The Macroeconomics of Narratives

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The human brain has always been highly tuned toward narratives, whether factual or not, to justify ongoing actions, even such basic actions as spending and investing... Narratives "go viral" and spread far, even worldwide, with economic impact.

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Our Question: To what extent do contagious, belief-altering narratives explain business cycles?

Our Approach and Key Findings

- Narratives: subjective, potentially misspecified models of the economy that gain or lose prevalence based on their popularity (contagiousness) and accuracy (associativeness)

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  - Predicts hiring
  - Spreads contagiously
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  - Predicts hiring
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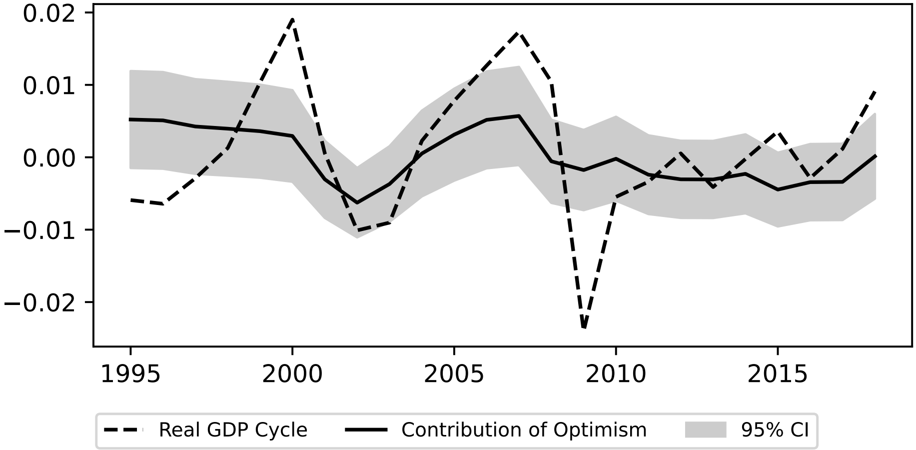
  - Shifts beliefs in a "non-fundamental" way
- **Quantitatively**, when model is calibrated to match the data, we find:
  - Narrative optimism explains 18% of Great Recession, 32% of Early 2000s Recession
  - But it is not contagious enough to generate hysteresis

Sneak Preview of Findings



To get here, we combine: **macro model**, **textual measurement**, and **micro estimates**

Plan for Today's Talk

Model and Theoretical Results

Empirics: Measuring Narratives and their Properties

Quantification

Firms and Dispersed Information

- Intermediate goods firms $i \in [0,1]$ use labor L_{it} to produce differentiated variety x_{it}

$$x_{it} = \theta_{it} L_{it}^{\alpha}$$

with productivity

$$\log \theta_{it} = \underbrace{\log \tilde{\theta}_{it}}_{N(0,\sigma^2_{\tilde{\theta}})} + \underbrace{\log \gamma_i}_{N(\mu_\gamma,\sigma^2_\gamma)} + \log \theta_t$$

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- Firms combine prior (to be specified) with idiosyncratic signals about aggregate component of productivity

$$s_{it} = \log \theta_t + \underbrace{\varepsilon_{it}}_{N(0,\sigma_\varepsilon^2)}$$

- Choose production quantity x_{it} under uncertainty

Narratives and Their Evolution

- Firms' priors come from one of two **narratives**, neither necessarily correct:
  - Optimistic Narrative $\text{opt}_{it} = 1$, $\log \theta_t \sim N(\mu_O, \sigma^2)$
  - Pessimistic Narrative $\text{opt}_{it} = 0$, $\log \theta_t \sim N(\mu_P, \sigma^2)$, $\mu_P < \mu_O$

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- Firms update narratives in random way that depends on own previous narrative, aggregate output Y and aggregate optimism Q

$$\underbrace{P_O(\log Y, Q) = \left[\frac{u}{2} + r \log Y + sQ\right]_0^1}_{\text{Probability optimist remains optimistic}} \quad \text{and} \quad \underbrace{P_P(\log Y, Q) = \left[-\frac{u}{2} + r \log Y + sQ\right]_0^1}_{\text{Probability pessimist becomes optimistic}}$$

"Stubbornness" $u \geqslant 0$, "Associativeness" $r \geqslant 0$, "Contagiousness" $s \geqslant 0$

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"Stubbornness" $u \geqslant 0$, "Associativeness" $r \geqslant 0$, "Contagiousness" $s \geqslant 0$

- Law of motion of optimism:

$$Q_{t+1} = Q_t P_O(\log Y_t, Q_t) + (1 - Q_t) P_P(\log Y_t, Q_t)$$

The Neoclassical Backbone: Technology and Preferences

- Final goods firm competitively produces aggregate output Y_t

$$Y_t = \left(\int_{[0,1]} x_{it}^{\frac{\epsilon-1}{\epsilon}} \mathrm{d}i \right)^{\frac{\epsilon}{\epsilon-1}}$$

- Representative household has isoelastic, separable, EDU preferences

$$\mathcal{U}\left(\{C_t, \{L_{it}\}_{i\in[0,1]}\}_{t\in\mathbb{N}}\right) = \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t \left(\frac{C_t^{1-\gamma}}{1-\gamma} - \int_{[0,1]} \frac{L_{it}^{1+\psi}}{1+\psi} \mathrm{d}i \right) \right]$$

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- Equilibrium: standard REE, but consistent with firms' mis-specified beliefs

Narratives Generate Non-Fundamentally Driven Business Cycles

- Assume $(\alpha, \epsilon, \gamma, \psi)$ s.t. strategic complementarity is "positive but not too large" Details

Proposition (Equilibrium Characterization)

There exists a unique equilibrium, in which:

$$\log Y(\log \theta_t, Q_t) = a_0 + a_1 \log \theta_t + f(Q_t)$$

for some coefficients a_0 and $a_1 > 0$, and a strictly increasing function f.

Static and Dynamic GE Forces in the Model

- *Static GE*: effect of optimism on GDP is *GE multiplier* × *PE effect* × *Aggregate optimism*

$$f(Q) \approx \frac{1}{1-\omega} \times \alpha\delta^{OP} \times Q$$

Multiplier > 1 if AD externality dominates wage pressure

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- *Dynamic GE*: static multiplier meets narrative evolution (contagiousness, associativeness):

$$Q_{t+1} = Q_t P_O(a_0 + a_1 \log\theta_t + f(Q_t), Q_t) + (1-Q_t) P_P(a_0 + a_1 \log\theta_t + f(Q_t), Q_t)$$

Understanding the Dynamics of Optimism: Fluctuations vs. Hysteresis

Transition maps: $Q_{t+1} = T(Q_t, \theta_t)$

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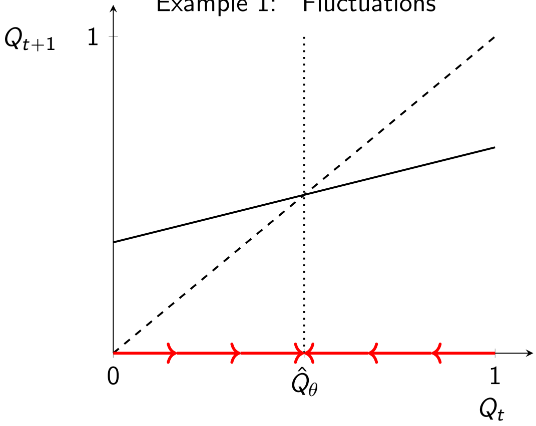
Example 1: "Fluctuations"



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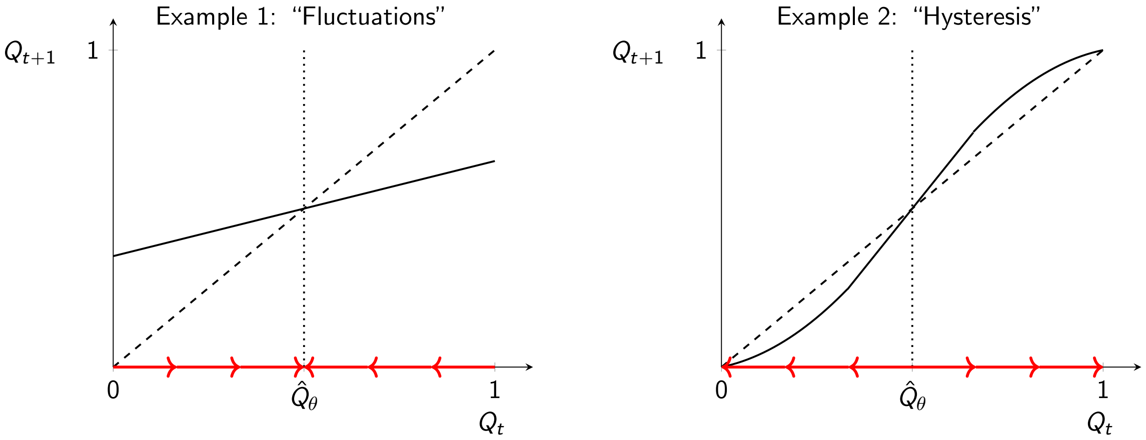
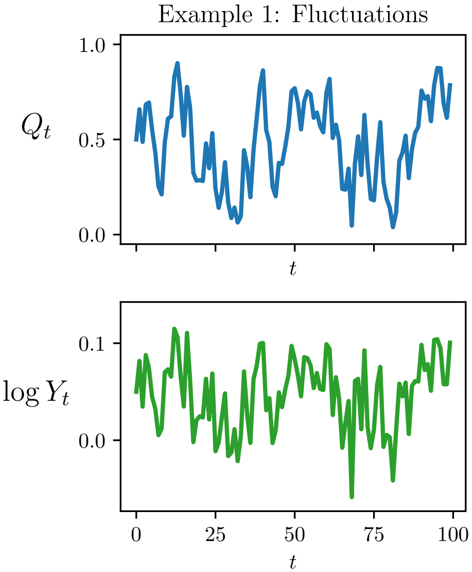


Fluctuations vs. Hysteresis: An Illustration



Persistent fluctuations around mean, despite IID fundamental

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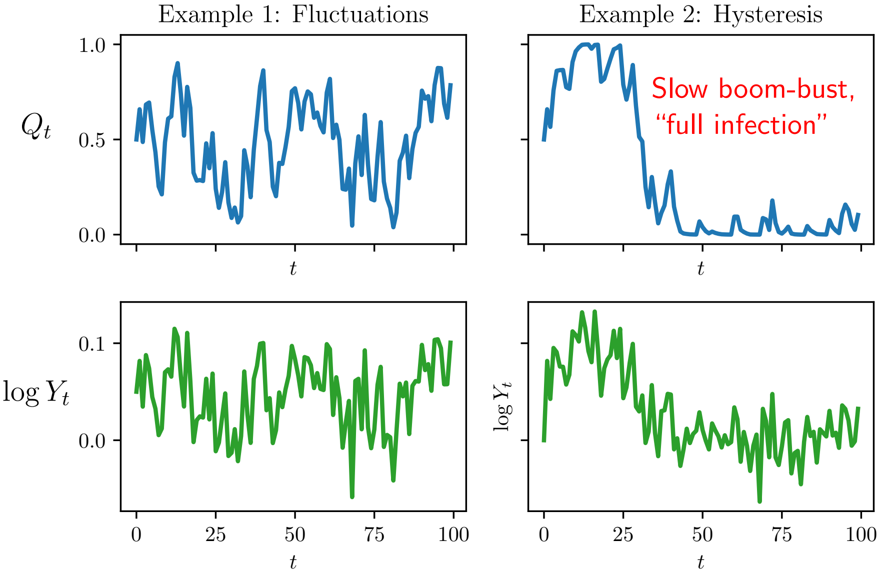

When Do Narratives Generate Hysteresis?

