THE MICRO AND MACRO OF MANAGERIAL BELIEFS

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Empirically, how accurate are managers’ beliefs about their own firm’s future business conditions?

What are the *quantitative* implications of biases in managerial beliefs? Specifically, for:

- Value, dynamic behavior of *individual* firms?
- *Aggregate* consumer welfare, efficiency?
Why Should We Care?

Managerial beliefs impact dynamic decisions, outcomes

Micro: Even benevolent managers acting under biased beliefs may fail to maximize firm value

Macro: If biases are pervasive, systematic inefficiencies in managerial decisions may affect aggregate outcomes
Why Should We Care?

Managerial beliefs impact dynamic decisions, outcomes

Micro: Even benevolent managers acting under biased beliefs may fail to maximize firm value

Macro: If biases are pervasive, systematic inefficiencies in managerial decisions may affect aggregate outcomes

Yet: few quantitative benchmarks on the magnitudes and costs of biases
Baseline Setup

Output: \( \log(y_t) = \log(z_t) + \alpha \log(n_t) \)

Idiosyncratic shocks:

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

Managers’ subjective beliefs:

\( \log(z_{t+1}) = \tilde{\mu} + \tilde{\rho} \log(z_t) + \tilde{\sigma} \varepsilon_{t+1} \)
Baseline Setup

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Idiosyncratic shocks:

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\]

Managers’ subjective beliefs:

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

Characterizing beliefs:

- Unbiased: \( \tilde{\mu} = \mu, \tilde{\sigma} = \sigma, \tilde{\rho} = \rho \)
- Overoptimistic: \( \tilde{\mu} > \mu \)
- Overconfident (a.k.a. overprecise): \( \tilde{\sigma} < \sigma \)
- Overextrapolative: \( \tilde{\rho} > \rho \)
Baseline Setup

Output: $\log(y_t) = \log(z_t) + \alpha \log(n_t)$

Idiosyncratic shocks:

$$\log(z_{t+1}) = \mu + \rho \log(z_t) + \sigma \varepsilon_{t+1}$$

Managers’ subjective beliefs:

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

Research questions:
Baseline Setup

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

Managers’ subjective beliefs:

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

Research questions:

1. How different are \( \tilde{\mu} \) vs. \( \mu \), \( \tilde{\sigma} \) vs. \( \sigma \), \( \tilde{\rho} \) vs \( \rho \)?
Baseline Setup

**Output:** \[ \log(y_t) = \log(z_t) + \alpha \log(n_t) \]

**Idiosyncratic shocks:**
\[ \log(z_{t+1}) = \mu + \rho \log(z_t) + \sigma \varepsilon_{t+1} \]

**Managers’ subjective beliefs:**
\[ \log(z_{t+1}) = \tilde{\mu} + \tilde{\rho} \log(z_t) + \tilde{\sigma} \varepsilon_{t+1} \]

**Research questions:**

2. What are the micro and macro costs of using \( \{\tilde{\mu}, \tilde{\sigma}, \tilde{\rho}\} \) instead of \( \{\mu, \sigma, \rho\} \) when choosing \( n_{t+1} \) under uncertainty?
This Paper

1. New survey evidence on US managers’ beliefs

2. Build GE model with heterogeneous firms run by managers with biased beliefs

3. Quantify impact of biased beliefs
This Paper

1. New survey evidence on US managers’ beliefs
   - Confidential responses
   - Subjective distribution of own-firm future sales growth

2. Build GE model with heterogeneous firms run by managers with biased beliefs

3. Quantify impact of biased beliefs
1. New survey evidence on US managers’ beliefs
   ▶ Confidential responses
   ▶ Subjective distribution of own-firm future sales growth
   Three facts: optimism, overconfidence, overextrapolation

2. Build GE model with heterogeneous firms run by managers with biased beliefs

3. Quantify impact of biased beliefs
1. **New survey evidence on US managers’ beliefs**
   Three facts: optimism, overconfidence, overextrapolation

2. **Build GE model with heterogeneous firms run by managers with biased beliefs**
   Estimate \{\hat{\mu}, \hat{\mu}, \sigma, \bar{\sigma}, \rho, \bar{\rho}\}, targeting the three facts from 1.
   & observed dynamic choices subject to frictions

3. **Quantify impact of biased beliefs**
This Paper

1. New survey evidence on US managers’ beliefs
   Three facts: optimism, overconfidence, overextrapolation

2. Build GE model with heterogeneous firms run by
   managers with biased beliefs
   Estimate \( \{ \mu, \tilde{\mu}, \sigma, \tilde{\sigma}, \rho, \tilde{\rho} \} \), targeting the three facts from 1.
   & observed dynamic choices subject to frictions

3. Quantify impact of biased beliefs
   Micro: Make a single firm’s manager unbiased
   Macro: Make all managers unbiased (GE)
PREVIEW OF RESULTS

Empirically, managers:

▶ Are not over-optimistic nor pessimistic: \( \tilde{\mu} \approx \mu \)
▶ Are overconfident: \( \tilde{\sigma} \approx 0.46 \times \sigma \)
▶ Overextrapolate: quarterly \( \tilde{\rho} \approx 0.91 \) but \( \rho \approx 0.80 \)

Eliminating biases results in:

▶ Micro: 1.9% higher firm value
▶ Macro: 1.0% higher consumption equivalent welfare
  ▶ Biased managers overreact to shocks
  ▶ Too many resources spent on reallocation

▶ Cost of business cycles: 0.1 - 1.5% (Krusell et al, 2009)
Related Literature


Outline

Evidence about Managers’ Subjective Beliefs

General Equilibrium Model of Employment Dynamics

Structural Estimation

Micro & Macro Implications of Biases

Extensions
Monthly panel survey collected by Atlanta Fed

- Developed in consultation with Stanford, Chicago-Booth
- \( \approx 300 \) responses per month
- 10/2014 - present
- Altig, Barrero, Bloom, Davis, Meyer, Parker (’18)
- Official survey website here
Survey goal: Elicit subjective probability distributions from high-level managers of US Firms

- Future own-firm outcomes. (This paper: sales growth)
- Individual responses are confidential
- Tracks beliefs & outcomes across time
- In progress: match up to Census Business Register/LBD
SBU Respondents are Primarily CFOs & CEOs

Notes: This figure shows the distribution of SBU panel members by job title as of July 2018.
SBU is Broadly Representative, Oversamples Larger, Older Firms

Notes: This figure shows (1) the share of employment across all SBU responses from 10/2014 to 7/2018 made by firms in each firm size category; (2) the share of employment for each firm size category in the US economy according to the US Census Bureau’s 2015 Statistics on US Businesses.
For the **current** quarter, what would you estimate the total dollar value of your **SALES REVENUE** will be?

$5,000,000$
Looking **ahead**, from now to four quarters from now, what approximate percentage **SALES REVENUE** growth rate would you assign to each of the following scenarios?

<table>
<thead>
<tr>
<th>The LOWEST percentage sales revenue growth rate would be about:</th>
<th>-2 %</th>
</tr>
</thead>
<tbody>
<tr>
<td>A LOW percentage sales revenue growth rate would be about:</td>
<td>0 %</td>
</tr>
<tr>
<td>A MIDDLE percentage sales revenue growth rate would be about:</td>
<td>4 %</td>
</tr>
<tr>
<td>A HIGH percentage sales revenue growth rate would be about:</td>
<td>6 %</td>
</tr>
<tr>
<td>The HIGHEST percentage sales revenue growth rate would be about:</td>
<td>10 %</td>
</tr>
</tbody>
</table>
Please assign a percentage likelihood to the **SALES REVENUE** growth rates you entered. (Values should sum to 100%)

<table>
<thead>
<tr>
<th>Likelihood</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOWEST: The likelihood of realizing a -2% sales revenue growth rate would be:</td>
<td>10%</td>
</tr>
<tr>
<td>LOW: The likelihood of realizing a 0% sales revenue growth rate would be:</td>
<td>20%</td>
</tr>
<tr>
<td>MIDDLE: The likelihood of realizing a 4% sales revenue growth rate would be:</td>
<td>40%</td>
</tr>
<tr>
<td>HIGH: The likelihood of realizing a 6% sales revenue growth rate would be:</td>
<td>20%</td>
</tr>
<tr>
<td>HIGHEST: The likelihood of realizing a 10% sales revenue growth rate would be:</td>
<td>10%</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>100%</strong></td>
</tr>
</tbody>
</table>
Forecast Errors

Sample: 1,574 forecast error obs. about sales growth

- Observation: beliefs in quarter $t$, realization in $t + 4$
- $Forecast = \text{mean of subjective distribution}$
- $Forecast \text{ error} = forecast - realized \ text{sales growth}$
- $\sim 100 \ new \ forecast \ error \ observations \ each \ month$
**Fact 0: Managerial Beliefs Predict Outcomes & Hiring Plans**

![Graph showing the relationship between forecast and realized sales growth](image)

**Notes:** This figure shows a bin-scatter of 4-quarter sales growth realizations against ex-ante forecasts for sales growth. Data are from the SBU covering all months between 10/2014 to 6/2018.

\[ b = 0.615 \pm 0.097, \ N = 1574 \]
**Fact 0: Managerial Beliefs Predict Outcomes & Hiring Plans**

This figure shows a bin-scatter of managerial hiring plans ( ) against ex-ante forecasts for sales growth. Data are from the *SBU* covering all months between 10/2014 to 6/2018.

\[ b = 0.416 \pm 0.049, \quad N = 3615 \]

**Notes:** This figure shows a bin-scatter of managerial hiring plans ( ) against ex-ante forecasts for sales growth. Data are from the *SBU* covering all months between 10/2014 to 6/2018.
**Fact 1: Managers are Neither Over-Optimistic Nor Pessimistic**

![Graph showing mean forecast and realized sales growth]

**Notes:** This figure shows the mean forecast and realized sales growth, as well as the mean forecast error (= forecast minus realized) for sales growth across all responses in the SBU for which I can construct forecast errors. 95 percent confidence intervals are based firm-clustered standard errors. Sample period is from 10/2014 to 6/2018. N = 1,574.
**Fact 2: Managers are Overconfident**

![Graph showing forecast errors](image)

**Notes:** This figure plots the empirical distribution of forecast errors as well as the distribution of forecast errors that would arise if sales growth realizations were drawn from SBU respondents’ subjective probability distributions. Sample period is from 10/2014 to 6/2018. N = 1,574.
**Fact 2: Managers are Overconfident**

Notes: This figure plots the empirical distribution of forecast errors as well as the distribution of forecast errors that would arise if sales growth realizations were drawn from SBU respondents’ subjective probability distributions. Sample period is from 10/2014 to 6/2018. N = 1,574.
**Fact 3: Managers Overextrapolate**

**Notes:** This figure shows a bin-scatter of realized forecast errors for sales growth between quarters $t$ and $t + 4$ against sales growth between quarters $t - 1$ and $t$. Data are from the SBU covering 10/2014 to 6/2018. N = 919.
Three Facts about Managerial Beliefs Concerning Own-Firm Sales Growth

1. Managers are not over-optimistic or pessimistic
   Forecast - Realized Sales Growth ≈ 0

2. Managers are overconfident
   Excess Absolute Forecast Error ≈ .14

3. Managers overextrapolate
   1 p.p. faster growth at time of forecast
   ⇒ 0.2 p.p larger Forecast - Realized Sales Growth
Three Facts about Managerial Beliefs Concerning Own-Firm Sales Growth

1. Managers are not over-optimistic or pessimistic
   \[ \tilde{\mu} \approx \mu \]

2. Managers are overconfident
   \[ \tilde{\sigma} < \sigma \]

3. Managers overextrapolate
   \[ \tilde{\rho} > \rho \]
Evidence about Managers’ Subjective Beliefs

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Extensions
Firm Technology & Shocks

Operating income = sales - wage bill:

\[ y(z_t, n_t; w_t) = z_t n_t^\alpha - w_t n_t \]

Idiosyncratic shocks to business conditions:

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

Labor chosen one quarter ahead:

\[ n_{t+1} = (1 - q)n_t + h_t \]

No aggregate risk
Managers’ Beliefs

Objective driving process:

$$\log(z_{t+1}) = \mu + \rho \log(z_t) + \sigma \varepsilon_{t+1}$$

Managers’ subjective beliefs:

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

Characterizing beliefs:

- Unbiased: $\tilde{\mu} = \mu$, $\tilde{\sigma} = \sigma$, $\tilde{\rho} = \rho$
- Overoptimistic: $\tilde{\mu} > \mu$
- Overconfident: $\tilde{\sigma} < \sigma$
- Overextrapolative: $\tilde{\rho} > \rho$
Firm Cash Flows

Cash flow = operating income - hiring/firing costs

\[
\pi(z_t, n_t, n_{t+1}; w_t) = [z_t n_t^\alpha - w_t n_t - \lambda n_t \left( \frac{n_{t+1} - n_t \ast (1 - q)}{n_t} \right)^2] 
\]

Adjustment costs govern dynamic hiring/firing choices

- Managers trade off adjustment costs vs. beliefs about future MPN
Managers compensated with $\theta \in (0, 1]$ equity share.

