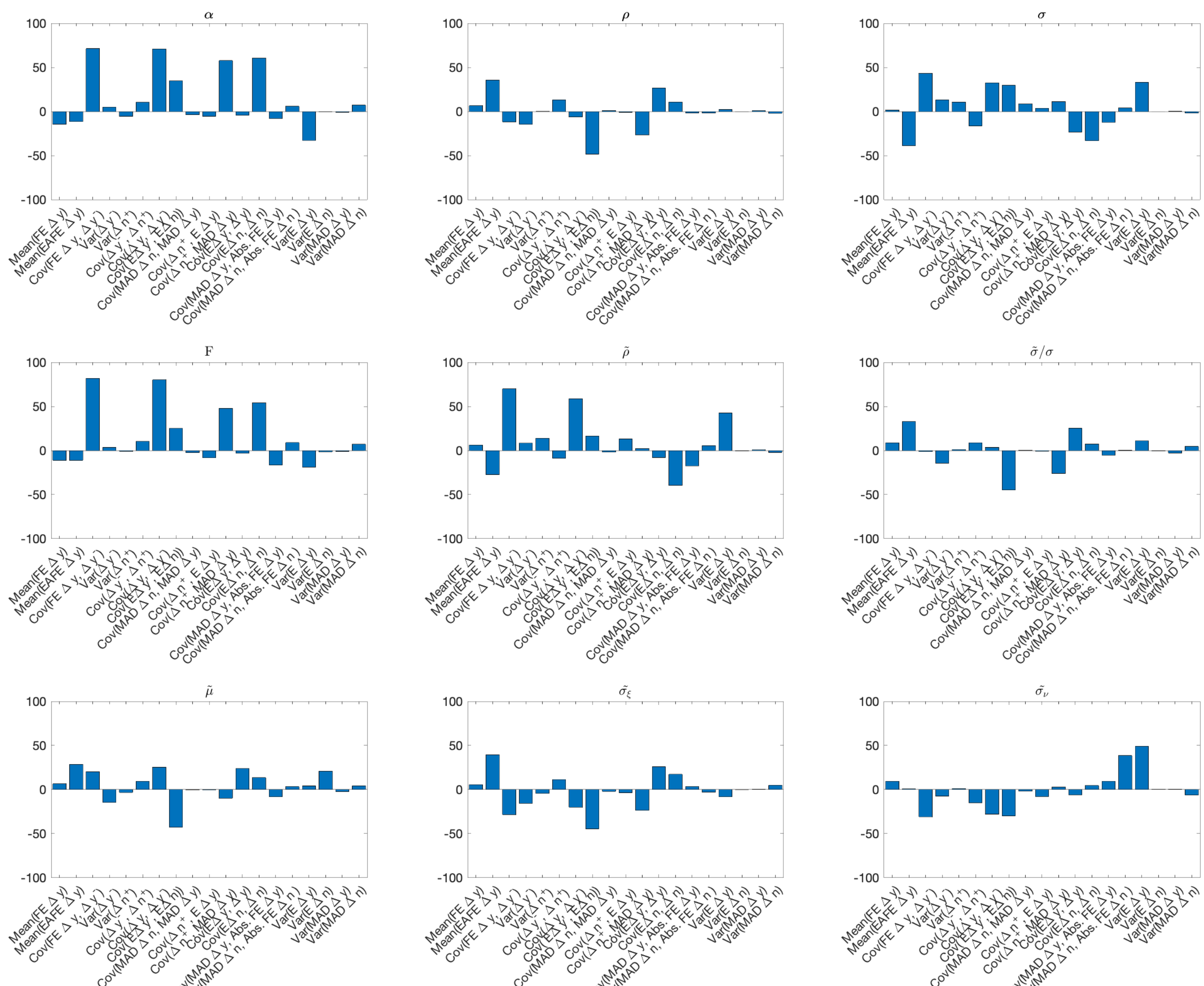
Moment	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
Mean(Forecast Error$_{t,t+4}$)									
Mean(Excess Absolute Forecast Error$_{t,t+4}$)									
Cov(Forecast Error$_{t,t+4}$, Sales Growth$_{t-1,t}$)									
Cov(Sales Growth Forecast$_{t,t+4}$, Hiring Plans$_{t,t+4}$)									
Cov(Sales Growth Uncertainty$_{t,t+4}$,Hiring Uncertainty$_{t,t+4}$)									
Cov(Net Hiring$_t$, Sales Growth Forecast$_{t,t+4}$)									
Cov(Net Hiring$_t$, Sales Growth Uncertainty$_{t,t+4}$)									
Cov(Sales Growth Forecast$_{t,t+4}$, Realized Sales Growth$_{t,t+4}$)									
Cov(Hiring Plans$_{t,t+4}$, Realized Employment Growth$_{t,t+4}$)									
Cov(Sales Growth Uncertainty$_{t,t+4}$, Sales Abs. Forecast Error$_{t,t+4}$)									
Cov(Hiring Uncertainty$_{t,t+4}$, Hiring Abs. Forecast Error$_{t,t+4}$)	1.03E-07								
Var(Sales Growth Forecast$_{t,t+4}$)	-6.38E-08	3.48E-07							
Var(Hiring Plans$_{t,t+4}$)	-1.75E-07	1.76E-07	4.71E-07						
Var(Sales Growth Uncertainty$_{t,t+4}$)	-2.08E-08	-1.62E-08	1.91E-08	2.72E-08					
Var(Hiring Uncertainty$_{t,t+4}$)	-4.39E-09	-2.00E-09	-3.18E-09	6.57E-09	1.45E-08				
Var(Sales Growth$_{t-1,t}$)	-7.86E-08	1.45E-07	1.82E-07	9.51E-09	2.65E-09	1.42E-07			
Var(Net Hiring$_t$)	-1.03E-07	1.10E-07	2.53E-07	2.21E-08	8.69E-09	1.21E-07	2.03E-07		
Cov(Net Hiring$_t$, Sales Growth$_{t-1,t}$)	-2.07E-07	1.87E-07	4.08E-07	1.58E-08	4.15E-09	1.95E-07	2.34E-07	5.11E-07	
Cov(Sales Growth$_{t,t+4}$,Sales Growth$_{t-1,t}$)	-2.59E-08	1.90E-08	3.92E-08	1.71E-08	1.56E-08	3.12E-08	4.70E-08	5.20E-08	8.27E-08