Definition: *A deterministic steady state* Q for productivity θ satisfies $Q = T(Q, \theta)$

Proposition (Characterization of Extremal Multiplicity)

The hysteresis case occurs if and only if*

$$M = \underbrace{u}_{\text{stubbornness}} + \underbrace{s}_{\text{contagiousness}} + \underbrace{r}_{\text{associativeness}} \times \underbrace{\frac{\alpha}{1-\omega}\delta^{OP}}_{\text{GE Impact}} - 1 \geqslant 0$$

$*$: *Extreme optimism* ($Q = 1$) *and pessimism* ($Q = 0$) *are simultaneously deterministic steady states for a non-empty set of productivities,* $\theta \in [\theta_O, \theta_P]$

IRFs

From Theory to Data

With **firm-level data on narratives and decisions**, we can measure:

From Theory to Data

With firm-level data on narratives and decisions, we can measure:

- How narratives affect firm decisions:

$$\Delta \log L_{it} = c_{0,i} + c_1 \log \theta_t + c_2 f(Q_t) + c_3 \log \theta_{it} + c_4 \log L_{i,t-1} + \delta^{OP} \text{opt}_{it} + \zeta_{it}$$

- How narratives spread:

$$\text{opt}_{it} = u \ \text{opt}_{i,t-1} + s \log Y_{t-1} + r \ Q_{t-1} + \xi_{it}$$

Then, we can use the model, plus our estimates, to assess:

- Do contagious narratives explain a large fraction of business cycles?
- Are they “strong” enough to generate hysteresis?

Plan for Today's Talk

Model and Theoretical Results

Empirics: Measuring Narratives and their Properties

Quantification

Data: Text from Regulatory Filings and Fundamentals from Compustat

- **Text:** Securities and Exchange Commission (SEC) Forms 10-K for all US-based public firms 101,000 total firm-year observations from 1995 to 2018
  - Accounting information + "a detailed picture of a company's business, the risks it faces, and the operating and financial results of the fiscal year."
  - Management's discussion & analysis: "perspective on the business results and what is driving them."
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Measuring Narratives: Sentiment, Narrative Identification, and Topics

Finer grained (↓)

More supervised (↑)

Sentiment Scoring

Count of positive, negative words

Narrative Identification

Similarity to Shiller's 9 *Perennial Economic Narratives*

Latent Dirichlet Allocation

Unsupervised groupings of words via machine learning

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Sentiment-scoring algorithm Words

1. With Loughran and McDonald (2011) positive words $\mathcal{W}_P$ + negative words $\mathcal{W}_N$,

$$\text{pos}_{it} = \sum_{w \in \mathcal{W}_P} \text{freq}(w)_{it} \qquad \text{neg}_{it} = \sum_{w \in \mathcal{W}_N} \text{freq}(w)_{it}$$

2. Construct difference of z-scores:

$$\text{sentiment}_{it} = \frac{\text{pos}_{it} - \overline{\text{pos}_{it}}}{\text{sd}(\text{pos}_{it})} - \frac{\text{neg}_{it} - \overline{\text{neg}_{it}}}{\text{sd}(\text{neg}_{it})}$$

3. Construct binary optimism as above median:

$$\text{opt}_{it} = \mathbb{I}\left[\text{sentiment}_{it} \geqslant \text{med}\left(\text{sentiment}_{it}\right)\right]$$

Premise 1: Do Optimistic Narratives Matter For Decisions?

Firm-by-fiscal-year regression:

$$\Delta \log L_{it} = \delta^{OP} \cdot \text{opt}_{it} + \gamma_i + \chi_{j(i),t} + \tau' X_{it} + \varepsilon_{it}$$

- $\Delta \log L_{it}$ is growth in number of employees ("hiring")
- Fixed effects: firm (i) and sector-by-time ($j(i) \times t$)
- Possible controls X_{it}: lagged labor, TFP, financial outcomes
- *Structural interpretation in model*, identified from noise in signals

Formal Derivation from Framework   Reasons for Controls

Optimistic Narratives Predict Hiring

	Outcome is				
	$\Delta \log L_{it}$				$\Delta \log L_{i,t+1}$
opt_{it}	0.0355	0.0305	0.0250	0.0322	0.0216
	(0.0030)	(0.0030)	(0.0032)	(0.0028)	(0.0037)
Industry-by-time FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓		✓
Lag labor		✓	✓	✓	✓
Current and lag TFP		✓	✓	✓	✓
Log BtM, Stock Return, Leverage			✓		
N	71,161	39,298	33,589	40,580	38,402
R^2	0.259	0.401	0.419	0.142	0.398

Notes: In all specifications, we trim the 1% and 99% tails of the outcome variable. Standard errors are two-way clustered by firm ID and industry-year.

Firm-Het | Time-Het | Other Inputs | Earnings Calls | CEOs | Continuous Measure | Clustering | Lag IV | Lag Controls | Oster

Narrative Optimism is Associated with *Worse* Future Fundamentals

Firm-by-fiscal-year projection regressions, for $-2 \leqslant k \leqslant 3$:

$$Z_{it} = \beta_k \cdot \text{opt}_{i,t-k} + \gamma_i + \chi_{j(i),t} + \varepsilon_{it}$$

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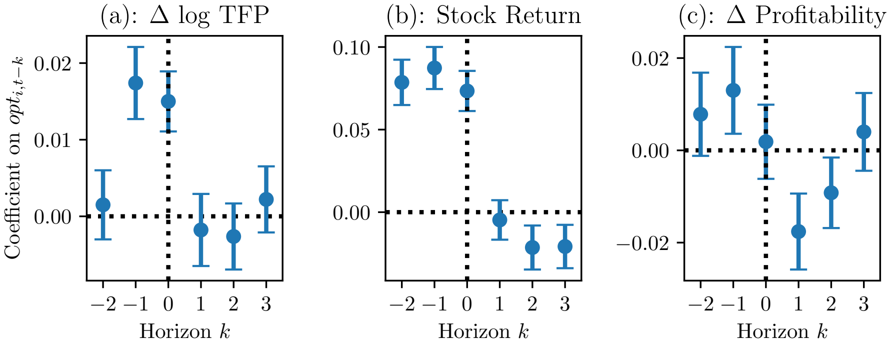

Notes: Stock returns are in log units and profitability is defined as the ratio of EBIT to lagged variable costs. In all specifications, we trim the 1% and 99% tails of the outcome variable. Error bars are 95% confidence intervals, based on standard errors clustered at the firm and industry-year level.

High-Frequency Impact | Other Financial Outcomes | Continuous Measure | Conference-Call Measure

Premise 2: How Does Optimism Spread?

Firm-by-fiscal-year regression:

$$\text{opt}_{it} = \underbrace{{\color{red}u}\ \text{opt}_{i,t-1}}_{\text{Stubbornness}} + \underbrace{{\color{red}s}\ \overline{\text{opt}}_{t-1}}_{\text{Contagiousness}} + \underbrace{{\color{red}r}\ \Delta \log Y_{t-1}}_{\text{Associativeness}} + \gamma_i + \varepsilon_{it}$$

- $\overline{\text{opt}}_{t-1}$ is aggregate average optimism
- $\Delta \log Y_{t-1}$ is US real GDP growth in corresponding calendar year
- *Structural interpretation*: directly estimates updating rule, identified from idiosyncratic randomness in those updates

Testing Premise 2: Optimistic Narrative is Contagious and Associative

$$\text{opt}_{it} = u\ \text{opt}_{i,t-1} + s\ \overline{\text{opt}}_{t-1} + r\ \Delta \log Y_{t-1} + \gamma_i + \varepsilon_{it}$$

	Outcome is opt_{it}	
Own lag, $\text{opt}_{i,t-1}$	0.209	0.214
	(0.0071)	(0.0080)
Aggregate lag, $\overline{\text{opt}}_{t-1}$	0.290	
	(0.0578)	
Real GDP growth, $\Delta \log Y_{t-1}$	0.804	
	(0.2204)	
Industry lag, $\overline{\text{opt}}_{j(i),t-1}$		0.276
		(0.0396)
Industry output growth, $\Delta \log Y_{j(i),t-1}$		0.0560
		(0.0309)
Firm FE?	✓	✓
Time FE?		✓
N	64,948	52,258
R^2	0.481	0.501

Industry Data | Peer Set Contagiousness | Continuous Measure | Alternative Clustering | Over-controlling

Testing Premise 2: Optimistic Narrative is Contagious and Associative

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Result: Can Optimism "Go Viral"?