Optimize their subjective valuation of the firm:

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

$\tilde{E}_t[\cdot]$ is the managers’ subjective expectations operator.
Manager’s Problem and Firm Value

Objective firm value under managers’ policy $\kappa(z, n)$:

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

$E_t[\cdot]$ operator uses the true stochastic process.
Lifetime utility maximization:

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

Budget constraint:

$$C_t + B_{t+1} = (1 + r_t)B_t + w_tN_t + (1 - \theta)\Pi_t$$

Household owns remaining share $1 - \theta$ of firms:

- Perfectly insured against firm-specific risk
Equilibrium consists of: \{w^*, r^*\}, \{C^*, N^*, B^*\}, \Phi(z, n)

In which:

- Managers choose $n_{t+1} = \kappa(z_t, n_t)$ to optimize subjective firm value
- Stationary distribution of firms $\Phi(z, n)$
- HH optimizes choosing $C_t = C^*$, $N^S_t = N^*$, $B_{t+1} = B^*$.
- Markets clear: $\int n d\Phi(z, n) = N^*$, $B^* = 0$
Evidence about Managers’ Subjective Beliefs

General Equilibrium Model of Employment Dynamics

**Structural Estimation**

Micro & Macro Implications of Biases

Extensions
STRUCTURAL ESTIMATION EXERCISE

Estimate 7 parameters:

\[ \theta = (\alpha, \lambda, \rho, \tilde{\rho}, \sigma, \tilde{\sigma}, \tilde{\mu})' \]

Target 8 moments:

<table>
<thead>
<tr>
<th>Forecast Error Moments (3)</th>
<th>Sales &amp; Emp. Moments (5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mathbb{E}[\text{ForecastError}] )</td>
<td>( \text{Cov} ) Matrix ( {\Delta n_{t+1}, \Delta y_t} )</td>
</tr>
<tr>
<td>( \mathbb{E}[\text{ExcessAbsForecastError}_{t,t+4}] )</td>
<td>( \text{Cov}(\Delta l y_{t+4}, \Delta n_{t+1}) )</td>
</tr>
<tr>
<td>( \text{Cov}(\text{ForecastError}_{t,t+4}, \Delta y_t) )</td>
<td>( \text{Cov}(\Delta l y_{t+4}, \Delta y_t) )</td>
</tr>
</tbody>
</table>

Notes: \( n_t \) denotes employment and \( y \) denotes sales. \( \text{ExcessAbsForecastError}_{t,t+4} \) is the difference between a firm’s actual absolute forecast error and its ex-ante subjective mean absolute deviation (subjective absolute forecast error). \( \Delta l y_{t+4} \) is the firm’s sales growth between quarters \( t \) and \( t + 4 \). All moments come from SBU data between 10/2014 and 6/2018.

Implementation: Overidentified GMM

Calibrate other parameters: \( \mu = 0 \)
## Parameter Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Explanation</th>
<th>Estimate (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>Revenue curvature</td>
<td>0.612 (0.036)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Quadratic adj.cost</td>
<td>27.3 (0.800)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>True shock persistence</td>
<td>0.801 (0.005)</td>
</tr>
<tr>
<td>$\tilde{\rho}$</td>
<td>Subjective shock pers.</td>
<td>0.913 (0.005)</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>True shock volatility</td>
<td>0.212 (0.0006)</td>
</tr>
<tr>
<td>$\tilde{\sigma}$</td>
<td>Subjective shock vol.</td>
<td>0.098 (0.0006)</td>
</tr>
<tr>
<td>$\tilde{\mu}$</td>
<td>Subjective shock mean</td>
<td>-0.003 (0.00003)</td>
</tr>
</tbody>
</table>

**Notes:** This table shows parameter estimates for the labor-based model specification with quadratic adjustment costs. I estimate the parameters by minimizing the distance between model-implied moments computed using the stationary distribution of firms across the $\left(z, n^-\right)$ state space and the set of empirical moments consisting of: (1) the variance-covariance matrix of net hiring and sales growth; (2) the two pairwise covariances of sales growth between $t$ and $t + 4$ with net hiring and recent growth; (3) three forecast error moments, namely: mean forecast error, mean excess absolute forecast error, and covariance of forecast error sales growth between $t - 1$ and $t$. The weighting matrix is the inverse of the firm-level clustered covariance matrix of the moments across the two sets of moments. I perform the numerical optimization using simulated annealing.

**Identification:**  
- Summary
Estimated Model & Data Moments

Notes: All data moments are estimated using data from the SBU with the sample period covering 10/2014 to 6/2018. All model moments are computed from the stationary distribution of firms across \((z, n)\) space.
Magnitude of Biases

No optimism or pessimism: \( \tilde{\mu} = -0.003 \quad \mu = 0 \)

- Underestimate mean innovation to \( \log(z) \) by 
  \( \approx 0.01 \times \sigma \)

Overconfidence: \( \tilde{\sigma} = 0.098 \quad \sigma = 0.212 \)

- Underestimate SD by 54%

Overextrapolation: \( \tilde{\rho} = 0.913 \quad \rho = 0.801 \)

- Believe half-life of shocks is 7.6 quarters
- True half-life only 3.1 quarters
Evidence about Managers’ Subjective Beliefs

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Micro & Macro Implications of Biases

Extensions
1. **Micro:** Replace a single biased manager at the beginning of quarter $t$

How much does objective firm value $V(\cdot)$ increase by hiring rationally $\forall \tau \geq t$?

Holding **all else equal**, including:
- Firm’s **current** business conditions, labor $(z, n)$
- Equilibrium wage
Micro Impact of Biased Beliefs

How much would firm value increase today by replacing biased manager?

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>$\Delta V^%$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{\rho} = \rho, \tilde{\sigma} = \sigma, \tilde{\mu} = \mu$</td>
<td>1.9</td>
</tr>
</tbody>
</table>

Notes: This table shows how much firm value would increase by replacing a biased manager with another who has correct beliefs. At each point in the $(z, n)$ state space I compute the objective value generated by the biased managers in my estimated economy, as well as the objective value generated by a counterfactual manager lacking pessimism, overconfidence, and/or overextrapolation. Then I compute the mean percent gain in firm value by averaging the gains across the state space under the stationary distribution of the economy with biases.
2. **Macro**: Economy with only unbiased managers

How do aggregate outcomes differ relative to baseline economy with biased managers?

Comparing aggregate steady-states in equilibrium
Consumer Welfare, Aggregate Output, & Labor Productivity are Higher Without Biases

Notes: This table shows the difference in household consumption-equivalent welfare, aggregate output (GDP), and aggregate labor productivity in an economy with unbiased managers relative to the steady state of my baseline economy with biases.

<table>
<thead>
<tr>
<th>∆ Cons. Welfare %</th>
<th>∆Y%</th>
<th>∆ (Y/N) %</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.99</td>
<td>1.6</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Model Aggregates  Magnitude of Welfare Implications
**Biases Encourage Excessive Reallocation**

**Notes:** This figure shows the joint distribution of log(labor productivity) on the horizontal axis and net hiring on the vertical axis in my baseline economy with biases and a counterfactual economy in which all managers are unbiased. I sort the stationary distribution of each economy into 20 quantiles by log-labor productivity and plot the mean in each quantile on the against the mean net hiring rate.
Notes: This figure shows the joint distribution of log(labor productivity) on the horizontal axis and net hiring on the vertical axis in my baseline economy with biases and a counterfactual economy in which all managers are unbiased. I sort the stationary distribution of each economy into 20 quantiles by log-labor productivity and plot the mean in each quantile on the against the mean net hiring rate.
Biases Encourage Excessive Reallocation

Overextrapolation ($\tilde{\rho} > \rho$)
- Shocks seem more persistent than they are
- Makes sense to hire/lay off workers in response

Overconfidence ($\tilde{\sigma} < \sigma$)
- Diminishes real-options, wait-and-see incentives
- Favors more aggressive hiring/firing

Both: Encourage excess spending on adjustment costs
Biases Encourage Excessive Reallocation

Economy without biases:

- Less reallocation
- Higher static “misallocation”
- Fewer resources spent on (unnecessary) adjustment costs
- Net positive for welfare, GDP, labor productivity

<table>
<thead>
<tr>
<th>Δ Realloc.</th>
<th>Δσ(MPN)</th>
<th>Δ(AC/Y) × 100</th>
</tr>
</thead>
<tbody>
<tr>
<td>- 81</td>
<td>6.6</td>
<td>- 2.2</td>
</tr>
</tbody>
</table>

Notes: This table shows the difference in reallocation (= total job creation and destruction), dispersion in the marginal product of labor, and adjustment costs as a share of GDP in an economy with unbiased managers relative to the steady state of my baseline economy with biases.
Tax on Hiring/Firing Can Increase Consumer Welfare

Add Tax on Hiring/Firing Expenditures:

\[
\pi(z_t, n_t, n_{t+1}; w_t) = \begin{bmatrix}
  z_t n_t^\alpha - w_t n_t \\
  \text{Revenue} - \text{Wage Bill} \\
  - (1 + \tau_f) \lambda n_t \left( \frac{n_{t+1} - n_t \ast (1 - q)}{n_t} \right)^2 \\
  \text{Quadratic Adjustment Costs}
\end{bmatrix}
\]

Transfer Tax Revenue Back to Household: \( T_t = \tau_f \ast AC \)

\[
C_t + B_{t+1} = (1 + r_t)B_t + w_t N_t + (1 - \theta)\Pi_t + T_t
\]
**Tax on Hiring/Firing Can Increase Consumer Welfare**

Notes: This figure shows the change in welfare across the steady state in an economy with a tax on hiring/firing expenditures relative to the baseline estimated economy. In both cases managers are biased. The curve shown uses a third-order polynomial to smooth out kinks due to numerical approximation of equilibrium.
Evidence about Managers’ Subjective Beliefs

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Extensions
**Conclusion**

Empirically, managers:
- Are not over-optimistic nor pessimistic: $\tilde{\mu} \approx \mu$
- Are overconfident: $\tilde{\sigma} < \sigma$
- Overextrapolate from current conditions: $\tilde{\rho} > \rho$

How costly are biases in managerial beliefs?
- **Micro**: 1.9% current firm value (holding all else constant)
- **Macro**: 1.0% consumer welfare
  - Biased managers overreact to shocks
  - Too many resources spent on reallocation
- Cost of business cycles: **0.1 - 1.5%** (Krusell et al, 2009)
Further Work

1. Business cycles

2. Innovation & creative destruction

3. Why do firms hire biased managers? Agency conflicts vs. information frictions

4. Capital structure
Further Work I: Business Cycles

Are managers also biased about aggregate risk?

- Do they still overextrapolate ($\tilde{\rho} > \rho$)?
- Are they still overconfident ($\tilde{\sigma} < \sigma$)?
- Possibly yes (e.g. Bordalo, Gennaioli, Ma & Shleifer, 2018)

Basic intuition: amplified business cycles (animal spirits)
Further Work I: Business Cycles

SBU data has no recessions: sample 10/2014 - present

Technical hurdles: Krusell-Smith (1998) on steroids
  - GE + firm heterogeneity
  - + Biased beliefs about aggregate shocks
  - + Biased beliefs about idiosyncratic shocks
  - Solving and computing such a model

Not obvious that basic intuition holds in DSGE
  - e.g. Khan & Thomas (2008) Bachman & Ma (2016)
Further Work II: Innovation & Creative Destruction

Biases may affect entry-exit margin

- **Overextrapolation** \((\hat{\rho} > \rho)\)
  Overreact to transitory positive/negative signals.

- **Overconfidence** \((\hat{\sigma} < \sigma)\)
  More willing to pay liquidation costs.

- Better selection \(\Rightarrow\) higher aggregate productivity?
Biases may affect incentives to innovate:

- Underestimate probability of competitor stealing my business?

- Or overestimate probability of success from R&D – over-invest in R&D?

- Or R&D overreacts to profitability (Terry, 2017)?
Further Work III: Why do firms hire biased managers?

Earlier work argues overconfidence may be a result of tournament incentives (e.g. Goel and Thakor, 2008)

Boards may also need years of forecasting data to determine whether a single manager is biased

- How much can tournaments account quantitatively for magnitude of overconfidence ($\bar{\sigma} < \sigma$) and/or overextrapolation ($\bar{\rho} > \rho$)?

- How much can information frictions account for?

- Working on a quantitative model for this
Biases affect perception of future profitability

- **Overconfidence** ($\tilde{\sigma} < \sigma$)
  
  Internal cash flows safe.
  Fewer precautionary savings motives (e.g. Hackbarth, 2008)
  Over-leverage?

- **Overextrapolation** ($\tilde{\rho} > \rho$)
  
  Overreact to transitory positive/negative signals.
  Leverage too volatile? Equity financing and payout?