Figure C.1: **Sensitivity of Estimated Parameters to Moments: Convex Only**



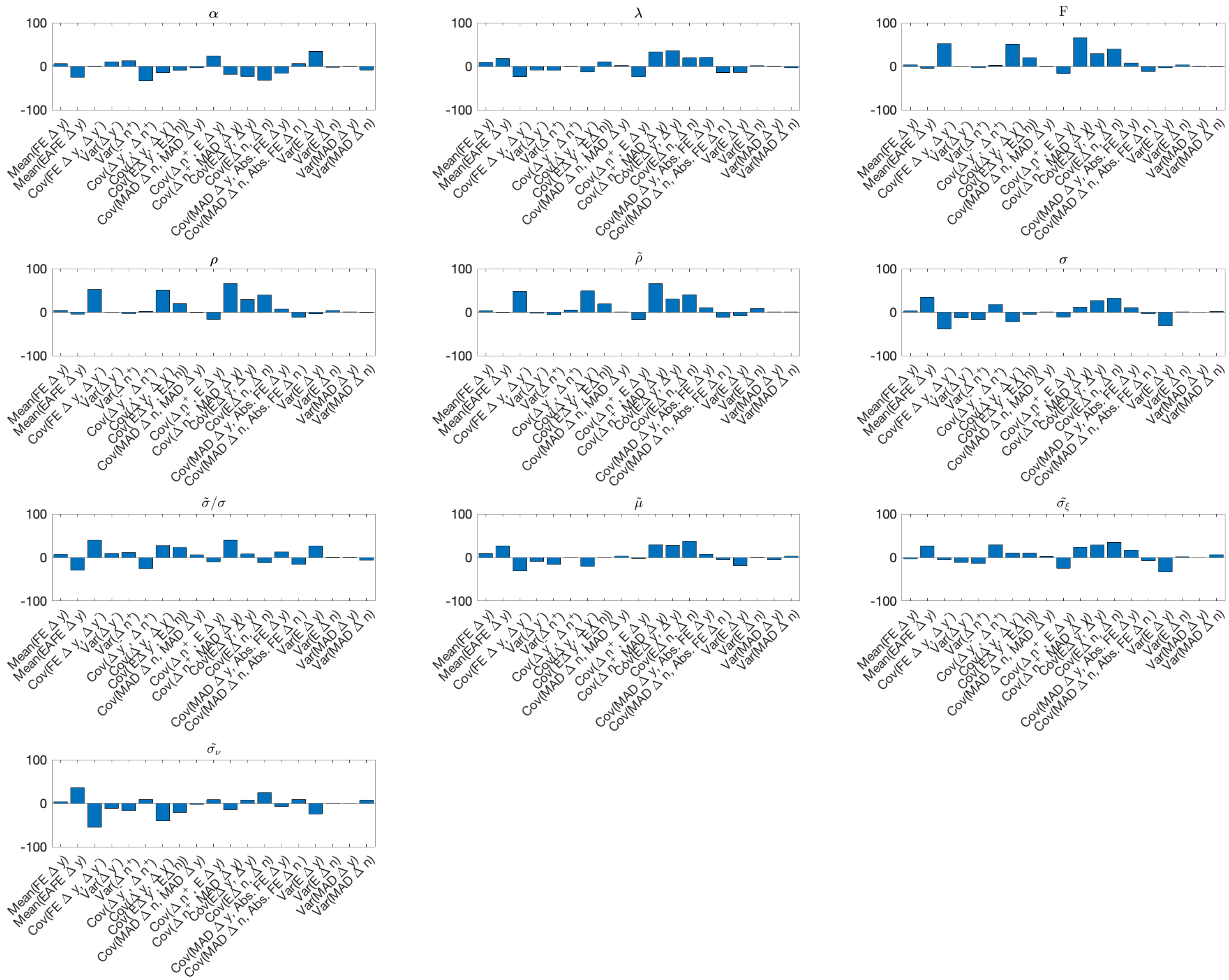
Notes: This figure shows Andrews-Gentzkow-Shapiro (2017) sensitivies for each of the parameters in the baseline model with convex adjustment costs with respect to targeted moments. Each bar corresponds to the coecient from a theoretical local regression of parameters on moments, with units expressed in terms of standard deviations.