- Recall our "M statistic," which delineates stable and hysteresis dynamics:

$$M = \underbrace{u}_{\text{stubbornness}} + \underbrace{s}_{\text{contagiousness}} + \underbrace{r}_{\text{associativeness}} \times \underbrace{\frac{\alpha}{1-\omega}\delta^{OP}}_{\text{GE Impact}} - 1$$

- If $M > 0$ in the data: then optimism induces hysteresis in the empirically relevant calibration (i.e., a culprit for low-frequency stagnation in the US)

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Multi-Narrative Model

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- If $M > 0$ in the data: then optimism induces hysteresis in the empirically relevant calibration (i.e., a culprit for low-frequency stagnation in the US)

- What we find: $\hat{M} = -0.44$ **(SE:** 0.05**)**, which comfortably rejects hysteresis

Result: Narrative Optimism's Effects on US GDP

Implied Shocks | Sensitivity Analysis

$$\text{Contribution of Optimism} \approx \underbrace{\frac{\alpha}{1-\omega}}_{\text{Calibration } \approx 2} \times \underbrace{\delta^{OP}}_{\text{Micro Estimate } \approx 3.6\%} \times \underbrace{Q_t}_{\text{Observed}}$$

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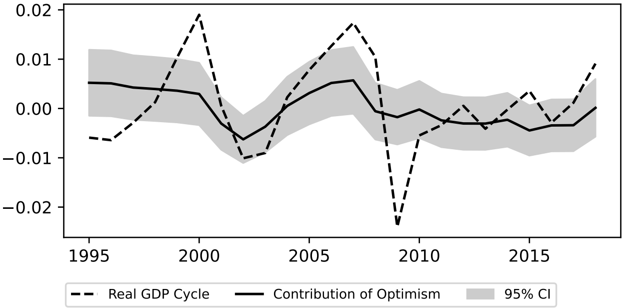
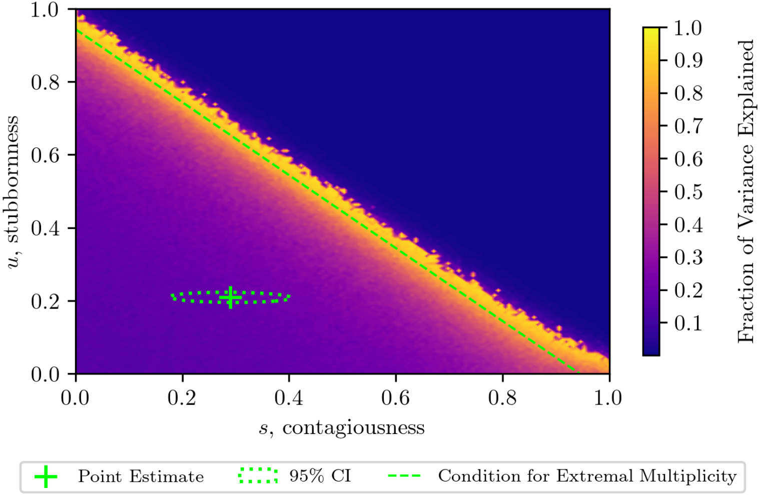


- Optimism explains 32% (SE: 2.7%) of Early 2000s Recession and 18% (SE: 1.5%) of Great Recession

How Close is Optimism to Going “Viral”?



Conclusion: Narratives Matter for the Business Cycle

To what extent do contagious, belief-altering narratives explain business cycles?

1. **Theory:** Contagious optimism generates fluctuations, can generate hysteresis
2. **Empirics:** Non-fundamental narrative optimism is decision-relevant and contagious
3. **Quantification:** Endogenous evolution of optimism explains 20% of the business cycle

Next steps in the agenda:

1. **Within this Framework:** understanding the interactions between multiple narratives and the importance of narratives for financial markets
2. **Moving Further:** understanding the determinants of narrativity, the role of narratives in encoding "cause and effect" in general equilibrium

Interpreting Contagiousness: Spillovers vs. Common Shocks Back

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     Next slide

  2. Use plausibly random variation in optimism as an instrument for aggregate optimism

     In the paper: (i) CEO turnover strategy and (ii) granular IV (Gabaix and Koijien, 2020)

Result: Optimism is Contagious, "Over-Controlling" for Fundamentals

$$\text{opt}_{it} = u\ \text{opt}_{i,t-1} + s\ \overline{\text{opt}}_{t-1} + \gamma_i + \sum_{k=-2}^{2} \left(\eta_k^{\text{agg}} \Delta \log Y_{t+k} + \eta_k^{\text{ind}} \Delta \log Y_{j(i),t+k} \right) + \varepsilon_{it}$$

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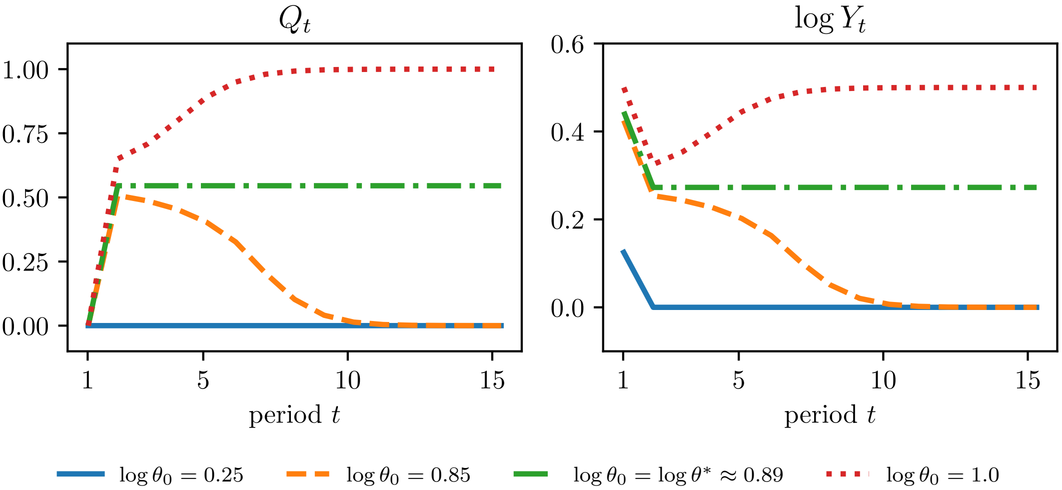
	Outcome is opt_{it}		
Aggregate lag, $\overline{\text{opt}}_{t-1}$	0.290	0.339	0.235
	(0.0578)	(0.0763)	(0.1278)
Firm FE	✓	✓	✓
Own lag, $\text{opt}_{i,t-1}$	✓	✓	✓
$(\Delta \log Y_{t+k})_{k=-2}^{2}$		✓	✓
$(\Delta \log Y_{j(i),t+k})_{k=-2}^{2}$			✓
N	64,948	49,631	38,132
R^2	0.481	0.484	0.497

Notes: The control variables are: real GDP growth (columns 2-3) and industry-level output growth (column 3). Standard errors are two-way clustered by firm ID and industry-year.

In Hysteresis Case: IRFs Have Humps, Discontinuities

Back



Calibrating the Model: From Micro to Macro

Details

Fixed	ϵ	Elasticity of substitution	2.6
	γ	Income effects in labor supply	0
	ψ	Inverse Frisch elasticity	0.4
	α	Returns to scale	1
Calibrated	$\mu_O - \mu_P$	Belief effect of optimism	
	κ	Signal-to-noise ratio	
	ρ	Persistence of productivity	
	σ	Std. dev. of the productivity innovation	
	u	Stubbornness	
	r	Associativeness	
	s	Contagiousness	
	σ_ε	Std. dev. of optimism shock	

1. Calibrate macro parameters at standard values

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	σ	Std. dev. of the productivity innovation	
	u	Stubbornness	0.208
	r	Associativeness	0.804
	s	Contagiousness	0.290
	σ_ε	Std. dev. of optimism shock	

2. Calibrate updating parameters from estimated updating rule

Calibrating the Model: From Micro to Macro

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3. Calibrate f and obtain one restriction on $(\mu_O - \mu_P, \kappa)$ using regression of hiring on optimism

Calibrating the Model: From Micro to Macro

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Calibrated	$\mu_O - \mu_P$	Belief effect of optimism	0.028
	κ	Signal-to-noise ratio	0.344
	ρ	Persistence of productivity	0.086
	σ	Std. dev. of the productivity innovation	0.011
	u	Stubbornness	0.208
	r	Associativeness	0.804
	s	Contagiousness	0.290
	σ_ε	Std. dev. of optimism shock	

4. Calibrate (κ, ρ, σ) using estimated ARMA process for $\log Y_t - f(Q_t)$

Calibrating the Model: From Micro to Macro

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	u	Stubbornness	0.208
	r	Associativeness	0.804
	s	Contagiousness	0.290
	σ_ε	Std. dev. of optimism shock	0.044

5. Calibrate σ_ε to match time series variance of optimism

Interpreting the Effect: Optimism Predicts (Over-)Optimistic Beliefs

- Take sales guidance data from IBES as a proxy for firms' beliefs
- Three findings establish that optimistic firms have more optimistic beliefs (skipping details for brevity)
  1. Optimistic firms predict higher sales growth Link
  2. Optimism predicts over-optimistic forecasts (e.g., predicted sales exceed sales) Link
  3. Conditional on sales forecasts, optimism is predictive of hiring Link

Premise I: Narratives are the Building Blocks of Beliefs

Back Hiring Back Updating

Goal: Establish conceptual framework in which we can formalize our notion of narratives and their macroeconomic consequences

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- Narrative is a model of fundamentals $N_k \in \Delta(\Theta)$, $\mathcal{N} = \{N_k\}_{k \in \mathcal{K}}$ – *e.g.*,

Optimism, N_O: "productivity is high" Pessimism, N_P: "productivity is low"

$$N_O \succeq_{FOSD} N_P$$

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- Agents place weights $\lambda \in \Lambda \subseteq \Delta(\mathcal{K})$ on different narratives to arrive at their own beliefs

$$\pi_\lambda(\theta) = \sum_{k \in \mathcal{K}} \lambda_k N_k(\theta)$$

e.g., optimist puts $(\lambda_O, \lambda_P) = (1,0)$, pessimist puts $(0,1)$, middle-ground puts $(1/2, 1/2)$

Premise II: Narrative Spread is Contagious and State-Dependent

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- Updating rule $P : \Lambda \times \mathcal{Y} \times \Delta(\Lambda) \to \Delta(\Lambda)$ – *i.e.*,

$$P_{\lambda'}(\lambda, Y, Q) = \text{Prob. agent with } \lambda \text{ moves to } \lambda' \text{ when } (Y, Q)$$

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Associative updating:
"Output is high, therefore the optimists are right"
P_O, P_P increasing in Y

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- Induces difference equation for distribution of narratives:

$$Q_{t+1,\lambda'} = \sum_{\lambda \in \Lambda} Q_{t,\lambda} P_{\lambda'}(\lambda, Y_t, Q_t)$$

Closing the Framework: From Beliefs to Actions to Outcomes

- Agents care about own actions $x_{it} \in \mathcal{X}$, aggregate outcomes $Y \in \mathcal{Y}$, and fundamentals $\theta \in \Theta$
- ... and have information set $\mathcal{I}_{it}$

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- Given conjecture about endogenous law of motion $\hat{Y}_t : \Theta \to \mathcal{Y}$, maximize expected utility:

$$\max_{x_{it} \in \mathcal{X}} \mathbb{E}_{\pi_{\lambda_{it}}} \left[u_{it}(x_{it}, \hat{Y}_t(\theta_t), \theta_t) \mid \mathcal{I}_{it} \right]$$

i.e, can be non-Bayesian over models, but always Bayesian within each model

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Definition (Equilibrium)