- Can equilibrium debt/equity prices discipline behavior?
BACK-UP SLIDES
Agency Conflict Examples

Empire building:
- Incentive to hire pessimistic managers
- I don’t find evidence of pessimism

Tournament incentives & unobservable manager ability.
- Incentive to hire overconfident managers (e.g. Goel & Thakor, 2008)
- I find is the least costly bias

Risk-averse manager & risk-neutral shareholders:
- Again, incentive to hire overconfident managers

Not sure about a conflict for overextrapolation:
- Most costly bias in this paper
Notes: We construct our 1st Moment Index by averaging individual subjective mean growth rates for employment (looking 12 months hence), sales growth (looking 4 quarters ahead), capital expenditures (looking 4 quarters ahead), and unit costs (looking 12 months hence) in each month. Similarly, our 2nd moment index averages individual subjective uncertainty about the growth rates of employment, sales, capital expenditures, and unit costs. Then we smooth each series using a backward-looking moving average.
Notes: This figure shows our 1st Moment Index against the growth rate of the Industrial Production Index. We smooth both series using a backward-looking moving average and standardize them to have zero mean and unit standard deviation.
Notes: This figure shows our 2nd Moment Index against the level of the VIX in the middle of each month. We smooth both series using a backward-looking moving average and standardize them to have zero mean and unit standard deviation.
SBU Firms Come From All Sectors

Notes: This figure shows (1) the share of employment across all SBU responses from 10/2014 to 7/2018 made by firms in each sector; (2) the share of employment in each sector of the US economy according to the US Census Bureau’s 2015 Statistics on US Businesses.
SBU Firms are Older

Notes: This figure shows (1) the share of employment across all SBU responses from 10/2014 to 7/2018 by the firm’s year of birth; (2) the share of employment across firms by year of birth in the US economy according to the US Census Bureau’s 2015 Business Dynamics Statistics.
Notes: This figure shows (1) the share of employment across all SBU responses from 10/2014 to 7/2018 made by firms in each region (i.e. Census Division); (2) the share of employment in each region of the US economy according to the US Census Bureau’s 2015 Statistics on US Businesses.
Notes: This figure shows the probability a firm in the SBU Sampling frame (from Dun & Bradstreet) ultimately agrees to join the survey panel, conditional on firm size (in log base 10 employment).
SBU Sampling

Notes: This figure shows the share of employment in: (1) the US economy; (2) the SBU sampling frame (3) firms contacted by survey recruiters; (4) SBU responses.
Notes: This figure shows the share of employment in: (1) the US economy; (2) the SBU sampling frame (3) firms contacted by survey recruiters; (4) SBU responses.
SBU Sampling

Notes: This figure shows the share of employment in: (1) the US economy; (2) the SBU sampling frame (3) firms contacted by survey recruiters; (4) SBU responses.
### SBU Sampling

<table>
<thead>
<tr>
<th>Firm Size (Emp.)</th>
<th>Employment Shares</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Census BDS</td>
</tr>
<tr>
<td>a) 1 to 4</td>
<td>4.90%</td>
</tr>
<tr>
<td>b) 5 to 9</td>
<td>5.50%</td>
</tr>
<tr>
<td>c) 10 to 19</td>
<td>6.80%</td>
</tr>
<tr>
<td>d) 20 to 49</td>
<td>9.90%</td>
</tr>
<tr>
<td>e) 50 to 99</td>
<td>6.90%</td>
</tr>
<tr>
<td>f) 100 to 249</td>
<td>8.30%</td>
</tr>
<tr>
<td>g) 250 to 499</td>
<td>5.80%</td>
</tr>
<tr>
<td>h) 500 to 999</td>
<td>5.40%</td>
</tr>
<tr>
<td>i) 1000 to 2499</td>
<td>7.10%</td>
</tr>
<tr>
<td>j) 2500 to 4999</td>
<td>5.70%</td>
</tr>
<tr>
<td>k) 5000 to 9999</td>
<td>5.70%</td>
</tr>
<tr>
<td>l) 10000+</td>
<td>28.10%</td>
</tr>
</tbody>
</table>

**Notes:** This figure shows the share of employment in: (1) the US economy; (2) the SBU sampling frame (3) firms contacted by survey recruiters; (4) SBU responses.
**Subjective Moments vs. Bin Probabilities**

**Notes:** *(Left)* Bin-scatter of probability assigned to each bin scenario against the subjective expectation of sales growth rates. *(Right)* Bin-scatter of probability assigned to each bin scenario against subjective uncertainty (log scale) of sales growth rates. Data are from the SBU covering the period 10/2014 to 6/2018, restricting attention to subjective probability distributions with forecast errors. N = 1,574.
Subjective Moments vs. Bin Estimates

Notes: (Left) Bin-scatter of probability assigned to each bin scenario against the subjective expectation of sales growth rates. (Right) Bin-scatter of probability assigned to each bin scenario against subjective uncertainty (log scale) of sales growth rates. Data are from the SBU covering the period 10/2014 to 6/2018, restricting attention to subjective probability distributions with forecast errors. N = 1,574.
Measuring Realized Growth

Start with survey response in month $m$ belonging to quarter $t$.

▶ These are beliefs about sales growth between $t$ and $t + 4$.
▶ I have the firm’s current quarterly sales: $y_t$

Ideally, measure the realized sales $y_{t+4}^R$ in quarter $t + 4$ reported in month $m + 12$.

If sales level missing in month $m + 12$ I proceed as follows:

▶ If $m$ is the 1st month of quarter $t$ (e.g January), try sales level reported in $m + 13$ or $m + 14$
▶ If $m$ is the 2nd month of quarter $t$ (e.g February), try sales level reported in $m + 11$ or $m + 13$
▶ If $m$ is the 3rd month of quarter $t$ (e.g March), try try sales level reported in $m + 11$ or $m + 10$

The realized growth rate is then: $g_t = \frac{y_{t+4}^R - y_t}{\frac{1}{2}(y_{t+4}^R + y_t)}$. ▶ Back
### Sample of Forecast Errors: Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employment</td>
<td>477.1</td>
<td>175</td>
<td>1823</td>
</tr>
<tr>
<td>Quarterly Sales ($M)</td>
<td>38.1</td>
<td>8.00</td>
<td>232</td>
</tr>
<tr>
<td>4-Qtr Sales Growth</td>
<td>0.046</td>
<td>0.043</td>
<td>0.266</td>
</tr>
</tbody>
</table>

**Notes:** Summary statistics on current employment, current sales, and measured sales growth realizations among firm-month forecast error observations in the SBU. An observation here is a survey response with a well-defined subjective probability distribution for sales growth looking four quarters ahead, and for which I also observe sales four quarters later.
SBU Respondents are Larger, Well-Established Firms

Notes: Distribution of current employment at the time of forecast, among all SBU responses with forecast errors. Sample period is from 10/2014 to 6/2018. N = 1,574
**SBU Respondents are Larger, Well-Established Firms**

**Notes:** Distribution of current sales ($M) at the time of forecast, among all SBU responses with forecast errors. Sample period is from 10/2014 to 6/2018. N = 1,574.
Heterogeneity in Measured 4-quarter Growth Rates

Notes: Distribution of four-quarter sales growth realizations, among all SBU responses with forecast errors. Sample period is from 10/2014 to 6/2018. N = 1,574.
**Firms w/ Forecast Errors are Older**

*Notes:* Number of forecast error observations, sorting firms by the decade in which they hired their first paid employee. Data are from the *SBU* covering the period 10/2014 to 6/2018, restricting attention to subjective probability distributions with forecast errors. N = 1,414.
Sectoral Composition

Notes: Number of forecast error observations by one-digit sector. Data are from the SBU covering the period 10/2014 to 6/2018.
Sales Growth Forecasts & Forecast Errors

\[
\tilde{E}_t[g_{t+4}] \equiv \mathbb{E}[g_{t+4} | \mathcal{I}_t] = \sum_{j=1}^{5} \tilde{p}_j g_{j,t+4}
\]

- \( \tilde{E}_t[\cdot] \) = subjective expectation given info. set at \( t \)
- \( g_{t+4} \) = growth rate of quarterly sales b/n quarters \( t, t + 4 \)
- \( g_{j,t+4} \) = 4-quarter sales growth under \( j \)th scenario
- \( \tilde{p}_{j,t+4} \) = subjective probability of scenario \( j \)

**Forecast Error:** Forecast - Realized Sales Growth

\[
ForecastError_{t,t+4} = \tilde{E}_t[g_{t+4}] - g_{t+4}
\]
**Low Macro Volatility During SBU Sample**

*Notes:* This figure shows the evolution of the annualized growth rate of US real GDP by quarter since Q1.2007. The red lines indicate the start and end of the Great Recession. The green line indicates the start of the SBU Sample.
Subjective Distributions Look Bell-Shaped on Average

Notes: (Left) Mean probability assigned to each bin. (Right) Mean sales growth rate assigned to each bin. Data are from the SBU covering the period 10/2014 to 6/2018, restricting attention to subjective probability distributions with forecast errors. N = 1,574.
**FACT 0: BELIEFS DATA PREDICTS OUTCOMES**

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>(1) Realized Sales Growth, t to t+4</th>
<th>(2) (3)</th>
<th>(4) Actual Hiring, t to t+4</th>
<th>(5) (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales Growth Forecast, t to t+4</td>
<td>1.013***</td>
<td>(0.147)</td>
<td>0.662**</td>
<td>(0.261)</td>
</tr>
<tr>
<td>Forecast (Planned) Hiring, t to t+4</td>
<td>0.715***</td>
<td>(0.105)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales Growth, t-1 to t</td>
<td>-0.020</td>
<td>(0.021)</td>
<td>-0.037*</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Net Hiring, t</td>
<td>-0.056</td>
<td>(0.062)</td>
<td>-0.042</td>
<td>(0.054)</td>
</tr>
<tr>
<td>log(Cap. Expenditures), t</td>
<td>0.008**</td>
<td>(0.004)</td>
<td>0.008**</td>
<td>(0.004)</td>
</tr>
<tr>
<td>log(Employees), t</td>
<td>-0.021**</td>
<td>(0.009)</td>
<td>-0.021***</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Industry FE (14)</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Region FE (9)</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Age FE (22)</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>517</td>
<td>517</td>
<td>1,313</td>
<td>609</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.452</td>
<td>0.523</td>
<td>0.160</td>
<td>0.241</td>
</tr>
</tbody>
</table>

Notes: Columns (1) to (3) regress actual sales growth between quarters t and t+4 on information available in the quarter of the forecast. Columns (4) to (6) do the same for actual net hiring between t and t+4. I respectively include the respondent's forecast for sales growth or net hiring to show it has significant predictive power and its inclusion increases the marginal R-squared. I weight regressions by measures of accuracy for realized sales growth and actual hiring. Standard errors in parentheses, clustered by firm. Data are from the SBU covering 10/2014 to 6/2018 collapsed to quarterly frequency. *** p<0.01, ** p<0.05, * p<0.1
**Fact 0: Beliefs Data Predicts Outcomes**

Notes: This figure shows a bin-scatter of 4-quarter sales growth realizations against ex-ante forecasts for sales growth, controlling for firm and date fixed effects. Data are from the SBU covering all months between 10/2014 to 6/2018.
FACT 0: BELIEFS DATA PREDICTS OUTCOMES

Notes: This figure shows a bin-scatter of managerial hiring plans () against ex-ante forecasts for sales growth, controlling for firm and date fixed effects. Data are from the SBU covering all months between 10/2014 to 6/2018.
**Fact 0: Beliefs Data Predicts Outcomes**

This figure shows a bin-scatter of empirical absolute forecast errors for sales growth between quarters $t$ to $t + 4$ versus ex-ante subjective mean absolute deviation for sales growth from $t$ to $t + 4$, controlling for firm and date fixed effects. Data are from the SBU covering all months between 10/2014 to 6/2018 $N = 1,574$.

**Notes:**

Firm level regression: coeff = .904, s.e. = .126, $R^2 = .043$, $N = 1574$. 
**FACT 0: BELIEFS DATA PREDICTS OUTCOMES**

Notes: This figure shows a bin-scatter of empirical absolute forecast errors for sales growth between quarters $t$ to $t + 4$ versus ex-ante subjective mean absolute deviation for sales growth from $t$ to $t + 4$, controlling for firm and date fixed effects. Data are from the SBU covering all months between 10/2014 to 6/2018 $N = 1,574$. 

$b = .369 ( .160) , N = 1491$
Managers’ Beliefs and Hiring Decisions

I have already shown you (1) & (2) hold:
Sales growth forecasts predict actual sales growth

I can show you (3) through (5) also hold

- Evidence on (5) somewhat weaker

Forecast Sales Growth \(\rightarrow\) Actual Sales Growth

\[(1)\]

\[(2)\]
Planned Hiring \(\downarrow\)

\[(3)\]

\[(4)\]

Actual Hiring

\[(5)\]
Planned Hiring Predicts Actual Hiring

Notes: This figure shows a bin-scatter of actual hiring for quarters $t$ to $t + 4$ against planned hiring for quarters $t$ to $t + 4$. Data are from the SBU covering 10/2014 to 6/2018.

Firm, Date FE

$b = .740 ( .096), N = 2143$
Actual Sales Growth Predicts Actual Hiring

Notes: This figure shows a bin-scatter of actual hiring for quarters $t$ to $t+4$ against actual sales growth for $t$ to $t+4$. Data are from the SBU covering 10/2014 to 6/2018.

$\beta = 0.142 \ (0.028), \ N = 1234$
Forecast Sales Growth Predicts Actual Hiring

Notes: This figure shows a bin-scatter of actual hiring for quarters $t$ to $t + 4$ against the firm’s sales growth forecast for $t$ to $t + 4$. Data are from the SBU covering 10/2014 to 6/2018.