Figure C.2: **Sensitivity of Estimated Parameters to Moments: Fixed Only**



Notes: This figure shows Andrews-Gentzkow-Shapiro (2017) sensitivities for each of the parameters in the baseline model with convex adjustment costs with respect to targeted moments. Each bar corresponds to the coecient from a theoretical local regression of parameters on moments, with units expressed in terms of standard deviations.

Figure C.3: **Sensitivity of Estimated Parameters to Moments: Hybrid (Fixed + Convex)**



Notes: This figure shows Andrews-Gentzkow-Shapiro (2017) sensitivies for each of the parameters in the baseline model with convex adjustment costs with respect to targeted moments. Each bar corresponds to the coecient from a theoretical local regression of parameters on moments, with units expressed in terms of standard deviations.

Table C.3: **Quantitative Results Robustness: Convex Adjustment Costs**

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

	Δ Objective Firm Value (%)				
Counterfactual	Baseline	High Adj. Costs	Low Adj. Costs	Low q (separation rate)	Low α
$\tilde{\sigma} = \sigma$ only	1.40	1.68	0.78	1.63	0.44
$\tilde{\rho} = \rho$ only	0.81	0.73	0.62	0.97	0.36
$\tilde{\rho} = \rho$ and $\tilde{\sigma} = \sigma$	1.96	1.55	1.66	2.26	0.63
$\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, and $\tilde{\mu} = \mu$	2.13	2.34	1.87	2.46	0.68

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

	Δ Consumer Welfare (%)				
Counterfactual	Baseline	High Adj. Costs	Low Adj. Costs	Low q (sep. rate)	Low α
$\tilde{\sigma} = \sigma$ only	0.28	0.58	0.19	0.21	0.22
$\tilde{\rho} = \rho$ only	0.22	0.32	0.18	0.20	0.14
$\tilde{\rho} = \rho$ and $\tilde{\sigma} = \sigma$	0.39	0.55	0.29	0.32	0.27
$\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, and $\tilde{\mu} = \mu$	0.50	0.66	0.35	0.39	0.35

Notes: Table C.3a *(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 correspons to different model specifications. Table C.3b *(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 3 in the main text. Specifications with high and low adjustment costs respectively have three times and one third my estimated adjustment cost parameter λ, which equals 30.3 in the baseline. The specification with a 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 column labeled "low α" imposes decreasing returns to scale on the order of $\alpha = 0.65$, lower than my baseline estimated value of α =083. All specifications in this table calibrate the managerial equity share to its baseline (conservative) level of $\theta = 0.05$. Note that managerial equity θ has no effect on the firm-value cost of non-rational managerial beliefs in Table C.3a.