An equilibrium (Y_t^*, G_t^*) comprises an aggregate outcome function $Y_t^* : \Theta \to \mathcal{Y}$ and an action distribution functional $G_t^* : \Theta \to \Delta(\mathcal{X})$ such that:

1. *Aggregate outcomes are consistent with aggregation: $Y_t^*(\theta) = F(G_t^*(\theta), \theta)$ for all $\theta \in \Theta$*
2. *Distributions are consistent with utility maximization: $G_t^*(x; \theta) = \int_{[0,1]} \mathbb{P}[x_{it}^* \leqslant x | \theta] \mathrm{d}i$ for all $\theta \in \Theta$ and $x \in \mathcal{X}$ where x_{it}^* is a solution to Equation 31 given Y_t^* for all $i \in [0, 1]$.*

From the Conceptual Framework to an Empirical Framework (I)

- Derive regression equations as linear approximation of framework

Proposition (Hiring Regression)

Under regularity conditions, we have that:

$$x_{it} = \gamma_i + \chi_t + \sum_{k=1}^{K} \delta_k \lambda_{k,it} + \varepsilon_{it} + O(||(x_{it}, Y_t, \theta_t, Q_t, \omega_i, \nu_{it}, \lambda_{it})||^2)$$

where ε_{it} *is a zero mean random variable that is uncorrelated with* γ_i, χ_t *and* λ_{it}. *Thus, net of the misspecification error, the conditional expectation function is given by:*

$$\mathbb{E}[x_{it}|i, t, \lambda_{it}] = \gamma_i + \chi_t + \sum_{k=1}^{K} \delta_k \lambda_{k,it}$$

From the Conceptual Framework to an Empirical Framework (II)

Proposition (Updating Regression)

Under regularity conditions, we have that:

$$\mathbb{P}[\lambda_{it} = \lambda | \lambda_{i,t-1}, Y_{t-1}, Q_{t-1}] = \zeta_\lambda + u'_\lambda \lambda_{i,t-1} + r'_\lambda Y_{t-1} + s'_\lambda Q_{t-1} + O(||(\lambda_{i,t-1}, Y_{t-1}, Q_{t-1})||^2)$$

Regularity Conditions for Hiring and Updating Regressions

Assumption

The utility function u is strictly concave and twice continuously differentiable.

Assumption

The agents' information sets are generated by location experiments, i.e., $s_{it} = \theta_t + \nu_{it}$, where ν_{it} is a zero-mean random variable that is independent of θ_t, ω_i, and λ_{it}. Moreover, conditional on the signal, the conditional expectation of θ_t under each narrative k is given by $\mathbb{E}_k[\theta_t | s_{it}] = \alpha s_{it} + c_k + O(||s_{it}||^2)$.

Assumption

The updating rule P is continuously differentiable.

Conceptual Framework with Firm Dynamics

Back

- Allow $\tilde{\theta}_{it}$ to follow arbitrary first-order Markov process
- Firm decisions subject to adjustment cost $\Phi(x - x_{-1})$
- Linearization of firm policy function in this setting yields:

$$x_{it} \approx \gamma_i + \chi_t + \sum_{k=1}^{K} \delta_k \lambda_{k,it} + \gamma \theta_{it-1} + \omega x_{it-1} + \varepsilon_{it}$$

- So we just need to control for lagged productivity and actions

Most Common Positive and Negative Words in Sentiment Scoring

Back

Positive	Negative
well	loss
good	decline
benefit	disclose
high	subject
gain	terminate
advance	omit
achieve	defer
improve	claim
improvement	concern
opportunity	default
satisfy	limitation
lead	delay

Narrative Identification from Shiller (2020)

Back

Main idea: compare similarity to text of each chapter about nine *Perennial Economic Narratives*

1. For each narrative k, take top 100 words by tf-idf score to obtain $\mathcal{W}_k$ narrative words:

$$\text{tf-idf}(w)_k = \text{tf}(w)_k \times \log\left(\frac{1}{\text{df}(w;\mathcal{D})}\right)$$

2. Score document (i, t) for narrative k by the total frequency of narrative words

$$\widehat{\text{Shiller}}_{it}^{k} = \sum_{w \in \mathcal{W}_k} \text{tf}(w)_{it}$$

3. Compute Shiller_{it}^{k} by taking the z-score.

List of Narratives

Narratives from *Narrative Economics*

Back

Narrative Economics: How Stories Go Viral and Drive Major Economic Events by Robert J. Shiller (2020). Princeton University Press.

1. Panic versus Confidence
2. Frugality versus Conspicuous Consumption
3. The Gold Standard versus Bimetallism
4. Labor-Saving Machines Replace Many Jobs
5. Automation and Artificial Intelligence Replace Almost All Jobs
6. Real Estate Booms and Busts
7. Stock Market Bubbles
8. Boycotts, Profiteers, and Evil Businesses
9. The Wage-Price Spiral and Evil Labor Unions

Latent Dirichlet Allocation

Back

Main idea: identify groups of co-occurring words with statistical method

1. Estimate latent set of $K = 100$ topics (distribution over words) using variational Bayes approach of Hoffman *et al.* (2010) Details
2. Obtain document level topic distribution as

$$\widehat{\text{Topic}}_{it}^{k} = \hat{p}(k|d_{it})$$

   i.e., the weight of the document on the topic is its score
3. Compute Topic_{it}^{k} by taking the z-score.

Latent Dirichlet Allocation: Model Details

Back

- LDA is three-level hierarchical Bayesian model
  1. Corpus $\mathcal{D} = \{10 - Ks\}$, comprises M documents, with W words
  2. Number of topics K
  3. Number of words in document $W \sim \text{Poisson}(\xi)$
  4. Distribution of topics $\theta = (\theta_1, \ldots, \theta_M) \sim \text{Dir}(\alpha)$ – α_k is the prior weight that topic k is in a document
  5. Distribution of words $\phi = (\phi_1, \ldots, \phi_K) \sim \text{Dir}(\beta)$ – β_{kj} is the prior weight that word j is in topic k
  6. Generate the W words in each document d: (i) Topic $z_n \sim \text{Mult}(\theta)$ (ii) Word $w \sim \text{Mult}(\phi_{z_n})$
- Estimation implemented in `Python` through `Gensim` using variational Bayes algorithm of Hoffman, Blei and Bach (2010)
- Based on subjective inspection and stabilization of coherence measures, select 100-topic model

Measuring Sector-Specific Production Functions

Back

1. For all firms in industry j, calculate the estimated materials share:

$$\text{Share}_{M,j'} = \frac{\sum_{i:j(i)=j'} \sum_t \text{MaterialExpenditure}_{it}}{\sum_{i:j(i)=j'} \sum_t \text{Sales}_{it}}$$

2. If $\text{Share}_{M,j'} \leqslant \mu^{-1}$, then set

$$\alpha_{M,j'} = \mu \cdot \text{Share}_{M,j'}$$
$$\alpha_{K,j'} = 1 - \alpha_{M,j'}$$

3. Otherwise, adjust shares to match the assumed returns-to-scale, or set

$$\alpha_{M,j'} = 1$$
$$\alpha_{K,j'} = 0$$

4. We calculate a “Sales Solow Residual” $\tilde{\theta}_{it}$ of the following form:

$$\log \tilde{\theta}_{it} = \log \text{Sales}_{it} - \frac{1}{\mu} \left(\alpha_{M,j(i)} \cdot \log \text{MatExp}_{it} + \alpha_{K,j(i)} \cdot \log \text{CapStock}_{it} \right)$$

5. We finally define our estimate $\log \hat{\theta}_{it}$ as the previous net of industry-by-time fixed effects

$$\log \hat{\theta}_{it} = \log \tilde{\theta}_{it} - \gamma_{j(i)}$$

Narratives are Cyclical and Persistent

Back

Narrative N_t	Correlation with N_{t-1}	u_{t-1}	u_t	u_{t+1}
Optimism	0.754	-0.283	-0.368	-0.287
Topic Narratives (25th)	0.810	-0.430	-0.307	-0.210
Topic Narratives (median)	0.935	0.003	-0.143	-0.092
Topic Narratives (75th)	0.965	0.339	0.252	0.077
Shiller Narratives (25th)	0.792	-0.379	-0.379	-0.367
Shiller Narratives (median)	0.805	0.043	0.088	-0.034
Shiller Narratives (75th)	0.884	0.541	0.422	0.246

Notes: Calculated with annual data from 1995 to 2018. u_t is the U.S. unemployment rate. The quantiles for Shiller Narratives and Topic Narratives are the quantiles of the distribution of the variable in that column within each set of narratives.

Almost All Narrative Variation is in the Cross-Section

Back

What is the R^2 of opt_{it} on fixed effects (means) at different levels?

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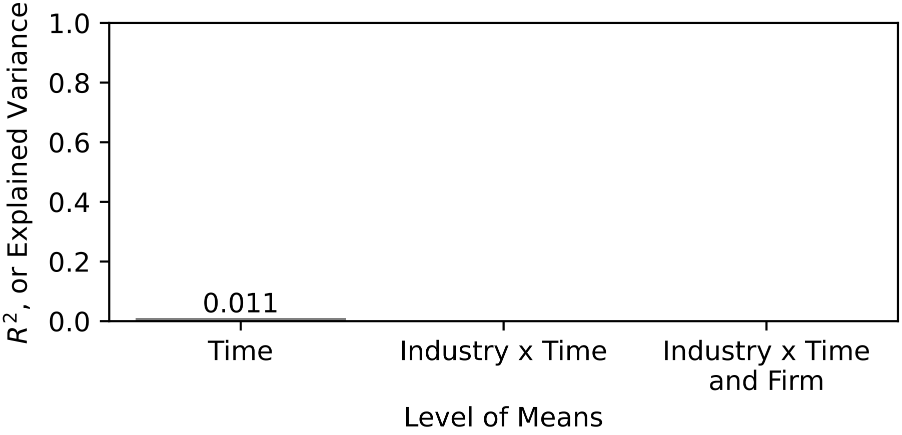

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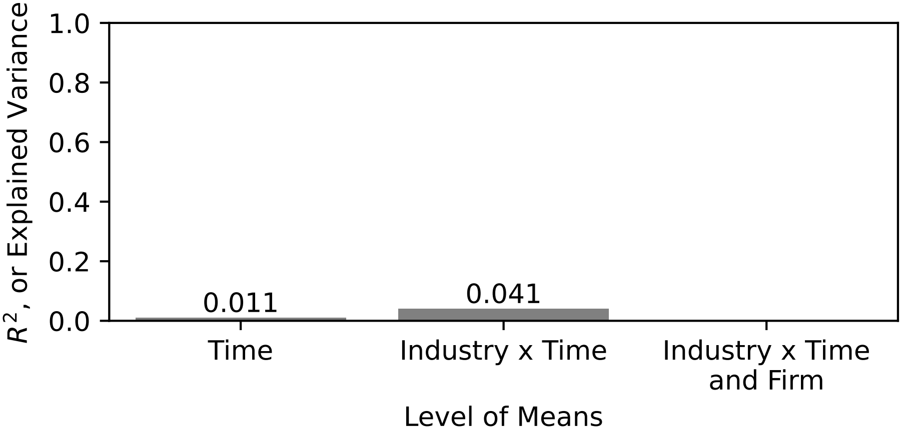