$b = .143 \ ( .099), N = 1514$
Planned Hiring Predicts Actual Hiring

Notes: his figure shows a bin-scatter of actual hiring for quarters $t$ to $t+4$ against planned hiring from $t$ to $t+4$, controlling for firm and date fixed effects. Data are from the SBU covering 10/2014 to 6/2018.
Actual Sales Growth Predicts Actual Hiring

Notes: this figure shows a bin-scatter actual hiring for quarters \( t \) to \( t + 4 \) against actual sales growth between quarters \( t \) and \( t + 4 \), controlling for firm and date fixed effects. Data are from the \( SBU \) covering 10/2014 to 6/2018.

\[ b = 0.077 (0.028), N = 1182 \]
Notes: This figure shows a bin-scatter of actual hiring for quarters $t$ to $t + 4$ against the firm’s sales growth forecast for $t$ to $t + 4$, controlling for firm and date fixed effects. Data are from the SBU covering 10/2014 to 6/2018.
Managers’ Beliefs and Current Hiring

What determines current hiring?
- Long-run forecast for performance (1)?
- RepONSE to latest shock (2)?

I’ll show you (2) is stronger: evidence of adjustment costs

Forecast Sales Growth $t$ to $t + 4$

Actual Hiring $t$

Sales Growth $t - 1$ to $t$
Sales Growth Innovations Predict Current Hiring

Notes: This figure shows a bin-scatter plot of net hiring in quarter $t$ against the firm’s sales growth between quarters $t - 1$ and $t$. Data are from the SBU covering 10/2014 to 6/2018.

$b = 0.068 (0.016), N = 2695$
Sales Growth Forecasts (Weakly) Predict Current Hiring

**Notes:** This figure shows a bin-scatter of net hiring in quarter $t$ against the firm’s sales growth forecast for $t$ to $t+4$. Data are from the SBU covering 10/2014 to 6/2018.
Sales Growth Innovations Predict Current Hiring

Notes: This figure shows a bin-scatter plot of net hiring in quarter $t$ against the firm’s sales growth between quarters $t - 1$ and $t$, controlling for firm and date fixed effects. Data are from the SBU covering 10/2014 to 6/2018.
Sales Growth Forecasts (Weakly) Predict Current Hiring

Notes: This figure shows a bin-scatter of net hiring in quarter $t$ against the firm’s sales growth forecast for $t$ to $t+4$, controlling for firm and date fixed effects. Data are from the SBU covering 10/2014 to 6/2018.
**Test: Mean Forecast Error in All Categories = 0**

<table>
<thead>
<tr>
<th>Categories</th>
<th>Months</th>
<th>Sectors</th>
<th>Sales Deciles</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-statistic</td>
<td>1.91</td>
<td>1.13</td>
<td>0.73</td>
</tr>
<tr>
<td>DF</td>
<td>(29, 396)</td>
<td>(14, 395)</td>
<td>(10, 396)</td>
</tr>
<tr>
<td>p-val</td>
<td>.0036</td>
<td>.33</td>
<td>.69</td>
</tr>
</tbody>
</table>

**Notes:** Data are from the *SBU* including all forecast errors sales growth (looking 4 quarter ahead) recorded between 10/2014 and 6/2018. Each column in the table displays results from a test of the null hypothesis that the mean forecast error is zero in each category after dividing forecast errors by: (1) month in which the forecast was made; (2) business sector of the firm; (3) decile of the sales distribution. N = 1,574.
## Fact 1: Managers are Neither Over-Optimistic Nor Pessimistic

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

**Notes:** This table shows the mean forecast and realized sales growth, as well as the mean forecast error (= forecast minus realized) for sales growth across all responses in the SBU for which I can construct forecast errors. Standard errors are clustered by firm. Sample period is from 10/2014 to 6/2018. N = 1,574.
**Fact 1**: Managers are Neither Over-Optimistic Nor Pessimistic

Notes: (Left) Mean forecast error by month. (Right) Mean forecast error by 1-digit sector. Data are from the SBU covering 10/2014 to 6/2018. 95% confidence bands and intervals are based on standard errors clustered by firm. N = 1,574
Fact 1: Managers are Neither Over-Optimistic Nor Pessimistic

Notes: Mean forecast error by decile of the current sales distribution. Data are from the SBU covering 10/2014 to 6/2018. Standard errors are clustered by firm. Bars are 95% confidence intervals based on standard errors clustered by firm. N = 1,574
**FACT 2: MANAGERS ARE OVERCONFIDENT**

**Notes:** This figure plots the empirical distribution of absolute forecast errors as well as the distribution of forecast errors that would arise under SBU respondents’ subjective probability distributions. Sample period is from 10/2014 to 6/2018. N = 1,574.
Is Overconfidence a Product of the Discrete 5-bin Approximation?

Short answer: No. They have 9 degrees of freedom.

Long answer: I try discretizing empirical distribution of sales growth using 2 approaches:

1. “Tauchen” approach: Pick 5 equidistant bins, ignoring $p$ tail mass. Assign probabilities according to CDF.

2. “Quantile” approach: Pick appropriate bins for typical probability vector, ignoring $p$ tail mass.

Under both approaches:
Ignoring tail mass $p \approx 0.4$ leads to an excess absolute forecast error less than half as large as in the data.
**“Tauchen” Approach**

1. Pick $p$ tail mass to disregard

2. Pick 5 equidistant bins $q_i \ i = 1, 2, 3, 4, 5$ on remaining support.

3. Assign probabilities $\pi_i, \ i = 1, 2, 3, 4, 5$ satisfying:
   
   \[ p_1 = F\left(\frac{q_1+q_2}{2}\right), \ p_2 = F\left(\frac{q_2+q_3}{2}\right) - F\left(\frac{q_1+q_2}{2}\right), \text{ etc.} \]

**How large are excess absolute forecast errors?**

<table>
<thead>
<tr>
<th>Mass Excluded $p$</th>
<th>0.01</th>
<th>0.05</th>
<th>0.1</th>
<th>0.2</th>
<th>0.4</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Abs. Error</td>
<td>0.024</td>
<td>0.012</td>
<td>0.022</td>
<td>0.042</td>
<td>0.074</td>
<td>0.145</td>
</tr>
</tbody>
</table>

**Notes:** This table shows 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” method of discretization. Before discretizing, I remove heterogeneity in realized sales growth attributable to differences in subjective first and second moments, leaving the empirical distribution of realized sales growth for the typical expectation and subjective uncertainty across all 1,574 forecast error observations in the SBU.
“Quantile” Approach

1. Start with typical probability vector in responses
   \[ \pi = (0.1, 0.2, 0.4, 0.2, 0.1)' \]

2. Pick \( p \) tail mass to disregard

3. Pick 5 bins \( q_i \)  \( i = 1, 2, 3, 4, 5 \) on remaining support satisfying:
   \[ \pi_1 = F\left( \frac{q_1+q_2}{2} \right), \pi_2 = F\left( \frac{q_2+q_3}{2} \right) - F\left( \frac{q_1+q_2}{2} \right), \text{ etc.} \]

How large are excess absolute forecast errors?

<table>
<thead>
<tr>
<th>Mass Excluded</th>
<th>0.01</th>
<th>0.05</th>
<th>0.1</th>
<th>0.2</th>
<th>0.4</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Abs. Error</td>
<td>-0.01</td>
<td>0.017</td>
<td>0.031</td>
<td>0.045</td>
<td>0.058</td>
<td>0.145</td>
</tr>
</tbody>
</table>

Notes: This table shows 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 “Quantile” method of discretization. Before discretizing, I remove heterogeneity in realized sales growth attributable to differences in subjective first and second moments, leaving the empirical distribution of realized sales growth for the typical expectation and subjective uncertainty across all 1,574 forecast error observations in the SBU.
“Tauchen” Approach for Normal Distribution

1. Pick $p$ tail mass to disregard
2. Pick 5 equidistant bins $q_i$ $i = 1, 2, 3, 4, 5$ on remaining support.
3. Assign probabilities $\pi_i$, $i = 1, 2, 3, 4, 5$ satisfying:
   
   $p_1 = F\left(\frac{q_1+q_2}{2}\right)$, $p_2 = F\left(\frac{q_2+q_3}{2}\right) - F\left(\frac{q_1+q_2}{2}\right)$, etc.

How large are excess absolute forecast errors?

<table>
<thead>
<tr>
<th>Mass Excluded $p$</th>
<th>0.01</th>
<th>0.05</th>
<th>0.1</th>
<th>0.2</th>
<th>0.4</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Abs. Error</td>
<td>0.016</td>
<td>0.012</td>
<td>0.015</td>
<td>0.027</td>
<td>0.059</td>
<td>0.145</td>
</tr>
</tbody>
</table>

Notes: This table shows the excess absolute forecast error that would arise from approximating a normal distribution with variance equal to that of the empirical distribution of sales growth between $t$ and $t+4$ under the “Tauchen” method of discretization. Before discretizing, I remove heterogeneity in realized sales growth attributable to differences in subjective first and second moments using SBU data. Then I simulate 1,574 draws from a Normal distribution and compute the excess absolute forecast error from using the discrete approximation to generate forecasts and subjective mean absolute deviations.
Quantile Approach for Normal Distribution

1. Start with typical probability vector in responses
   \[ \pi = (0.1, 0.2, 0.4, 0.2, 0.1)' \]
2. Pick \( p \) tail mass to disregard
3. Pick 5 bins \( q_i \ i = 1, 2, 3, 4, 5 \) on remaining support
   satisfying:
   \[ \pi_1 = \Phi(\frac{q_1+q_2}{2}), \pi_2 = \Phi(\frac{q_2+q_3}{2}) - \Phi(\frac{q_1+q_2}{2}), \text{ etc.} \]

How large are excess absolute forecast errors?

<table>
<thead>
<tr>
<th>Mass Excluded ( p )</th>
<th>0.01</th>
<th>0.05</th>
<th>0.1</th>
<th>0.2</th>
<th>0.4</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Abs. Error</td>
<td>0.013</td>
<td>0.027</td>
<td>0.036</td>
<td>0.045</td>
<td>0.056</td>
<td>0.145</td>
</tr>
</tbody>
</table>

Notes: This table shows the excess absolute forecast error that would arise from approximating a normal distribution with variance equal to that of the empirical distribution of sales growth between \( t \) and \( t + 4 \) under the “Quantile” method of discretization. Before discretizing, I remove heterogeneity in realized sales growth attributable to differences in subjective first and second moments using \( SBU \) data. Then I simulate 1,574 draws from a Normal distribution and compute the excess absolute forecast error from using the discrete approximation to generate forecasts and subjective mean absolute deviations.
Absolute Forecast Errors

Absolute forecast error (AFE):

$$|\tilde{E}[SalesGrowth_{t,t+4}] - SalesGrowth_{t,t+4}|$$

Subjective mean absolute deviation (SMAD):

$$\tilde{E} \left[ |\tilde{E}[SalesGrowth_{t,t+4}] - SalesGrowth_{t,t+4}| \right]$$

Excess absolute forecast error

$$= \text{Mean(AFE- SMAD)}:$$

$$\mathbb{E} \left[ |\tilde{E}[SalesGrowth_{t,t+4}] - SalesGrowth_{t,t+4}| - \tilde{E} \left[ |\tilde{E}[SalesGrowth_{t,t+4}] - SalesGrowth_{t,t+4}| \right] \right]$$
### Fact 2: Managers are Overconfident

| Absolute Forecast Error | Excess Error |   |
|-------------------------|--------------|
|                         | Empirical    | Subjective | Empirical - Subjective |
| **Mean**                | 0.185        | 0.039      | 0.146                  |
| **SE**                  | (0.007)      | (0.002)    | (0.006)                |
| **Obs.**                | 1,574        | 1,574      | 1,574                  |
| **Firms**               | 397          | 397        | 397                    |

**Notes:** Means of empirical and subjective absolute forecast errors. A respondent’s subjective absolute forecast error is the subjective mean absolute deviation from her forecast. Standard errors are clustered by firm. Sample period is from 10/2014 to 6/2018. N = 1,574.
**Fact 2: Managers are Overconfident Also Across Time, Sectors**

Notes:  *(Left)* Mean excess absolute forecast error by month. *(Right)* Mean excess absolute forecast error by 1-digit sector. Data are from the *SBU* covering 10/2014 to 6/2018. 95% confidence intervals and bands are based on standard errors clustered by firm. \(N = 1,574\)
**Fact 2: Managers are Overconfident Especially at Small Firms**

![Graph showing excess absolute forecast error by sales decile]

**Notes:** Mean excess absolute forecast error by decile of the current sales distribution, accounting for differences in subjective uncertainty across firms. Data are from the *SBU* covering 10/2014 to 6/2018. Bars are 95% confidence intervals based on standard errors are clustered by firm. N = 1,574
Subjective Uncertainty Accounts for Slope, Not Level of Errors

Notes: Bin-scatter plot of realized and subjective absolute forecast errors against ex-ante subjective uncertainty, i.e. the standard deviation of respondents’ subjective probability distributions. Data are from the SBU covering 10/2014 to 6/2018. N = 1,574.
Fact 3: Managers Overextrapolate: Across Firm Sizes

Notes: In this figure, I plot the coefficients from regression of forecast errors for sales growth looking four quarters ahead on sales growth in the quarter prior to providing a subjective probability distribution, allowing for different coefficients for each quintile of the sales distribution. Bars reflect 95% confidence intervals based on standard errors clustered by firm.
**Fact 3: Overconfidence Distinct From Overextrapolation**

**Notes:** This figure shows a bin-scatter plot of excess absolute forecast errors for quarters $t$ to $t+4 = (\text{absolute forecast error} - \text{subjective mean absolute deviation})$ on the vertical axis against sales growth for the firm between quarters $t - 1$ to $t$. Data are from the SBU covering 10/2014 to 6/2018. $N = 1,574$. 