Table C.4: **Quantitative Results Robustness: Hybrid (Fixed + Convex) Adjustment Costs**

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

	Δ Objective Firm Value (%)				
Counterfactual	Baseline	High Adj. Costs	Low Adj. Costs	Low q (separation rate)	Low α
$\tilde{\sigma} = \sigma$ only	0.87	1.65	-2.94	1.26	0.55
$\tilde{\rho} = \rho$ only	5.44	3.96	6.02	6.34	1.10
$\tilde{\rho} = \rho$ and $\tilde{\sigma} = \sigma$	6.61	4.70	7.83	7.54	1.26
$\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, and $\tilde{\mu} = \mu$	6.83	4.85	8.05	7.76	1.28

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

Counterfactual	Δ Consumer Welfare (%)				
	Baseline	High Adj. Costs	Low Adj. Costs	Low q (sep. rate)	Low α
$\tilde{\sigma} = \sigma$ only	0.32	0.38	0.23	0.34	0.27
$\tilde{\rho} = \rho$ only	0.94	0.78	0.96	0.92	0.48
$\tilde{\rho} = \rho$ and $\tilde{\sigma} = \sigma$	1.06	0.90	1.08	1.01	0.54
$\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, and $\tilde{\mu} = \mu$	1.10	0.96	1.14	1.06	0.58

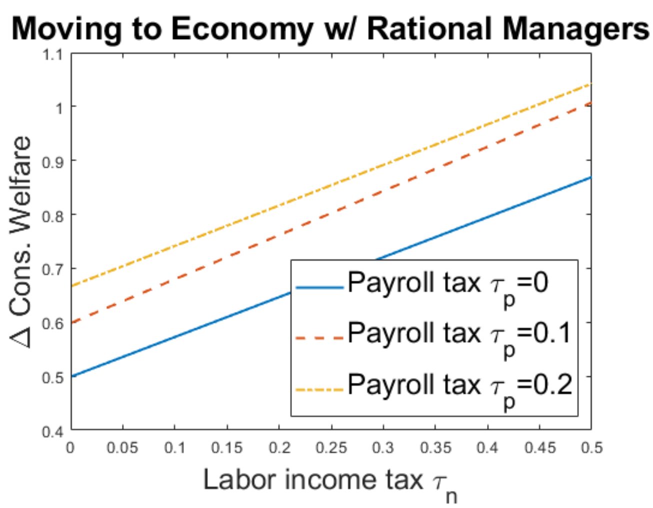
Notes: Table C.4a *(top)* shows how much firm value would increase by replacing a biased manager with another who has fewer or no subjective beliefs biases, holding all else constant. Columns correspons to different model specifications. Table C.4b *(bottom)* shows the change in consumer welfare we would 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 3 in the main text. Specifications with high and low adjustment costs respectively have ten percent higher or lower adjustment cost parameters λ and F, which equal 30.3 and 0.039 in the baseline. The specification with a 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 column labeled "low α" imposes decreasing returns to scale on the order of $\alpha = 0.65$, lower than my baseline estimated value of α =083. All specifications in this table calibrate the managerial equity share to its baseline (conservative) level of $\theta = 0.05$. Note that managerial equity θ has no effect on the firm-value cost of non-rational managerial beliefs in Table C.4a.

Table C.5: **Counterfactuals with Constant Prices**

Managerial equity share θ	Δ Consumer Welfare %	ΔY %	ΔN%	$\Delta\,(Y/N)$ %
0.05	-6.04	19.66	24.99	-4.26
0.25	-6.81	19.66	24.99	-4.26
0.50	-7.89	19.66	24.99	-4.26

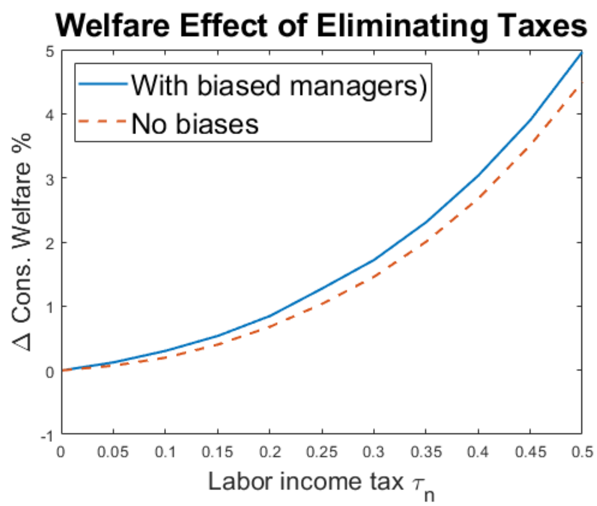
Notes: This table computes the long-run difference in consumption-equivalent welfare, aggregate output (GDP), and labor productivity between an economy in which managers have rational expectations and my baseline economy with biased managers, but wages in the counterfactual economy remain constant at the level implied by the equilibrium of the baseline economy.

Figure C.4: **Taxes Amplify Welfare Impact of Managerial Biases**



Notes: This figure shows the difference in welfare between an economy in which managers have rational expectations and my baseline economy as a function of distortionary payroll and labor income taxes. 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 economy with the combination of taxes in the figure.

Figure C.5: **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 τ_n and no payroll taxes ($\tau_p = 0$). Each line shows this welfare change depending on whether managers are biased or have rational expectations.

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