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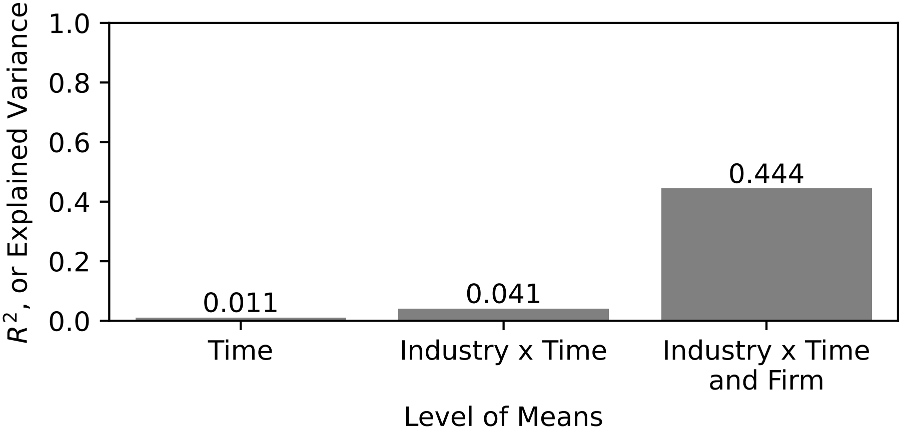
What is the R^2 of opt_{it} on fixed effects (means) at different levels? Full Table



Narratives Have Mostly Cross-Sectional Variation

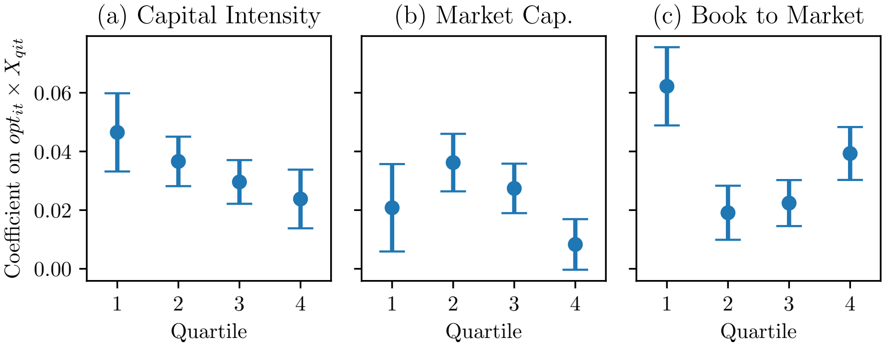
Back

Narrative N_{it}	Fraction Variance Explained By Means t	Ind.	Ind. x t	Firm	All
Net Sentiment	0.014	0.053	0.082	0.511	0.530
Optimism	0.011	0.041	0.067	0.427	0.444
Topic Narratives (25th)	0.010	0.003	0.049	0.252	0.306
Topic Narratives (median)	0.035	0.014	0.099	0.420	0.575
Topic Narratives (75th)	0.087	0.071	0.237	0.645	0.735
Shiller Narratives (25th)	0.002	0.050	0.062	0.758	0.761
Shiller Narratives (median)	0.002	0.071	0.087	0.763	0.770
Shiller Narratives (75th)	0.003	0.095	0.109	0.793	0.794

Notes: Calculated with annual data from 1995 to 2018. u_t is the U.S. unemployment rate. The quantiles for Shiller Narratives and Topic Narratives are the quantiles of the distribution of the variable in that column within each set of narratives.

Heterogeneous Effects of Optimism on Hiring

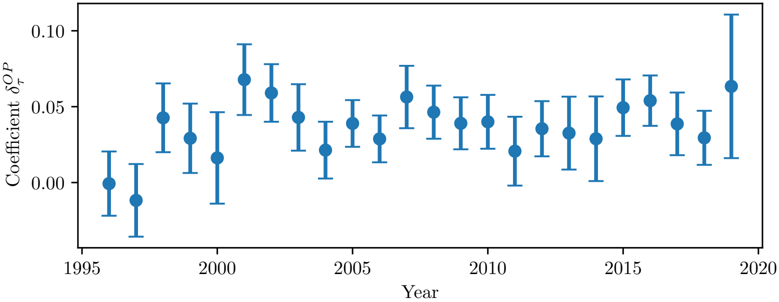
Back



Notes: In each panel, we show estimates from the regression $\Delta \log L_{it} = \sum_{q=1}^{r} \beta_q \cdot (\text{opt}_{it} \times X_{qit}) + \gamma_i + \chi_{j(i),t} + \epsilon_{it}$, where X_{qit} indicates quartile q of the studied variable: one minus the variable cost share of sales, market capitalization, or book-to-market ratio. In all specifications, we drop the 1% and 99% tails of the outcome variable. Error bars are 95% confidence intervals.

Time-Variation in Effect of Optimism on Hiring

Back



Notes: Each dot is a coefficient δ_τ^{OP} from $\Delta \log L_{it} = \sum_{\tau=1996}^{2017} \delta_\tau^{OP} (\text{opt}_{it} \times \mathbb{I}[t = \tau]) + \gamma_i + \chi_{j(i),t} + +\varepsilon_{it}$. In all specifications, we drop the 1% and 99% tails of the outcome variable. Error bars are 95% confidence intervals, based on standard errors clustered by firm and industry-time.

Optimistic Narratives Drive Hiring: Conference-Call Data

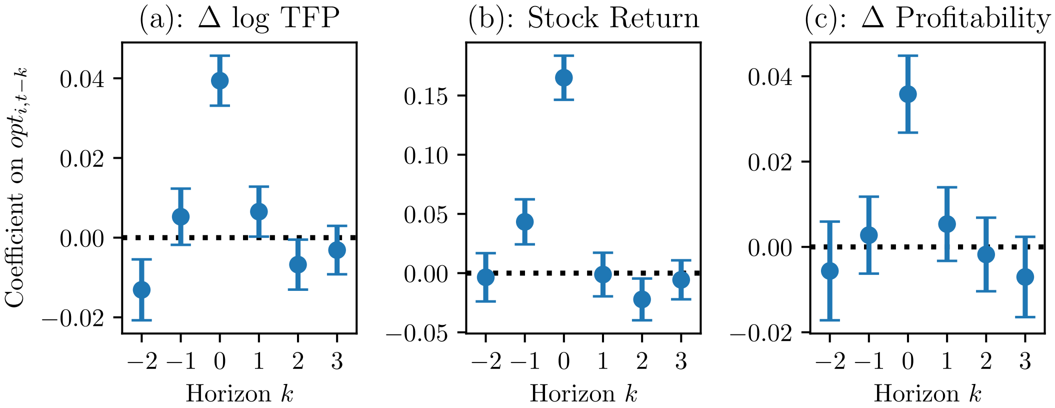
Back Dynamics

	(1)	(2)	(3)	(4)	(5)
	Outcome is				
	$\Delta \log L_{it}$				$\Delta \log L_{i,t+1}$
optCC_{it}	0.0277	0.0173	0.0121	0.0237	0.0123
	(0.0038)	(0.0040)	(0.0038)	(0.0038)	(0.0044)
Industry-by-time FE	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓		✓
Lag labor		✓	✓	✓	✓
Current and lag TFP		✓	✓	✓	✓
Log BtM, Stock Return, Leverage			✓		
N	19,625	11,565	10,851	11,919	11,416
R^2	0.300	0.461	0.467	0.172	0.429

Notes: Standard errors are two-way clustered by firm ID and industry-year. In all specifications, we drop the 1% and 99% tails of the outcome variable. In column 5, control variables are dated $t+1$.

Optimistic Narratives are Non-Fundamental: Conference-Call Data

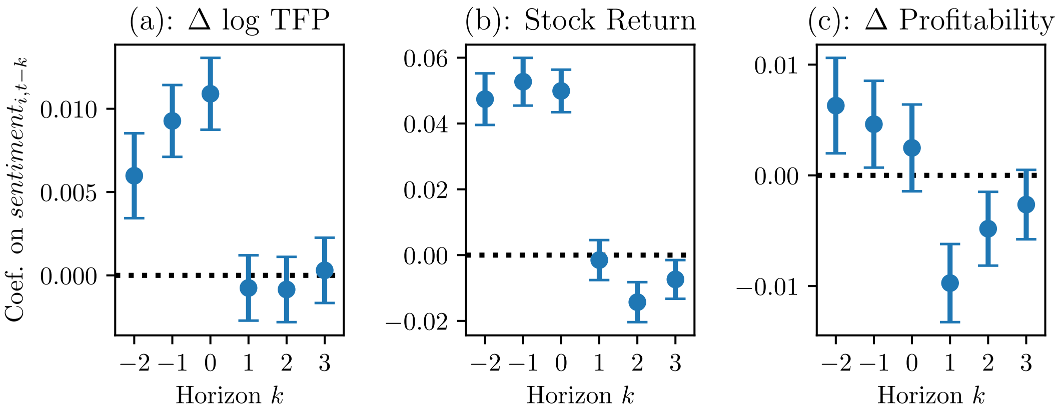
Back



Notes: Stock returns are in log units and profitability is defined as the ratio of EBIT to lagged variable costs. In all specifications, we trim the 1% and 99% tails of the outcome variable. Error bars are confidence intervals, based on standard errors clustered at the firm and industry-year level.

Optimistic Narratives are Non-Fundamental: Continuous Sentiment

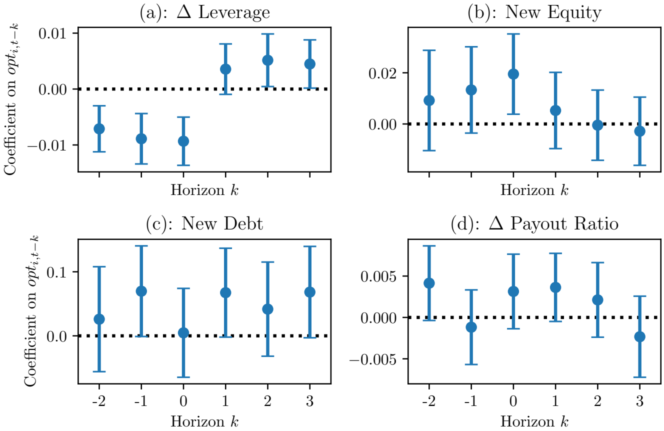
Back



Notes: Stock returns are in log units and profitability is defined as the ratio of EBIT to lagged variable costs. In all specifications, we trim the 1% and 99% tails of the outcome variable. Error bars are confidence intervals, based on standard errors clustered at the firm and industry-year level.