[Bin-scatter plot image]
**FACT 3: MANAGERS OVEREXTRAPOLATE**

![Graph showing bin-scatter of realized and forecast sales growth]

**Notes:** This figure shows a bin-scatter of realized and forecast sales growth in quarters $t$ to $t + 4$ against sales growth between the quarters $t-1$ and $t$. Data are from the *SBU* covering 10/2014 to 6/2018. $N = 1,574$. 
### Fact 3: Managers Overextrapolate: Not Explained by Time, Firm Effects

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

**Notes:** Robust standard errors in parentheses, clustered by firm. Data are subjective probability distributions and forecast errors about sales growth looking 4 quarters ahead from the *Survey of Business Uncertainty* covering all months between October 2014 and June 2018. An observation is a forecast error for a particular firm in a particular month. *** p<0.01, ** p<0.05, * p<0.1
Fact 3: Managers Overextrapolate: Based on Reported Sales Growth

Notes: This figure shows a bin-scatter of forecast minus realized sales growth over quarters $t$ to $t + 4$ on the y-axis against the respondent’s reported sales growth in the 12 months prior. Data are from the SBU covering 10/2014 to 6/2018. N = 1,071.

Back
**Fact 3: Managers Overextrapolate: Based on Reported Sales Growth**

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast - Realized Sales Growth, quarters t to t+4</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reported Sales Growth, 12 months up to t</td>
<td>0.261**</td>
<td>0.267***</td>
<td>0.266**</td>
<td>0.390***</td>
</tr>
<tr>
<td></td>
<td>(0.101)</td>
<td>(0.100)</td>
<td>(0.104)</td>
<td>(0.111)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.018*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Date FE</td>
<td>Y</td>
<td></td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Date x Sector FE</td>
<td></td>
<td>Y</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm FE</td>
<td></td>
<td></td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1,071</td>
<td>1,071</td>
<td>1,062</td>
<td>1,021</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.021</td>
<td>0.039</td>
<td>0.159</td>
<td>0.504</td>
</tr>
</tbody>
</table>

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

*** p<0.01, ** p<0.05, * p<0.1
**Fact 3: Managers Overextrapolate: Errors Serially Correlated**

**Notes:** This figure shows a bin-scatter of forecast minus realized sales growth over quarters $t$ to $t + 4$ on the y-axis against forecast minus realized sales growth between quarters $t - 4$ and $t$. Data are from the SBU covering 10/2014 to 6/2018. N = 502.
**Fact 3: Managers Overextrapolate: Errors Serially Correlated**

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forecast - Realized Sales Growth, quarters t to t+4</td>
<td>-0.201***</td>
<td>-0.212***</td>
<td>-0.161**</td>
<td>-0.508***</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.062)</td>
<td>(0.077)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.020</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Date FE</td>
<td></td>
<td>Y</td>
<td></td>
<td>Y</td>
</tr>
<tr>
<td>Date x Sector FE</td>
<td></td>
<td></td>
<td>Y</td>
<td></td>
</tr>
<tr>
<td>Firm FE</td>
<td></td>
<td></td>
<td></td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>502</td>
<td>502</td>
<td>428</td>
<td>451</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.042</td>
<td>0.068</td>
<td>0.241</td>
<td>0.495</td>
</tr>
</tbody>
</table>

**Notes:** Robust standard errors in parentheses, clustered by firm. Data are subjective probability distributions and forecast errors about sales growth looking 4 quarters ahead from the **Survey of Business Uncertainty** covering all months between October 2014 and June 2018. An observation is a forecast error for a particular firm in a particular month. *** p<0.01, ** p<0.05, * p<0.1
Notes: This figure shows a bin-scatter of the marginal effect on planned hiring for quarters $t$ to $t + 4$ by the firm’s sales growth forecast for $t$ to $t + 4$, controlling for sales growth between quarters $t - 1$ and $t$ and firm and date fixed effects. Data are from the SBU covering 10/2014 to 6/2018.
**Sales Growth Innovations Do NOT Predict Actual Hiring**

**Notes:** this figure shows a bin-scatter of the marginal effect on actual hiring for quarters $t$ to $t+4$ by sales growth between quarters $t-1$ and $t$, controlling for the firm’s sales growth forecast for $t$ to $t+4$ and firm and date fixed effects. Data are from the *SBU* covering 10/2014 to 6/2018.


Issue: If realized sales growth is imprecise, could result in large measured absolute forecast errors. Even if managers are not overconfident.

Test: Do my measured absolute forecast errors look implausibly large?

- Sales growth forecast errors, 4-quarter horizon, I/B/E/S
- Magnitude of analysts errors vs. SBU measured errors
- Magnitude of analysts’ errors vs. SBU subjective errors
Are Managers’ Empirical Forecast Errors implausibly Large?

**Notes:** This figure plots the empirical distribution of managers’ forecast errors for sales growth looking four quarters ahead from the SBU as well as the empirical distribution of analyst forecast errors for sales growth four quarters ahead from IBES. Sample period for the SBU is from 10/2014 to 6/2018 and for IBES it is 1990 to 2017. N = 1,574 in the SBU, and N = 755,685 in IBES.
Are Managers’ Subjective Forecast Errors implausibly Small?

Notes: This figure plots the subjective distribution of managers’ forecast errors for sales growth looking four quarters ahead from the SBU as well as the empirical distribution of analyst forecast errors for sales growth four quarters ahead from IBES. Sample period for the SBU is from 10/2014 to 6/2018 and for IBES it is 1990 to 2017. N = 1,574 in the SBU, and N = 755,685 in IBES.
Firm-Level Mean Excess Abs. Forecast Errors

Notes: This figure shows the distribution of firm fixed effects from a regression of empirical absolute forecast errors on firm and date effects and subjective uncertainty about sales growth. An observation is the effect for a particular firm. NFirms = 301.
Managers compensated with $\theta \in (0, 1]$ equity share.

Optimize their subjective valuation of the firm:

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

$\tilde{E}_t[\cdot]$ is the managers’ subjective expectations operator.
Manager’s Problem and True Firm Value

True firm value under managers’ policy $\kappa(z, n)$:

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

$E_t[\cdot]$ operator uses the true stochastic process.
Solving the Model

1. Solve for managers’ policy functions $n_{t+1} = \kappa(z, n; w)$:
   - **Algorithm**: Value function iteration on discretized state-space
   - Use biased Markov chain for $Pr(z_{t+1}|z_t)$

2. Compute stationary distribution $\Phi(z, n)$ of firms using:
   - Biased policy function $n_{t+1} = \kappa(z, n; w)$
   - True Markov chain for $Pr(z_{t+1}|z_t)$
   - **Implementation**: non-stochastic simulation (Young, 2010)

3. Wage $w^*$ clears the labor market: $N^* = N^S = \int n d\Phi(z, n)$

**Note**: Household’s Euler equation $\Rightarrow 1 + r^* = 1/\beta$. 

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## SBU Variables & Model Equivalents

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Name</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta y_t$</td>
<td>Sales Growth</td>
<td>$2 \frac{y_t - y_{t-1}}{y_t + y_{t-1}}$</td>
</tr>
<tr>
<td>$\Delta^l y_{t+4}$</td>
<td>Sales Growth (Long)</td>
<td>$2 \frac{y_{t+4} - y_t}{y_{t+4} + y_t}$</td>
</tr>
<tr>
<td>$\Delta n_{t+1}$</td>
<td>Net Hiring $t$ to $t + 1$</td>
<td>$2 \frac{n_{t+1} - n_t}{n_{t+1} + n_t}$</td>
</tr>
<tr>
<td>$FcastError_{t,t+4}$</td>
<td>Forecast Error</td>
<td>$\tilde{E}<em>t[\Delta^l y</em>{t+4}] - \Delta^l y_{t+4}$</td>
</tr>
<tr>
<td>$ExcessAbsFcastError_{t,t+4}$</td>
<td>Excess AFE</td>
<td>$|FcastError_{t,t+4}| - \tilde{E}<em>t[|FcastError</em>{t,t+4}|]$</td>
</tr>
</tbody>
</table>

**Notes:** I select quarterly observations from the SBU taking the last observation of the calendar quarter. I assume a firm’s new hires in quarter $t$ are not yet productive, so I identify $n_{t+1}$ with the firm’s employment at the end of period $t$. The operator $\tilde{E}_t[\cdot]$ denotes a subjective expectation as of date $t$. 

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GMM Estimation Details

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

Implementation:

- Numerical optimization using Simulated Annealing
- Weight matrix \( W = \text{Cov}(m(X))^{-1} \)
- At each iteration, compute \( m(\theta) \) numerically:
  \[
  \mathbb{E}[X(z, n)] = \sum_{z, n} X(z, n) \phi(z, n)
  \]

- Computing 4-Quarters Ahead Forecast Errors and Moments
Forecast Error Moments in Model

Future sales $y_{t+4}|z_t, k_t$ are a function of $\zeta = \{z_{t+1}...z_{t+4}\}$ under repeated application of the manager’s policy fn $n_{t+1} = \kappa(z_t, n_t)$

- $y_{t+4}(\zeta|z_t, n_t)$ occurs with probability $Pr(\zeta|z_t)$
- Manager believes it happens with probability $\tilde{Pr}(\zeta|z_t)$
- Manager’s Forecast $= \tilde{E}[y_{t+4}|z_t, n_t] = \sum_\zeta y_{t+4}(\zeta|z_t, n_t) * \tilde{Pr}(\zeta|z_t)$
- Define $Forecast\ Error(\zeta|z_t, n_t) \equiv \tilde{E}[y_{t+4}|z_t, n_t] - y_{t+4}(\zeta|z_t, n_t)$

First I compute: $Forecast\ Error(\zeta|z_t, n_t) \ \forall (z_t, n_t)$

Then I apply LIE using the stationary distribution $\phi(z_t, n_t)$:

1. $\mathbb{E}[Forecast\ Error|z_t, n_t] = \sum_\zeta Forecast\ Error(\zeta|z_t, n_t)\tilde{Pr}(\zeta|z_t)$
2. $\mathbb{E}[Forecast\ Error] = \sum_{z_t, k_t} \mathbb{E}[Forecast\ Error|z_t, k_t] * \phi(z_t, k_t)$
## Calibrated Parameters

<table>
<thead>
<tr>
<th>Param.</th>
<th>Value</th>
<th>Description</th>
<th>Target/Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$q$</td>
<td>0.08</td>
<td>Quarterly separation rate</td>
<td>Shimer (2005)</td>
</tr>
<tr>
<td>$\mu$</td>
<td>0</td>
<td>Mean log($z$)</td>
<td>Normalization</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>2</td>
<td>Inverse IES</td>
<td>Hall (2009)</td>
</tr>
<tr>
<td>$\eta$</td>
<td>2</td>
<td>Inverse Frisch elasticity</td>
<td>Chetty et al (2011)</td>
</tr>
<tr>
<td>$\beta$</td>
<td>$0.96^{1/4}$</td>
<td>HH discount factor</td>
<td>Ann. interest rate 4%</td>
</tr>
<tr>
<td>$\chi$</td>
<td>29.67</td>
<td>Disutility of work</td>
<td>S.S. labor $N^* = 1/3$</td>
</tr>
<tr>
<td>$\theta$</td>
<td>0.05</td>
<td>Manager share of equity</td>
<td>Nikolov &amp; Whited (2014)</td>
</tr>
</tbody>
</table>
## Estimated Model & Data Moments

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

**Notes:** All data moments are estimated using data from the SBU with the sample period covering 10/2014 to 6/2018. All model moments are computed from the stationary distribution of firms across \((z,n)\) space.
**Overconfidence: Model vs Data**

Notes: This figure shows the t-statistics for tests of the null hypothesis that each targeted model moment minus its data equivalent is zero. All data moments are estimated using data from the SBU with the sample period covering 10/2014 to 6/2018. Standard errors are clustered by firm.
Notes: Bin-scatter plots of actual absolute forecast errors against ex-ante subjective absolute forecast errors (mean absolute deviations) in the estimated model, and in the SBU data. I compute all model-implied moments from the stationary distribution for firms across the \((z, n)\) state space.
Notes: Bin-scatter plots of forecast errors for sales growth from quarter $t$ to $t + 4$ against sales growth in $t - 1$ to $t$ in the estimated model and in the SBU data. I compute all model-implied moments from the stationary distribution for firms across the $(z, n)$ state space.
Notes: Bin-scatter plots of net hiring in quarter $t$ against sales growth in $t - 1$ to $t$ in the estimated model and in the SBU data. I compute all model-implied moments from the stationary distribution for firms across the $(z, n)$ state space.
Hiring & MPN: Model vs Data

Notes: Smoothed non-parametric plots of net hiring against the natural logarithm of the sales/(lag employment) ratio in the SBU data and my estimated model. I construct each line by creating a bin-scatter of net hiring against the sales/employment ratio on 50 quantiles and smooth the resulting plot by averaging each point with its nearest neighbors. I compute all model-implied moments from the stationary distribution for firms across the \((z, n)\) state space.
Forecast error moments help pin down \( \{\tilde{\mu} - \mu, \tilde{\sigma}/\sigma, \tilde{\rho} - \rho\} \), conditional on \( \{\alpha, \lambda, \sigma, \rho\} \),

Labor and sales dynamics help pin down \( \{\alpha, \lambda, \sigma, \rho\} \), conditional on \( \{\tilde{\mu}, \tilde{\sigma}, \tilde{\rho}\} \).