Optimistic Narratives and Financial Outcomes

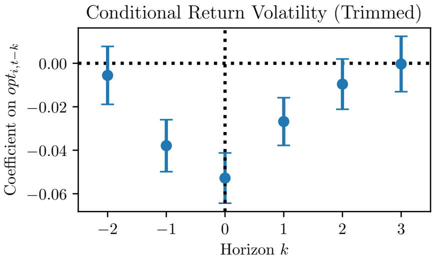
Back



Notes: Each coefficient is estimated from a separate projection regression. The outcome variables are: (a) the fiscal-year-to-fiscal-year difference in leverage, which is total debt (short-term debt plus long-term debt); (b) sale of common and preferred stock minus buybacks, normalized by the total equity outstanding in the previous fiscal year; (c) short-term debt plus long-term debt issuance, normalized by the total debt in the previous fiscal year; and (d) total dividends divided by earnings before interest and taxes (EBIT). In all specifications, we trim the 1% and 99% tails of the outcome variable. Error bars are 95% confidence intervals. Standard errors are two-way clustered by firm ID and industry-year.

Optimistic Narratives and Financial Outcomes

Back



Notes: Each coefficient is estimated from a separate projection regression. The outcome variables are: (a) the fiscal-year-to-fiscal-year difference in leverage, which is total debt (short-term debt plus long-term debt); (b) sale of common and preferred stock minus buybacks, normalized by the total equity outstanding in the previous fiscal year; (c) short-term debt plus long-term debt issuance, normalized by the total debt in the previous fiscal year; and (d) total dividends divided by earnings before interest and taxes (EBIT). In all specifications, we trim the 1% and 99% tails of the outcome variable. Error bars are 95% confidence intervals. Standard errors are two-way clustered by firm ID and industry-year.

High-Frequency Impact of Optimism on Stock Prices

Back

	(1)	(2)	(3)	(4)	(5)	(6)
	Outcome is stock return on					
	Filing Day		Prior Four Days		Next Four Days	
opt_{it}	0.000145	-0.000142	0.00106	0.000963	0.00173	0.00249
	(0.0007)	(0.0007)	(0.0011)	(0.0014)	(0.0012)	(0.0016)
Firm FE	✓	✓	✓	✓	✓	✓
Industry-by-FY FE	✓	✓	✓	✓	✓	✓
Industry-FF3 inter.		✓		✓		✓
N	39,457	39,457	39,396	17,710	39,346	19,708
R^2	0.189	0.246	0.190	0.345	0.206	0.317

Notes: The regression equation for columns (1), (3), and (5) is $R_{i,w(t)} = \beta \text{opt}_{it} + \gamma_i + \chi_{j(i),y(i,t)} + \varepsilon_{it}$ where i indexes firms, t is the 10K filing day, $w(t)$ is a window around the day (the same day, the prior four days, or the next four days), and $y(i,t)$ is the fiscal year associated with the specific 10-K. In columns (2), (4), and (6), we add interactions of industry codes with the filing day's (i) the market minus risk free rate, (ii) high-minus-low return, and (iii) small-minus-big return. Standard errors are two-way clustered by firm ID and industry-year.

Optimistic Narratives Drive All Input Choices

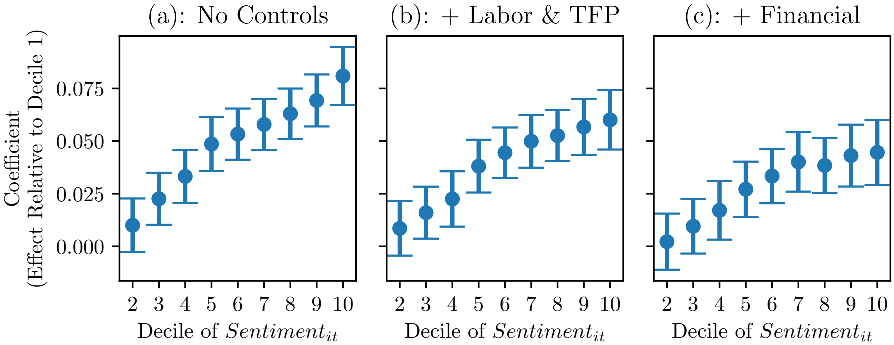
Back

	(1)	(2)	(3)	(4)	(5)	(6)
			Outcome is			
	$\Delta \log L_{it}$		$\Delta \log M_{it}$		$\Delta \log K_{it}$	
opt_{it}	0.0355	0.0305	0.0397	0.0193	0.0370	0.0273
	(0.0030)	(0.0030)	(0.0034)	(0.0033)	(0.0034)	(0.0036)
Industry-by-time FE	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Lag input		✓		✓		✓
Current and lag TFP		✓		✓		✓
N	71,161	39,298	66,574	39,366	68,864	36,005
R^2	0.259	0.401	0.298	0.418	0.276	0.383

Notes: $\Delta \log M_t$ is the log difference of all variable cost expenditures ("materials"), the sum of cost of goods sold (COGS) and sales, general, and administrative expenses (SGA). $\Delta \log K_t$ is the value of the capital stock is the log difference level of net plant, property, and equipment (PPE) between balance-sheet years $t-1$ and t. In all specifications, we trim the 1% and 99% tails of the outcome variable. Standard errors are two-way clustered by firm ID and industry-year.

Sentiment and Hiring: Non-Parametric Relationship

Back



Notes: In each panel, we show estimates from the regression $\Delta \log L_{it} = \sum_{q=1}^{10} \beta_q \cdot (\text{sentiment}_{iqt}) + \tau' X_{it} + \gamma_i + \chi_{j(i),t} + \epsilon_{it}$, where sentiment_{iqt} indicates quartile q of the continuous sentiment variable. Panel (a) estimates this equation without controls; panel (b) adds controls for lagged labor and current and lagged log TFP; and panel (c) adds controls for the log book to market ratio, log stock return, and leverage. The excluded category in each regression is the first decile of sentiment_{it}. In all specifications, we trim the 1% and 99% tails of the outcome variable. Error bars are 95% confidence intervals. Standard errors are double-clustered by firm ID and industry-year.

State-Dependent Effects of Sentiment

Back

$$\Delta \log L_{it} = \delta_0 \text{sentiment}_{it} + \delta_1 \text{sentiment}_{i,t-1} + \delta_2 (\text{sentiment}_{it} \times \text{sentiment}_{i,t-1}) + \gamma_i + \chi_{j(i),t} + \tau'$$

	Outcome is $\Delta \log L_{it}$		
sentiment_{it}	0.0218	0.0172	0.0130
	(0.0017)	(0.0018)	(0.0020)
$\text{sentiment}_{i,t-1}$	0.00605	0.00877	0.00830
	(0.0015)	(0.0016)	(0.0016)
$\text{sentiment}_{it} \times \text{sentiment}_{i,t-1}$	-0.00497	-0.00501	-0.00404
	(0.0008)	(0.0008)	(0.0008)
N	63,302	35,768	31,071
R^2	0.257	0.394	0.416
Ind.-by-time FE	✓	✓	✓
Firm FE	✓	✓	✓
Lag labor		✓	✓
Current and lag TFP		✓	✓
Log Book to Market, Stock Return, Leverage			✓

Notes: We trim the 1% and 99% tails of the outcome variable. Standard errors are two-way clustered by firm ID and industry-year.

Optimistic Firms Forecast Growth

Back

Data: I/B/E/S Guidance, linked to analyst consensus forecasts

- Restrict to first forecast for this fiscal year
- Observe manager guidance (midpoint, if range); analyst consensus; realized value

Construct, for $Z \in \{\text{Sales}, \text{Capx}, \text{EPS}\}$:

$$\text{ForecastGrowthZ}_{it} = \log \text{GuidanceForX}_{it} - \log Z_{i,t-1}$$

Firm-by-fiscal-year regression model on guidance-linked subsample:

$$\text{ForecastGrowthZ}_{i,t+1} = \delta^{OP}\text{opt}_{it} + +\gamma_i + \chi_{j(i),t} + \varepsilon_{it}$$

Optimistic Firms Forecast Growth

Back

$$\text{ForecastGrowthZ}_{i,t+1} = \delta^{OP}\text{opt}_{it} + +\gamma_i + \chi_{j(i),t} + \varepsilon_{it}$$

	ForecastGrowthZ$_{i,t+1}$ for		
	Sales	CapX	EPS
opt_{it}	0.019	0.002	0.051
	(0.010)	(0.015)	(0.059)
Ind.-by-time FE	✓	✓	✓
Firm FE	✓	✓	✓
N	3,044	7,662	1,286
R^2	0.267	0.448	0.0771

Notes: In all specifications, we trim the 1% and 99% tails of the outcome variable. Standard errors are two-way clustered by firm ID and industry-year.

Comparing Predictive Power of Narratives vs. Measured Beliefs

Back Investment

Data: I/B/E/S Guidance, linked to analyst consensus forecasts

- Restrict to first forecast for this fiscal year
- Observe manager guidance (midpoint, if range); analyst consensus; realized value

Construct, for $Z \in \{\text{Sales}, \text{Capx}, \text{EPS}\}$:

$$\text{ForecastGrowthZ}_{it} = \log \text{GuidanceForX}_{it} - \log Z_{i,t-1}$$

Firm-by-fiscal-year regression model on guidance-linked subsample:

$$\Delta \log L_{it} = \delta^{OP} \text{opt}_{it} + \delta^{Z} \, \text{ForecastGrowthZ}_{it} + \gamma_i + \chi_{j(i),t} + \varepsilon_{it}$$

Comparing Predictive Power of Narratives vs. Measured Beliefs

Back Investment

$$\Delta \log L_{it} = \delta^{OP} \text{opt}_{it} + \delta^{Z} \text{ForecastGrowthZ}_{it} + \gamma_i + \chi_{j(i),t} + \varepsilon_{it}$$

	Outcome is $\Delta \log L_{it}$			
opt_{it}	0.0355	0.0232	0.0311	0.0203
	(0.0030)	(0.0129)	(0.0068)	(0.0164)
$\text{ForecastGrowthSales}_{it}$		0.157		
		(0.0329)		
$\text{ForecastGrowthCapx}_{it}$			0.0564	
			(0.0062)	
$\text{ForecastGrowthEps}_{it}$				0.000961
				(0.0104)
Ind.-by-time FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
N	71,161	2,908	7,312	1,290