<table>
<thead>
<tr>
<th>Moment</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean(Forecast Error)</td>
<td>( \tilde{\mu} - \mu )</td>
</tr>
<tr>
<td>Mean(Excess Abs. Forecast Error)</td>
<td>( \tilde{\sigma}/\sigma )</td>
</tr>
<tr>
<td>Cov(Forecast Error, Sales Growth(t-1,t))</td>
<td>( \tilde{\rho} - \rho )</td>
</tr>
<tr>
<td>Var(Net Hiring)</td>
<td>( \alpha, \lambda )</td>
</tr>
<tr>
<td>Var(Sales Growth(t-1,t))</td>
<td>( \sigma, \lambda )</td>
</tr>
<tr>
<td>Cov(Net Hiring(t,t+1), Sales Growth(t-1,t))</td>
<td>( \lambda, \alpha )</td>
</tr>
<tr>
<td>Cov(Sales Growth(t,t+4), Sales Growth(t-1,t))</td>
<td>( \rho, \lambda )</td>
</tr>
<tr>
<td>Cov(Sales Growth(t,t+4), Net Hiring(t-1,t))</td>
<td>( \lambda, \alpha, \tilde{\sigma}/\sigma )</td>
</tr>
</tbody>
</table>
**Local Identification Diagnostic**

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

How much would firm value increase today by replacing biased manager?

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>$\Delta V$%</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{\sigma} = \sigma$ only</td>
<td>0.4</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho$ only</td>
<td>1.3</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho, \tilde{\sigma} = \sigma$</td>
<td>1.9</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho, \tilde{\sigma} = \sigma, \tilde{\mu} = \mu$</td>
<td>1.9</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>$\Delta V^0 %$</th>
<th>Baseline</th>
<th>Hi AC</th>
<th>Lo AC</th>
<th>Low $q$</th>
<th>Hi $\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{\rho} = \rho, \tilde{\sigma} = \sigma, \tilde{\mu} = \mu$</td>
<td>1.9</td>
<td>0.7</td>
<td>1.5</td>
<td>2.1</td>
<td>5.5</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** This table shows how much firm value would increase by replacing a biased manager with another who has no biases in beliefs. At each point in the $(z, n)$ state space I compute the objective value generated by the biased managers in my estimated economy, as well as the objective value generated by the counterfactual unbiased manager. Then I compute the mean percent gain in firm value by averaging the gains across the state space under the stationary distribution of the economy with biases. Columns correspond to alternative model specifications: (1) is the baseline estimated model (2) and (3) have high and adjustment costs, with triple and one-third my estimated value (4) a model with durable labor, i.e. a low separation rate of $q = 0.026$ rather than $q = 0.085$ (both quarterly).
### Micro Results Robustness

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<tr>
<th>Counterfactual</th>
<th>Baseline</th>
<th>Hi AC</th>
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<th>Hi $\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{\sigma} = \sigma$ only</td>
<td>0.4</td>
<td>0.2</td>
<td>0.2</td>
<td>0.1</td>
<td>0.7</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho$ only</td>
<td>1.3</td>
<td>0.5</td>
<td>1.0</td>
<td>1.5</td>
<td>3.2</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho, \tilde{\sigma} = \sigma$</td>
<td>1.9</td>
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<td>0.7</td>
<td>1.5</td>
<td>2.1</td>
<td>5.5</td>
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## Firm Value Impact of Biases In Perspective

<table>
<thead>
<tr>
<th>Impact of</th>
<th>$\Delta$ Firm Val. %</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>CEO entrenchment</td>
<td>3.1</td>
<td>Taylor (2010)</td>
</tr>
<tr>
<td>Agency conflicts &amp; cash</td>
<td>3 - 8</td>
<td>Nikolov &amp; Whited (2014)</td>
</tr>
<tr>
<td>Short-termism</td>
<td>1.0</td>
<td>Terry (2017)</td>
</tr>
<tr>
<td>Dividend-smoothing</td>
<td>2.0</td>
<td>Wu (2018)</td>
</tr>
<tr>
<td>Biased beliefs</td>
<td>1.9</td>
<td>This paper</td>
</tr>
</tbody>
</table>
Model Aggregates (1/2)

Notes:

- Manager is risk-neutral, owns $\theta \in (0, 1]$ of her firm’s equity, consumes her share of profits (losses).
- The manager’s policy function is $\kappa(z, n)$

**GDP:**

$$Y = \int_{z,n} zn^\alpha - \lambda \left( \frac{\kappa(z, n) - (1 - q)n}{n} \right)^2 n d\Phi(z, n)$$

$$= \hat{Y} - AC$$

$$= C + \theta \Pi$$

$$= wN + \Pi$$

**Labor:** $N = \int_{z,n} n d\Phi(z, n)$

**Consumption:** $C = wN + (1 - \theta) \Pi$
Profits:

\[ \Pi = \int_{z,n} \left[ -\lambda \left( \frac{zn^\alpha - wn}{\kappa(z,n) - n(1-q)} \right) n \right] d\Phi(z, n; w, r) \]

\[ = \int_{z,n} \left[ \pi(z, n, \kappa(z, n); w) \right] d\Phi(z, n) \]
## Welfare Impact of Biases In Perspective

<table>
<thead>
<tr>
<th>Welfare Impact of</th>
<th>% C. Equiv.</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>General misallocation</td>
<td>30 - 40</td>
<td>Hsieh &amp; Klenow (2009)</td>
</tr>
<tr>
<td>Business cycles</td>
<td>0.1 - 1.5</td>
<td>Krusell et al (2009)</td>
</tr>
<tr>
<td>Gains from trade</td>
<td>1.1 - 8.1</td>
<td>Melitz &amp; Redding (2015)</td>
</tr>
<tr>
<td>Information frictions</td>
<td>4.0</td>
<td>David et al (2016)</td>
</tr>
<tr>
<td>Short-termism</td>
<td>0.44</td>
<td>Terry (2017)</td>
</tr>
<tr>
<td>Biased beliefs</td>
<td>0.99</td>
<td>This paper</td>
</tr>
</tbody>
</table>
# Macro Impact of Individual Biases

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>Δ C. Welfare %</th>
<th>Δσ(MPN) %</th>
<th>Δ(AC/Y) × 100</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{\sigma} = \sigma$ only</td>
<td>0.28</td>
<td>0.8</td>
<td>-0.3</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho$ only</td>
<td>0.68</td>
<td>7.7</td>
<td>-2.5</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$</td>
<td>0.91</td>
<td>6.4</td>
<td>-2.2</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho$, $\tilde{\sigma} = \sigma$, $\tilde{\mu} = \mu$</td>
<td>0.99</td>
<td>6.6</td>
<td>-2.2</td>
</tr>
</tbody>
</table>

**Notes:** This table shows the difference in household consumption-equivalent welfare, reallocation (= total job creation and destruction), static dispersion in the marginal product of labor, and adjustment costs paid as a share of GDP in the steady state of an economy whose managers lack one or more of overconfidence ($\tilde{\sigma} = \sigma$), overextrapolation ($\tilde{\rho} = \rho$), or pessimism ($\tilde{\mu} = \mu$) relative to the steady state of my baseline economy with biased managers.
**Macro Results Robustness**

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>Δ C. Welfare %</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho, \tilde{\sigma} = \sigma, \tilde{\mu} = \mu$</td>
<td>0.99</td>
</tr>
</tbody>
</table>

**Notes:** This table shows the difference in household consumption-equivalent welfare in the steady state of an economy whose managers are rational ($\tilde{\sigma} = \sigma, \tilde{\rho} = \rho,$ and $\tilde{\mu} = \mu$) relative to the steady state of my baseline economy with beliefs biases. Columns correspond to alternative model specifications: (1) is the baseline estimated model (2) and (3) have high and adjustment costs, with triple and one-third my estimated value (4) a model with durable labor, i.e. a low separation rate of $q = 0.026$ rather than $q = 0.085$ (both quarterly). Column 5 imposes returns to scale $\alpha = 0.8$ rather than my estimated $\alpha = 0.61$. Columns 6 and 7 respectively use three times and one third the manager’s equity share $\theta$ relative to the baseline level of $\theta = 0.05$. 

[Back]
## Macro Results Robustness

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>(\Delta \text{ C. Welfare} %)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline</td>
</tr>
<tr>
<td>(\tilde{\sigma} = \sigma) only</td>
<td>0.40</td>
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<td>0.68</td>
</tr>
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<td>0.91</td>
</tr>
<tr>
<td>(\tilde{\rho} = \rho, \tilde{\sigma} = \sigma, \tilde{\mu} = \mu)</td>
<td>0.99</td>
</tr>
</tbody>
</table>

**Notes:** This table shows the difference in household consumption-equivalent welfare in the steady state of an economy whose managers lack one or more of overconfidence \((\tilde{\sigma} = \sigma)\), over extrapolation \((\tilde{\rho} = \rho)\), or pessimism \((\tilde{\mu} = \mu)\) relative to the steady state of my baseline economy with beliefs biases. Columns correspond to alternative model specifications: (1) is the baseline estimated model (2) and (3) have high and adjustment costs, with triple and one-third my estimated value (4) a model with durable labor, i.e. a low separation rate of \(q = 0.026\) rather than \(q = 0.085\) (both quarterly).
**General Equilibrium Effects**

Key question for aggregate outcomes in GE:

Does aggregate labor demand $N$ increase/decrease when adding/removing biases?

- Wages respond to changes in labor demand $N$
- Higher wages ⇒ shift gains toward consumers
- Higher wages ⇒ lower firms’ profits $\pi(\cdot)$, $\Pi$
### Biases Have GE Effects via Labor Demand & Supply

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>$\Delta N%$</th>
<th>$\Delta w%$</th>
<th>$\Delta C.$ Welfare$%$</th>
<th>$\Delta \Pi%$</th>
<th>$\Delta C$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{\sigma} = \sigma$ only</td>
<td>1.1</td>
<td>4.1</td>
<td>0.28</td>
<td>-3.7</td>
<td>0.9</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho$ only</td>
<td>-0.7</td>
<td>-0.6</td>
<td>0.68</td>
<td>2.0</td>
<td>0.3</td>
</tr>
<tr>
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<td>6.1</td>
<td>0.99</td>
<td>-4.4</td>
<td>1.7</td>
</tr>
</tbody>
</table>

**Notes:** This table shows the difference in household consumption-equivalent welfare, aggregate firm value, capital, and wages in the steady state of an economy whose managers lack one or more of overconfidence ($\tilde{\sigma} = \sigma$), overextrapolation ($\tilde{\rho} = \rho$), or pessimism ($\tilde{\mu} = \mu$) relative to the steady state of my baseline economy with beliefs biases.
How do other distortions change the welfare impact of biases?

Do managerial biases amplify the impact of other distortions?
Managerial Biases &
Other Public Policies

Add Labor Income Tax to Household Budget:

\[ C_t + B_{t+1} = (1 + r_t)B_t + (1 - \tau_n)w_tN_t + (1 - \theta)\Pi_t + T_t \]

Add Payroll Tax to Firm Cash Flows:

\[
\pi(z_t, n_t, n_{t+1}; w_t) = \begin{cases} 
\begin{aligned}
& z_t n_t^\alpha \\
& \text{Revenue}
\end{aligned}, & \begin{aligned}
& - (1 + \tau_p)w_t n_t \\
& \text{Wage Bill}
\end{aligned} \end{cases} - \lambda n_t \left( \frac{n_{t+1} - n_t \ast (1 - q)}{n_t} \right)^2
\begin{aligned}
& \text{Quadratic Adjustment Costs}
\end{aligned}
\]

Transfers: \( T_t = (\tau_n + \tau_p)w_tN_t \)
**Taxes Amplify Welfare Impact of Managerial Biases**

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

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

Labor is a relatively flexible, short-lived input
Costs of biased beliefs might be larger for investment decisions

Model based on physical capital:  
- Estimate using SBU + Compustat Moments  
- Higher micro costs of biases:  
  - 3.0 % Firm Value  
- Similar macro costs of biases:  
  - 0.42 % Cons. Welfare  
- Intuition: k is longer lived, less adjustable
How do biases relate to agency problems, managerial misbehavior, other proxies of managerial bias?

Test: Do biases look worse if I estimate my model on subsamples of firms where these issues seem to be worse?
Extensions II: Oversight, Managerial Misbehavior, and Bias

Test: Do biases look worse if I estimate my model on subsamples of firms where these issues seem to be worse?

1. Small vs. large firms in the SBU
   Smaller private firms more likely to be owner-operated

2. Well- vs. poorly-governed public firms
   High vs. low entrenchment (Bebchuk et al, 2009)

3. Public firms doing M&A vs. not
   Firms with (w/o) acquisitions ($AQCQ > 0$) in past 8 qtrs

4. Public firms with “overconfident” CEOs vs. not
   Firms w/ “longholder” CEOs in Malmendier & Tate (2015)
Extensions II: Oversight, Managerial Misbehavior, and Bias

Subsamples with weaker oversight, M&A, “overconfident” managers:

Q: Do managers appear more biased?

A: Yes, they overextrapolate more (bigger $\hat{\rho} - \rho$ gap) and are more overconfident (smaller $\hat{\sigma}/\sigma$ ratio)

Q: Do managers destroy a larger share of firm value?

A: Not necessarily. These firms are often less volatile (smaller $\sigma$) $\Rightarrow$ fewer opportunities to overreact
**Firm Technology & Shocks**

Quarterly Earnings = Sales - Wage Bill  
(Labor \( n \) Optimized Statically):  

\[
y(z, k; w) = A(w)zk^\alpha
\]

**Idiosyncratic Shocks:**  

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

**NoAggregate Risk**
Managers’ Beliefs

Objective driving process:

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

Managers’ subjective beliefs:

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

Characterizing beliefs:

- Unbiased: \( \tilde{\mu} = \mu, \tilde{\sigma} = \sigma, \tilde{\rho} = \rho \)
- Overoptimistic: \( \tilde{\mu} > \mu \)
- Overconfident: \( \tilde{\sigma} < \sigma \)
- Overextrapolative: \( \tilde{\rho} > \rho \)
Firm Cash Flows

Cash flow = earnings - investment - adjustment costs

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

\[ \left. + \lambda_i[k_{t+1} - k_t(1 - \delta)]1(k_{t+1} < k_t(1 - \delta)) \right] \]

\[ \left. - \lambda_q \left( \frac{k_{t+1} - (1 - \delta)k_t}{k_t} \right)^2 k_t \right] \]

\[ \text{Earnings} \]

\[ \text{Investment} \]

\[ \text{Capital Resale Loss} \]

\[ \text{Quadratic Adjustment Costs} \]
Managers compensated with $\theta \in (0, 1]$ equity share.

Optimize their subjective valuation of the firm:

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

$\tilde{E}_t[\cdot]$ is the managers’ subjective expectations operator.
**Manager’s Problem & True Firm Value**

**True firm value under managers’ policy** \( \kappa(z, k; w, r) \):

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

\( \mathbb{E}_t[\cdot] \) operator uses the **true** stochastic process.
Lifetime utility maximization:

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

Budget constraint:

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

Household owns remaining share \(1 - \theta\) of firms:

- Perfectly insured against firm-specific risk
Stationary General Equilibrium

Equilibrium consists of: \( \{w^*, r^*\}, \{C^*, N^*, B^*\}, \Phi(z, k) \)

In which:

- Managers choose \( k_{t+1} = \kappa(z_t, k_t) \) to optimize subjective firm value
- Stationary distribution of firms \( \Phi(z, k) \)
- HH optimizes choosing \( C_t = C^*, N_t^S = N^*, B_{t+1} = B^* \).
- Markets clear: \( \int n(z, k; w) d\Phi(z, k) = N^*, B^* = 0 \)
Production, Costs, & Earnings

Sales Production Function: \( \hat{y} = A^{1-\hat{\nu}} \hat{z} k^{\hat{\alpha}} n^{\hat{\nu}} \)

Labor \( n \) chosen statically to optimize earnings:

\[
y(\hat{z}, k, n; w) = \max_n A^{1-\hat{\nu}} \hat{z} k^{\hat{\alpha}} n^{\hat{\nu}} - wn \\
= \hat{\nu}^{\hat{\nu}/(1-\hat{\nu})} (1 - \hat{\nu}) A^{\hat{z}^{1/(1-\hat{\nu})} (1-\hat{\nu}) k^{\hat{\alpha}/(1-\hat{\nu})} \over w^{\hat{\nu}/(1-\hat{\nu})}}
\]

Optimal sales \( \hat{y} \) proportional to earnings \( y \):

\[
\hat{y}(\hat{z}, k, n^*(\hat{z}, k, w)) = \hat{\nu}^{\hat{\nu}/(1-\hat{\nu})} A^{\hat{z}^{1/(1-\hat{\nu})} (1-\hat{\nu}) k^{\hat{\alpha}/(1-\hat{\nu})} \over w^{\hat{\nu}/(1-\hat{\nu})}} = \frac{1}{1 - \hat{\nu}} y(\hat{z}, k, n^*; w)
\]

Define \( z, A(w) \) in terms of parameters and scale factor \( A \):

\[
z \equiv \hat{z}^{1/(1-\hat{\nu})} \quad A(w) = \hat{\nu}^{\hat{\nu}/(1-\hat{\nu})} (1 - \hat{\nu}) A^{\hat{z}^{1/(1-\hat{\nu})} (1-\hat{\nu}) k^{\hat{\alpha}/(1-\hat{\nu})} \over w^{\hat{\nu}/(1-\hat{\nu})}}
\]

Let \( \alpha = \hat{\alpha}/(1 - \hat{\nu}) \) & earnings become:

\[
y(z, k; w) = A(w) z k^{\alpha}
\]
Managers compensated with $\theta \in (0, 1]$ equity share.

Optimize their subjective valuation of the firm:

$$\tilde{V}(z_0, k_0) = \max_{\{k_{t+1}\}_{t=0}^\infty} \tilde{E}_0 \left[ \sum_{t=0}^\infty \theta \frac{\pi(z_t, k_t, k_{t+1}; w_t)}{R_t} \right]$$

$\tilde{E}_t[\cdot]$ is the managers’ subjective expectations operator.
True firm value under managers’ policy $\kappa(z, k)$:

$$V(z_0, k_0) = E_0 \left[ \sum_{t=0}^{\infty} \theta \frac{\pi(z_t, k_t, \kappa(z_t, k_t); w_t)}{R_t} \right]$$

$E_t[\cdot]$ operator uses the true stochastic process.
Solving the Model in Steady State

Steady-state prices:

- \( w^* \) consistent with:
  - Steady-state earnings \( y(z, k; w^*) = A(w^*)zk^\alpha = zk^\alpha \)
  - Labor market clearing \( N^* = N^D = N^S \)
  - Household’s Euler equation \( \Rightarrow 1 + r^* = 1/\beta \).

Solve for managers’ policy functions \( \kappa(z, k) \):

- Algorithm: Value function iteration on discretized state-space
- Use biased Markov chain for \( Pr(z_{t+1}|z_t) \)

Compute stationary distribution \( \phi(z, k) \) of firms across state space \( Z \times K \) consistent with:

- Biased policy function \( k_{t+1} = \kappa(z_t, k_t) \)
- Objective stochastic process for \( z \)
- Implementation: non-stochastic simulation (Young, 2010)
\textbf{Structural Estimation Exercise}

Estimate 8 parameters:

\[ \theta = (\alpha, \lambda_q, \lambda_i, \rho, \tilde{\rho}, \sigma, \tilde{\sigma}, \tilde{\mu})' \]

Target 9 moments:

\begin{align*}
\mathbb{E}[\text{ForecastError}] & \quad \text{Source: SBU} \\
\text{Cov} (\text{ForecastError}_{t,t+4}, \Delta y_t) & \quad \text{Definitions} \\
\mathbb{E}[\text{ExcessAbsForecastError}_{t,t+4}] & \quad \text{Definitions} \\
\text{Cov Matrix } \{i_t, \Delta y_{t+1}\} & \quad \text{Source: Compustat} \\
\text{Cov} (\Delta y_t, \Delta^l y_{t+4}) & \quad \text{EMP < 7500} \\
\text{Cov} (i_t, \Delta^l y_{t+4}) & \quad \text{Definitions} \\
\text{Autocorr} (\log(y/k)_t) &
\end{align*}

Notes: \(i_t\) is net investment, \(y\) is sales. \(\text{ExcessAbsForecastError}_{t,t+4}\) is the difference between a firm’s actual absolute forecast error and its ex-ante subjective mean absolute deviation (subjective absolute forecast error). \(\Delta x_t = 2(x_t - x_{t-1})(x_t + x_{t-1}), \Delta^l x_{t+4} = 2(x_{t+4} - x_t)(x_{t+4} + x_t).\)

\textbf{Implementation:} Overidentified GMM

Calibrate other parameters: \(\mu = 0, \quad \text{Calibrated Parameters} \)
### Baseline Parameter Estimates

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Explanation</th>
<th>Estimate (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>Earnings curvature</td>
<td>0.596 (0.003)</td>
</tr>
<tr>
<td>$\lambda_q$</td>
<td>Quadratic adj.cost</td>
<td>0.088 (0.003)</td>
</tr>
<tr>
<td>$\lambda_i$</td>
<td>$K$ resale loss</td>
<td>0.091 (0.001)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>True shock persistence</td>
<td>0.864 (0.0009)</td>
</tr>
<tr>
<td>$\tilde{\rho}$</td>
<td>Subjective shock pers.</td>
<td>0.960 (0.0009)</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>True shock volatility</td>
<td>0.200 (0.0002)</td>
</tr>
<tr>
<td>$\tilde{\sigma}$</td>
<td>Subjective shock vol.</td>
<td>0.100 (0.0002)</td>
</tr>
<tr>
<td>$\tilde{\mu}$</td>
<td>Subjective shock mean</td>
<td>-0.001 (0.000007)</td>
</tr>
</tbody>
</table>

**Notes:** This table shows parameter estimates for the baseline model specification with quadratic adjustment costs and partial irreversibility. I estimate the parameters by minimizing the distance between model-implied moments (computed from the stationary distribution of firms across the $(z, k)$ state space) and the set of empirical moments. My targets include six moments about firm-level output and investment dynamics, and three moments from the SBU, namely: the mean forecast minus realized sales growth, mean excess absolute forecast error, and the covariance of forecast minus realized sales growth with sales growth in the quarter to making the forecast. The weighting matrix is the firm-level clustered covariance matrix of the moments across the two sets of moments, setting equal total weight on moments from Compustat and the SBU. I perform the numerical optimization using simulated annealing.

**Identification:**

- Summary
- Back
## Estimated Model & Data Moments

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

**Notes:** The covariance matrix of within-firm Net Investment, and Sales Growth, the pairwise covariances of Sales Growth<sub>t,t+4</sub> with Sales Growth<sub>t−1,t</sub> and Net Investment<sub>t</sub> and the Autocorrelation of log(Sales/Lag Capital) are estimated in a sample of 292,236 observations belonging to 9,885 firms in Compustat Quarterly between 1990 and 2017 with less than 7,500 employees. Forecast Error moments are estimated from a sample of 1,265 Forecast Error observations belonging to 382 firms in the SBU.
# SBU Variables & Model Equivalents

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Name</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta y_t$</td>
<td>Sales Growth</td>
<td>$\frac{y_t - y_{t-1}}{y_t + y_{t-1}}$</td>
</tr>
<tr>
<td>$\Delta l y_{t+4}$</td>
<td>Sales Growth (Long)</td>
<td>$\frac{y_{t+4} - y_t}{y_{t+4} + y_t}$</td>
</tr>
<tr>
<td>$FcastError_{t,t+4}$</td>
<td>Forecast Error</td>
<td>$\tilde{E}<em>t[\Delta l y</em>{t+4}] - \Delta l y_{t+4}$</td>
</tr>
<tr>
<td>$ExcessAbsFcastError_{t,t+4}$</td>
<td>Excess AFE</td>
<td>$|FcastError_{t,t+4}| - \tilde{E}<em>t[|FcastError</em>{t,t+4}|]$</td>
</tr>
</tbody>
</table>

**Notes:** I select quarterly observations from the SBU taking the last observation of the calendar quarter. The operator $\tilde{E}_t[\cdot]$ denotes a subjective expectation.
# Compustat Variables & Model Equivalents

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Name</th>
<th>Formula</th>
<th>Data Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>$k_{t+1}$</td>
<td>Capital</td>
<td>N/A</td>
<td>PPENTQ (end of period)</td>
</tr>
<tr>
<td>$\log(y/k)_t$</td>
<td>log(Sales/Capital)</td>
<td>$\log(y_t/k_t)$</td>
<td>log(SALEQ/Lag PPENTQ)</td>
</tr>
<tr>
<td>$\Delta y_{t+1}$</td>
<td>Sales Growth</td>
<td>$2 \frac{y_{t+1}-y_t}{y_{t+1}+y_t}$</td>
<td>Use $y_t = SALEQ$</td>
</tr>
</tbody>
</table>

**Notes:** My Compustat Variables are a subset of Compustat Quarterly with less than 7500 employees (the 99th percentile of employment in my SBU sample), non-missing investment, sales, sales growth, and dropping observations where PPENT of SALEQ change by more than 200% across quarters. The operator $\beta(y, x)$ denotes the coefficient from regressing variable $y$ on $x$ and a constant.
GMM Estimation Details

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

Implementation:

- Numerical optimization using Simulated Annealing
- Weight matrix \( W = Cov(m(X)) \), putting equal total weight on Compustat & SBU Moments
- At each iteration, compute \( m(\theta) \) numerically:
  \[
  \mathbb{E}[X(z, u, k)] = \sum_{z,k} X(z, u, k)\phi(z, k)
  \]