Interpretation:

- Both have independent predictive power
- Take-away within model: different measurement strategy for same (latent) beliefs
- Purely empirical take-away: narratives may capture non-numerical "soft information" (Liberti

Narratives vs. Measured Beliefs: Capital

Back to Main Back to Hiring

$$\Delta \log L_{it} = \delta^{OP}\text{opt}_{it} + \delta^{Z}\,\text{ForecastGrowthZ}_{it} + \gamma_i + \chi_{j(i),t} + \varepsilon_{it}$$

	Outcome is $\Delta \log K_{it}$			
opt_{it}	0.0370	0.0238	0.0251	0.00503
	(0.0034)	(0.0177)	(0.0072)	(0.0193)
$\text{ForecastGrowthSales}_{it}$		0.172		
		(0.0423)		
$\text{ForecastGrowthCapx}_{it}$			0.0943	
			(0.0079)	
$\text{ForecastGrowthEps}_{it}$				-0.0147
				(0.0102)
Ind.-by-time FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
N	68,864	2,748	7,048	1,245
R^2	0.276	0.496	0.472	0.661

Notes: $\text{ForecastGrowthZ}_{it}$ is defined in the text as the log difference between manager guidance about statistic Z, for fiscal

Optimistic Narratives Predict Hiring: Alternative Clustering

Back to Main

	Outcome is				
	$\Delta \log L_{it}$				$\Delta \log L_{i,t+1}$
opt_{it}	0.0355	0.0305	0.0250	0.0322	0.0216
	(0.0030)	(0.0030)	(0.0032)	(0.0028)	(0.0037)
	[0.0031]	[0.0026]	[0.0031]	[0.0040]	[0.0034]
	{0.0035}	{0.0026}	{0.0025}	{0.0043}	{0.0036}
Firm FE	✓	✓	✓		✓
Industry-by-time FE	✓	✓	✓	✓	✓
Lag labor		✓	✓	✓	✓
Current and lag TFP		✓	✓	✓	✓
Log Book to Market			✓		
Stock Return			✓		
Leverage			✓		
N	71,161	39,298	33,589	40,580	38,402
R^2	0.259	0.401	0.419	0.142	0.398

Notes: Standard errors in parentheses are two-way clustered by firm ID and industry-year; those in square brackets are

Optimistic Narratives Predict Hiring: IV With Lag

Back to Main

$$\Delta \log L_{it} = \delta^{OP} \cdot \text{opt}_{it} + \gamma_i + \chi_{j(i),t} + \tau' X_{it} + \varepsilon_{it}$$

$$\text{opt}_{it} = \alpha \cdot \text{opt}_{i,t-1} + \tilde{\gamma}_i + \tilde{\chi}_{j(i),t} + \tilde{\tau}' X_{it} + \tilde{\varepsilon}_{it}$$

opt_{it}	0.0925	0.106	0.102	0.0470
	(0.0130)	(0.0160)	(0.0168)	(0.0053)
Firm FE	✓	✓	✓	
Industry-by-time FE	✓	✓	✓	✓
Lag labor		✓	✓	✓
Current and lag TFP		✓	✓	✓
Log Book to Market			✓	
Stock Return			✓	
Leverage			✓	
First-stage F	773	478	366	3,597
N	63,302	35,768	31,071	36,953

Notes: Standard errors in parentheses are two-way clustered by firm ID and industry-year.

Optimistic Narratives Predict Hiring: More Adjustment-Cost Controls

Back

	(1)	(2)	(3)	(4)
	Outcome is $\Delta \log L_{it}$			
opt_{it}	0.0305	0.0257	0.0235	0.0184
	(0.0030)	(0.0034)	(0.0037)	(0.0039)
Firm FE	✓	✓	✓	✓
Industry-by-time FE	✓	✓	✓	✓
$\log L_{i,t-1}$	✓	✓	✓	✓
$(\log \hat{\theta}_{it}, \log \hat{\theta}_{i,t-1})$	✓	✓	✓	✓
$(\log L_{i,t-2}, \log \hat{\theta}_{i,t-2})$		✓	✓	✓
$(\log L_{i,t-3}, \log \hat{\theta}_{i,t-3})$			✓	✓
Log Book to Market, Stock Return, Leverage				✓
N	39,298	31,236	25,156	21,913
R^2	0.401	0.395	0.396	0.415

Notes: Standard errors in parentheses are two-way clustered by firm ID and industry-year.

Robustness to Omitted Variables Bias

Back

Table: Robustness to Assumptions About Unobserved Selection When Estimating the Effect of Narrative Optimism on Hiring

Oster (2019) Statistics

	(1)	(2)
	$\bar{R}^2$ is	
	$\hat{\bar{R}}^2 = 0.459$	$\bar{R}^2_{\Pi} = 0.387$
$\lambda^* \; (\delta^{OP} = 0)$	1.691	2.151
$\delta^*_{OP} \; (\lambda = 1)$	0.0126	0.0165

Notes: Panel B prints the two statistics of Oster (2019). In column 1, we set $\bar{R}^2$ equal to our estimated value of 0.459, calculated from an "over-controlled" regression of current hiring on lagged controls and future hiring and productivity. In column 2, we use $\bar{R}^2$ given by three times the R^2 in the controlled hiring regression. The first row (λ^* ($\delta^{OP} = 0$) reports the degree of proportional selection that would generate a null coefficient. The second row ($\delta^*_{OP}(\lambda = 1)$) is the bias corrected effect assuming that unobservable controls have the same proportional effect as observable controls.

CEO Change Strategy: Measurement

Back 1 Back 2

Dataset: CEO exits coded by Gentry, Harrison, Quigley and Boivie (2021)

- 9000 CEO turnover events by reason by inspection of primary sources
- "Exogenous" changes: we subset to CEO exits caused by death, illness, personal issues, and voluntary retirements
- Idea: these changes affect firm outcomes via their effects on corporate narratives

Firm-by-fiscal-year regression model on CEO-change subsample:

$$\Delta \log L_{it} = \chi_{j(i),t} + \delta^{CEO}\text{opt}_{it} + \delta_{-1}^{CEO}\text{opt}_{i,t-1} + \tau' X_{it} + \varepsilon_{it}$$

Note that (industry-and-year-varying) direct effect of exit is in constants

Optimistic Narratives Induced by CEO Changes Predict Hiring

Back 1 Back 2

$$\Delta \log L_{it} = \chi_{j(i),t} + \delta^{CEO}\text{opt}_{it} + \delta^{CEO}_{-1}\text{opt}_{i,t-1} + \tau' X_{it} + \varepsilon_{it}$$

	Outcome is $\Delta \log L_{it}$			
opt_{it}	0.0253	0.0404	0.0362	0.0253
	(0.0131)	(0.0131)	(0.0132)	(0.0029)
$\text{opt}_{it} \times \text{ChangeCEO}_{it}$				0.0220
				(0.0099)
ChangeCEO_{it}				-0.0232
				(0.0088)
Industry-by-time FE	✓	✓	✓	✓
Lag optimism	✓	✓	✓	✓
Lag labor		✓	✓	✓
Current and lag TFP		✓	✓	✓
Log BtM, Stock Return, Leverage			✓	
N	1,725	982	905	36,953
R^2	0.243	0.375	0.375	0.134

Narrative Optimism Predicts Irrationally Optimistic Forecasts

Back

Data: I/B/E/S Guidance, linked to analyst consensus forecasts

- Restrict to first forecast of sales for this fiscal year
- Observe manager guidance (midpoint, if range); analyst consensus; realized value
- $\text{GuidOptExAnte}_{it}$: Guidance - Analyst exceeds sample median
- $\text{GuidOptExPost}_{it}$: Guidance - Realization exceeds sample median

Firm-by-fiscal-year regression model on guidance-linked subsample:

$$\text{GuidanceOpt}_{i,t+1} = \beta \cdot \text{opt}_{it} + \tau' X_{it} + \chi_{j(i),t} + \varepsilon_{it}$$

Narrative Optimism Predicts Irrationally Optimistic Forecasts

Back

$$\text{GuidanceOpt}_{i,t+1} = \beta \cdot \text{opt}_{it} + \tau' X_{it} + \chi_{j(i),t} + \varepsilon_{it}$$

	(1)	(2)	(3)	(4)
	Outcome is			
	$\text{GuidanceOptExPost}_{i,t+1}$		$\text{GuidanceOptExAnte}_{i,t+1}$	
opt_{it}	0.0354	0.0561	0.0267	-0.000272
	(0.0184)	(0.0257)	(0.0231)	(0.0353)
Ind.-by-time FE	✓	✓	✓	✓
Lag labor		✓		✓
Current and lag TFP		✓		✓
N	3,817	2,159	3,044	1,718
R^2	0.173	0.193	0.161	0.192

Notes: Standard errors are two-way clustered by firm ID and industry-year.

Industry- and Peer-Level Data Sources

Back

- Industry-level output data $\Delta \log Y_{j(i),t}$, based on linking BEA tables to NAICS-based industry codes
- Industry-level average optimism $\overline{\text{opt}}_{j(i),t}$, based on taking leave-one-out averages
- NYSE analyst peer network (Kaustia and Rantala, 2021): average optimism among peer set $p(i,t)$, where $p(i,t)$ is set of firms with more than C common analysts, where C is chosen to make the "type I error rate" 1%

Contagiousness Across NYSE Peers

Back

NYSE analyst peer network (Kaustia and Rantala, 2021): average opt. among peer set $p(i,t)$, where $p(i,t)$ is set of firms with more than C common analysts (C chosen to make type I error rate 1%)

	Outcome is opt_{it}		
Own lag, $\text{opt}_{i,t-1}$	0.209	0.214	0.135
	(0.0071)	(0.0080)	(0.0166)
Aggregate lag, $\overline{\text{opt}}_{t-1}$	0.290		
	(0.0578)		
Real GDP growth, $\Delta \log Y_{t-1}$	0.804		
	(0.2204)		
Industry lag, $\overline{\text{opt}}_{j(i),t-1}$		0.276	0.207
		(0.0396)	(0.0733)
Industry output growth, $\Delta \log Y_{j(i),t-1}$		0.0560	0.0549
		(0.0309)	(0.0632)
Peer lag, $\overline{\text{opt}}_{p(i),t-1}$			0.0356
			(0.0225)
Firm FE?	✓	✓	✓
Time FE?		✓	✓
N	64,948	52,258	8,514
R^2	0.481	0.501	0.501