- Computing 4-Quarters Ahead Forecast Errors and Moments

Back
# Calibrated Parameters

<table>
<thead>
<tr>
<th>Param.</th>
<th>Value</th>
<th>Description</th>
<th>Target/Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta$</td>
<td>0.1</td>
<td>Annual Depreciation</td>
<td>NIPA</td>
</tr>
<tr>
<td>$\mu$</td>
<td>0</td>
<td>Mean log($z$)</td>
<td>Normalization</td>
</tr>
<tr>
<td>$\hat{\alpha}$</td>
<td>0.275</td>
<td>$\partial \log(\hat{y})/\partial \log(k)$</td>
<td>$\alpha = 0.61$, 2/3 lab. share</td>
</tr>
<tr>
<td>$\hat{\nu}$</td>
<td>0.551</td>
<td>$\partial \log(\hat{y})/\partial \log(n)$</td>
<td>$\alpha = 0.61$, 2/3 lab. share</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>2</td>
<td>Inverse IES</td>
<td>Hall (2009)</td>
</tr>
<tr>
<td>$\eta$</td>
<td>2</td>
<td>Inverse Frisch Elasticity</td>
<td>Chetty et al (2011)</td>
</tr>
<tr>
<td>$\beta$</td>
<td>$0.96^{1/4}$</td>
<td>HH Discount Factor</td>
<td>Ann. interest rate 4%</td>
</tr>
<tr>
<td>$\chi$</td>
<td>0.114</td>
<td>Disutility of Work</td>
<td>S.S. Labor $N^* = 1/3$</td>
</tr>
<tr>
<td>$\theta$</td>
<td>0.05</td>
<td>Manager share of equity</td>
<td>Nikolov &amp; Whited (2014)</td>
</tr>
</tbody>
</table>
**Identification**

- Conditional on \( \{\alpha, \lambda_q, \lambda_i, \sigma, \rho\} \) forecast error moments help pin down \( \{\tilde{\mu} - \mu, \tilde{\sigma}/\sigma, \tilde{\rho} - \rho\} \)

- Conditional on \( \{\tilde{\mu}, \tilde{\sigma}, \tilde{\rho}\} \), sales & investment dynamics help pin down \( \{\alpha, \lambda_q, \lambda_i, \sigma, \rho\} \)

<table>
<thead>
<tr>
<th>Moment</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean(Forecast Error)</td>
<td>( \tilde{\mu} )</td>
</tr>
<tr>
<td>Mean(Excess Abs. Forecast Error)</td>
<td>( \tilde{\sigma}/\sigma )</td>
</tr>
<tr>
<td>Cov(Forecast Error, Sales Growth(_{t-1,t}))</td>
<td>( \tilde{\rho} - \rho )</td>
</tr>
<tr>
<td>Var(Net Investment)</td>
<td>( \alpha, \lambda_q, \tilde{\sigma}/\sigma )</td>
</tr>
<tr>
<td>Var(Sales Growth)</td>
<td>( \sigma, \alpha )</td>
</tr>
<tr>
<td>Cov(Net Investment, Sales Growth)</td>
<td>( \lambda_i, \lambda_q, \alpha, \tilde{\sigma}/\sigma )</td>
</tr>
<tr>
<td>Cov(Sales Growth(<em>{t-1,t}, Sales Growth</em>{t,t+4}))</td>
<td>( \rho, \lambda_q )</td>
</tr>
<tr>
<td>Cov(Net Investment(<em>{t,t+1}, Sales Growth</em>{t,t+4}))</td>
<td>( \alpha, \lambda_q, \lambda_i )</td>
</tr>
<tr>
<td>Autocorr(log(Sales/Lag Capital))</td>
<td>( \rho, \lambda_q )</td>
</tr>
</tbody>
</table>
Micro Impact of Biased Beliefs

How much would firm value increase today by replacing biased manager?

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>$\Delta V%$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{\sigma} = \sigma$ only</td>
<td>0.4</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho$ only</td>
<td>2.8</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho, \tilde{\sigma} = \sigma$</td>
<td>3.0</td>
</tr>
<tr>
<td>$\tilde{\rho} = \rho, \tilde{\sigma} = \sigma, \tilde{\mu} = \mu$</td>
<td>3.0</td>
</tr>
</tbody>
</table>

Notes: This table shows instantaneous partial equilibrium gain in firm-value from eliminating subjective beliefs biases in my estimated model. At each point in the $(z, k)$ state space I compute the objective value generated by the biased managers in my estimated economy, as well as the objective value generated by a counterfactual manager lacking pessimism, overconfidence, and/or overextrapolation. Then I compute the mean percent gain in firm value by averaging the gains across the state space under the stationary distribution of the economy with biases.
## Macro Impact of Biased Beliefs

<table>
<thead>
<tr>
<th>Δ Cons. Welfare %</th>
<th>Δσ(MRPK) %</th>
<th>ΔAC/Y × 100</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.42</td>
<td>11.1</td>
<td>-1.4</td>
</tr>
</tbody>
</table>

**Notes:** This table shows the difference in household consumption-equivalent welfare, reallocation, dispersion in the marginal product of capital, and adjustment costs as a share of GDP in the aggregate steady state of an economy with unbiased managers relative to the steady state of my baseline economy with beliefs biases.
## Small SBU Firms Are More Biased

<table>
<thead>
<tr>
<th>Param.</th>
<th>Explanation</th>
<th>Estimate (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Small</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Earnings curvature</td>
<td>0.611 (0.089)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Quadratic adj.cost</td>
<td>28.71 (1.42)</td>
</tr>
<tr>
<td>$\rho$</td>
<td>True shock persistence</td>
<td>0.752 (0.008)</td>
</tr>
<tr>
<td>$\tilde{\rho}$</td>
<td>Subjective shock pers.</td>
<td>0.889 (0.007)</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>True shock volatility</td>
<td>0.232 (0.001)</td>
</tr>
<tr>
<td>$\tilde{\sigma}$</td>
<td>Subjective shock vol.</td>
<td>0.086 (0.002)</td>
</tr>
<tr>
<td>$\tilde{\mu}$</td>
<td>Subjective shock mean</td>
<td>-0.004 (0.0001)</td>
</tr>
</tbody>
</table>

**Notes:** This table shows parameter estimates for the baseline model specification estimated on subsamples of SBU firms with below and above median employment.
### Small SBU Firms Are More Biased

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>$\Delta V^%$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{\rho} = \rho, \tilde{\sigma} = \sigma, \tilde{\mu} = \mu$</td>
<td>Small: 2.0, Large: 0.8</td>
</tr>
</tbody>
</table>

**Notes:** This table shows the percent change in firm value from replacing a biased manager with an unbiased one based on estimates of the baseline model. I show numbers separately for subsamples of SBU firms with below vs. above median employment.
**Poorly-Governed Firms Are More Biased, Face Smaller Shocks**

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>Earnings curvature</td>
<td>0.601 (0.014)</td>
<td>0.591 (0.011)</td>
<td></td>
</tr>
<tr>
<td>$\lambda_q$</td>
<td>Quadratic adj.cost</td>
<td>0.154 (0.010)</td>
<td>0.121 (0.002)</td>
<td></td>
</tr>
<tr>
<td>$\lambda_i$</td>
<td>$K$ resale loss</td>
<td>0.103 (0.006)</td>
<td>0.131 (0.003)</td>
<td></td>
</tr>
<tr>
<td>$\rho$</td>
<td>True shock persistence</td>
<td>0.805 (0.003)</td>
<td>0.863 (0.003)</td>
<td></td>
</tr>
<tr>
<td>$\tilde{\rho}$</td>
<td>Subjective shock pers.</td>
<td>0.965 (0.006)</td>
<td>0.969 (0.001)</td>
<td></td>
</tr>
<tr>
<td>$\sigma$</td>
<td>True shock volatility</td>
<td>0.158 (0.001)</td>
<td>0.187 (0.0003)</td>
<td></td>
</tr>
<tr>
<td>$\tilde{\sigma}$</td>
<td>Subjective shock vol.</td>
<td>0.062 (0.003)</td>
<td>0.089 (0.0006)</td>
<td></td>
</tr>
<tr>
<td>$\tilde{\mu}$</td>
<td>Subjective shock mean</td>
<td>-0.002 (0.0001)</td>
<td>-0.002 (0.0001)</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** This table shows parameter estimates for the capital-based model specification for subsamples of Compustat firms with highly-entrenched vs. not highly-entrenched management (Bebchuk et al 2009).
**Poorly-Governed Firms Are More Biased, Face Smaller Shocks**

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>( \tilde{\rho} = \rho, \tilde{\sigma} = \sigma, \tilde{\mu} = \mu )</th>
<th>( \Delta V% )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low Entrench.</td>
<td>3.3</td>
<td>High Entrench.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4.1</td>
</tr>
</tbody>
</table>

**Notes:** This table shows percent change in firm value from replacing a biased manager with an unbiased one based on estimates of the capital-based model. I show numbers separately for subsamples of Compustat with highly-entrenched vs. not highly-entrenched management (Bebchuk et al 2009).
Firms that do M&A Are More Biased, Face Smaller Shocks

<table>
<thead>
<tr>
<th>Param.</th>
<th>Explanation</th>
<th>Estimate (SE)</th>
<th>Acquirors</th>
<th>Non-Acquirors</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>Earnings curvature</td>
<td>0.602 (0.049)</td>
<td>0.606 (0.006)</td>
<td></td>
</tr>
<tr>
<td>$\lambda_q$</td>
<td>Quadratic adj.cost</td>
<td>0.089 (0.093)</td>
<td>0.083 (0.002)</td>
<td></td>
</tr>
<tr>
<td>$\lambda_i$</td>
<td>$K$ resale loss</td>
<td>0.128 (0.006)</td>
<td>0.102 (0.001)</td>
<td></td>
</tr>
<tr>
<td>$\rho$</td>
<td>True shock persistence</td>
<td>0.831 (0.012)</td>
<td>0.856 (0.002)</td>
<td></td>
</tr>
<tr>
<td>$\tilde{\rho}$</td>
<td>Subjective shock pers.</td>
<td>0.959 (0.008)</td>
<td>0.951 (0.001)</td>
<td></td>
</tr>
<tr>
<td>$\sigma$</td>
<td>True shock volatility</td>
<td>0.182 (0.001)</td>
<td>0.212 (0.0001)</td>
<td></td>
</tr>
<tr>
<td>$\tilde{\sigma}$</td>
<td>Subjective shock vol.</td>
<td>0.079 (0.002)</td>
<td>0.108 (0.0001)</td>
<td></td>
</tr>
<tr>
<td>$\tilde{\mu}$</td>
<td>Subjective shock mean</td>
<td>-0.001 (0.0004)</td>
<td>-0.001 (0.00003)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table shows parameter estimates for the capital-based model specification for subsamples of Compustat firms with employment under 7500 comparing those that have made acquisitions in the past 8 quarters (AQCQ≤0) versus those who have not.
Firms that do M&A Are More Biased, Face Smaller Shocks

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>Non-Acquirors</th>
<th>Acquirors</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{\rho} = \rho, \tilde{\sigma} = \sigma, \tilde{\mu} = \mu$</td>
<td>3.3</td>
<td>2.8</td>
</tr>
</tbody>
</table>

Notes: This table shows percent change in firm value from replacing a biased manager with an unbiased one based on estimates of the capital-based model. I show numbers separately for subsamples of Compustat firms with employment under 7500 comparing those that have made acquisitions in the past 8 quarters (AQCQ\text{\textless}0) versus those who have not.
**Firms with “Overconfidence” CEOs Are More Biased, Face Smaller Shocks**

<table>
<thead>
<tr>
<th>Param.</th>
<th>Explanation</th>
<th>Estimate (SE)</th>
<th>“Overconfident”</th>
<th>Not</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>Earnings curvature</td>
<td>0.620 (0.004)</td>
<td>0.590 (0.024)</td>
<td></td>
</tr>
<tr>
<td>$\lambda_q$</td>
<td>Quadratic adj.cost</td>
<td>0.095 (0.001)</td>
<td>0.100 (0.088)</td>
<td></td>
</tr>
<tr>
<td>$\lambda_i$</td>
<td>$K$ resale loss</td>
<td>0.097 (0.006)</td>
<td>0.104 (0.093)</td>
<td></td>
</tr>
<tr>
<td>$\rho$</td>
<td>True shock persistence</td>
<td>0.781 (0.001)</td>
<td>0.821 (0.007)</td>
<td></td>
</tr>
<tr>
<td>$\tilde{\rho}$</td>
<td>Subjective shock pers.</td>
<td>0.973 (0.003)</td>
<td>0.969 (0.002)</td>
<td></td>
</tr>
<tr>
<td>$\sigma$</td>
<td>True shock volatility</td>
<td>0.137 (0.001)</td>
<td>0.159 (0.0005)</td>
<td></td>
</tr>
<tr>
<td>$\tilde{\sigma}$</td>
<td>Subjective shock vol.</td>
<td>0.054 (0.002)</td>
<td>0.066 (0.001)</td>
<td></td>
</tr>
<tr>
<td>$\tilde{\mu}$</td>
<td>Subjective shock mean</td>
<td>-0.002 (0.0004)</td>
<td>-0.002 (0.0001)</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** This table shows parameter estimates for the capital-based model specification for sub-samples of Compustat firms with “Longholder” (i.e. “overconfident”) CEOs versus not, based on Malmendier & Tate (2015) data.
Firms with “Overconfidence” CEOs Are More Biased, Face Smaller Shocks

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>$\Delta V%$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{\rho} = \rho, \tilde{\sigma} = \sigma, \tilde{\mu} = \mu$</td>
<td>“Overconfident” CEO</td>
</tr>
<tr>
<td></td>
<td>3.7</td>
</tr>
</tbody>
</table>

Notes: This table shows percent change in firm value from replacing a biased manager with an unbiased one based on estimates of the capital-based model. I show numbers separately for subsamples of Compustat firms with “Longholder” (i.e. “overconfident”) CEOs versus not, based on Malmendier & Tate (2015) data.