Contagiousness and Associativeness of Continuous Sentiment

Back

	(1)	(2)	(3)
	Outcome is sentiment$_{it}$		
Own lag, sentiment$_{i,t-1}$	0.259	0.279	0.226
	(0.0091)	(0.0106)	(0.0166)
Aggregate lag, $\overline{\text{sentiment}}_{t-1}$	0.253		
	(0.0519)		
Real GDP growth, $\Delta \log Y_{t-1}$	2.632		
	(0.5305)		
Industry lag, $\overline{\text{sentiment}}_{j(i),t-1}$		0.175	0.108
		(0.0360)	(0.0763)
Industry output growth, $\Delta \log Y_{j(i),t-1}$		0.108	0.142
		(0.0522)	(0.1312)
Peer lag, $\overline{\text{sentiment}}_{p(i),t-1}$			0.0234
			(0.0188)
Firm FE	✓	✓	✓
Time FE		✓	✓
N	63,881	51,555	8,338
R^2	0.568	0.599	0.602

Notes: Aggregate, industry, and peer average sentiment are averages of the narrative sentiment variable over the respective sets of firms. Industry output growth is the log difference in sectoral value added calculated from BEA data, linked to

Optimistic Narrative is Contagious and Associative: Alternative Clustering

Back

	Outcome is opt_{it}		
Own lag, $\text{opt}_{i,t-1}$	0.209	0.214	0.135
	(0.0071)	(0.0080)	(0.0166)
	[0.0214]	[0.0220]	[0.0281]
	{0.0218}	{0.0221}	{0.0273}
Aggregate lag, $\overline{\text{opt}}_{t-1}$	0.290		
	(0.0578)		
	[0.180]		
	{0.179}		
Real GDP growth, $\Delta \log Y_{t-1}$	0.804		
	(0.2204)		
	[0.635]		
	{0.627}		
Industry lag, $\overline{\text{opt}}_{j(i),t-1}$		0.276	0.207
		(0.0396)	(0.0733)
		[0.0434]	[0.0563]
		{0.0496}	{0.0656}
Industry output growth, $\Delta \log Y_{j(i),t-1}$		0.0560	0.0549
		(0.0309)	(0.0632)
		[0.0328]	[0.0668]
		{0.0428}	{0.0772}
Peer lag, $\overline{\text{opt}}_{p(i),t-1}$			0.0356
			(0.0225)
			[0.0259]
			{0.0329}
Firm FE	✓	✓	✓
Time FE		✓	✓
N	64,948	52,258	8,514
R^2	0.481	0.501	0.501

The Reflection Problem (Manski, 1993) and Why it Doesn't Apply

Back

- Simple model with social effects:

$$Y_i = \alpha + \beta \bar{Y} + \varepsilon_i, \quad \mathbb{E}[\varepsilon_i] = 0 \quad \text{and} \quad \mathbb{E}[\varepsilon_i | \bar{Y}] = 0$$

- The reflection problem:

$$\bar{Y} = \alpha + \beta \bar{Y} \implies \alpha = 0, \beta = 1$$

- However, we are in a panel setting:

$$Y_{it} = \alpha + \beta \bar{Y}_{t-1} + \varepsilon_{it}, \quad \mathbb{E}[\varepsilon_{it}] = 0 \quad \text{and} \quad \mathbb{E}[\varepsilon_{it} | \bar{Y}_{t-1}] = 0$$

- As a result, the reflection problem does not manifest (as noted by Section 4 in Manski (1993)):

$$\mathbb{E}[Y_{it} | \bar{Y}_{t-1}] = \alpha + \beta \bar{Y}_{t-1}$$

- Of course, endogeneity could still be a problem!

Optimistic Narrative is Contagious, Associative: CEO Change Strategy

Back 1 Back 2

Construct networks based on exposure to CEO changes (“granular IV”):

$$\overline{\text{opt}}^{\text{ceo}}_{j(i),t-1} = \frac{1}{|M_{j(i),t}|} \sum_{k \in M^{c}_{j(i),t}} \text{opt}_{k,t-1}$$

where $M_{j(i),t}$ is the set of firms in industry $j(i)$ at time t, and $M^{c}_{j(i),t} \subseteq M_{j(i),t}$ is the subset that had plausibly exogenous CEO changes (similar within peer sets).

Optimistic Narrative is Contagious, Associative: CEO Change Strategy

Back 1 Back 2

	(1)	(2)	(3)	(4)
	Outcome is opt_{it}			
	OLS	IV	OLS	IV
Industry lag, $\overline{\text{opt}}_{j(i),t-1}$	0.275	0.260	0.195	0.272
	(0.0407)	(0.2035)	(0.0760)	(0.5270)
Peer lag, $\overline{\text{opt}}_{p(i),t-1}$			0.0437	0.129
			(0.0236)	(0.1677)
Firm FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Industry output growth, $\Delta \log Y_{j(i),t-1}$	✓	✓	✓	✓
N	50,604	50,604	7,873	7,873
R^2	0.503	0.051	0.508	0.020
First-stage F	—	29.7	—	36.8

Notes: Standard errors are two-way clustered by firm ID and industry-year. The IV strategies instrument the industry and/or peer lag with the CEO change variables.

Optimistic Narrative is Contagious, Granular IV Strategy

Back 1 Back 2

1. Estimate a firm-level updating regression that controls non-parametrically for aggregate trends and parametrically for firm-level conditions

$$\text{opt}_{it} = \tau' X_{it} + \chi_{j(i),t} + \gamma_i + u_{it}$$

2. For *aggregate*: sales-weighted average of residuals

$$\overline{\text{opt}}_t^{g,sw} = \sum_i \frac{\text{sales}_{it}}{\sum_i \text{sales}_{it}} \hat{u}_{it}$$

3. For *industry*: leave-one-out sales-weighted average

$$\overline{\text{opt}}_t^{g,sw} = \sum_{i':j(i)=j(i'),i'\neq i} \frac{\text{sales}_{i't}}{\sum_i \text{sales}_{i't}} \hat{u}_{i't}$$

4. Variables for comparison: aggregate and (leave-one-out) industry averages of optimism

Optimistic Narrative is Contagious, Granular IV Strategy

Back 1 Back 2

	(1)	(2)	(3)	(4)	(5)	(6)
			Outcome is opt_{it}			
	OLS	OLS	IV	OLS	OLS	IV
Own lag, $\text{opt}_{i,t-1}$	0.212	0.213	0.210	0.219	0.220	0.219
	(0.0071)	(0.0071)	(0.0073)	(0.0080)	(0.0081)	(0.0081)
Agg. sales-wt. lag, $\overline{\text{opt}}^{sw}_{t-1}$	0.0847		0.308			
	(0.0421)		(0.1044)			
Real GDP growth, $\Delta \log Y_{t-1}$	1.058	1.104	0.768			
	(0.2205)	(0.2110)	(0.2607)			
Agg. sales-wt. granular lag, $\overline{\text{opt}}^{g,sw}_{t-1}$		0.150				
		(0.0506)				
Ind. sales-wt. lag, $\overline{\text{opt}}^{sw}_{j(i),t-1}$				0.0728		0.0195
				(0.0209)		(0.0459)
Ind. output growth, $\Delta \log Y_{j(i),t-1}$				0.0851	0.0903	0.0886
				(0.0325)	(0.0336)	(0.0333)
Ind. sales-wt. granular lag, $\overline{\text{opt}}^{g,sw}_{j(i),t-1}$					0.00913	
					(0.0216)	
Firm FE	✓	✓	✓	✓	✓	✓
Time FE				✓	✓	✓
N	64,948	64,948	64,948	52,258	50,842	50,842
R^2	0.481	0.481	0.049	0.500	0.503	0.051
First-stage F	—	—	99.1	—	—	262.3

Over-Controlling for News for Industry-Level Contagiousness

Back

$$\text{opt}_{it} = u\ \text{opt}_{i,t-1} + s\ \overline{\text{opt}}_{t-1} + \gamma_i + \sum_{k=-2}^{2} \left(\eta_k^{\text{agg}} \Delta \log Y_{t+k} + \eta_k^{\text{ind}} \Delta \log Y_{j(i),t+k} + \eta_k^{\text{firm}} \Delta \log \theta_{i,t+k}\right) + \varepsilon_{it}$$

	Outcome is opt_{it}						
Aggregate lag, $\overline{\text{opt}}_{t-1}$	0.290	0.339	0.235	0.222			
	(0.0578)	(0.0763)	(0.1278)	(0.2044)			
Ind. lag, $\overline{\text{opt}}_{j(i),t-1}$					0.276	0.241	0.262
					(0.0396)	(0.0434)	(0.0705)
Time FE					✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Own lag, $\text{opt}_{i,t-1}$	✓	✓	✓	✓	✓	✓	✓
$(\Delta \log Y_{t+k})_{k=-2}^{2}$		✓	✓	✓			
$(\Delta \log Y_{j(i),t+k})_{k=-2}^{2}$			✓	✓		✓	✓
$(\Delta \log \hat{\theta}_{i,t+k})_{k=-2}^{2}$				✓			✓
N	64,948	49,631	38,132	13,272	52,258	38,132	13,272
R^2	0.481	0.484	0.497	0.543	0.501	0.498	0.545

Over-Controlling for News, Continuous Measure

Back

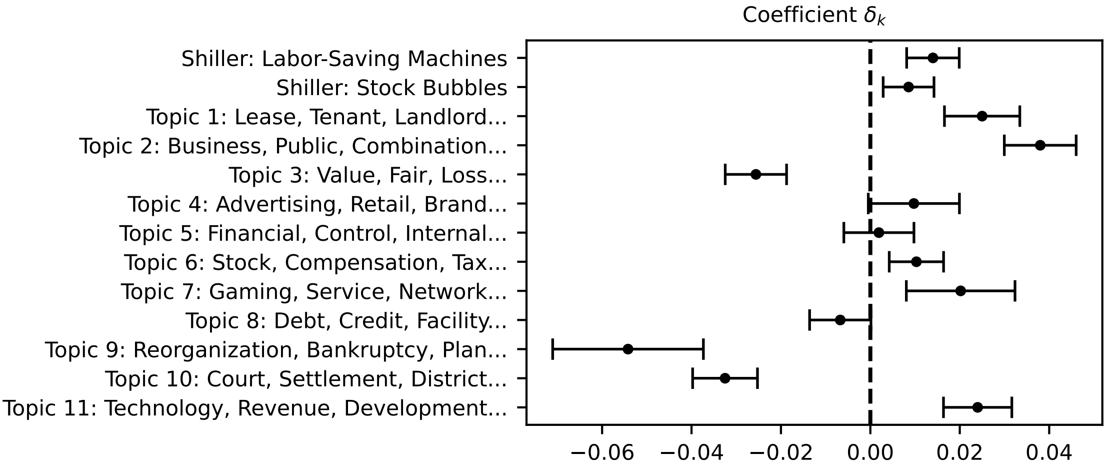
$$\text{sent}_{it} = u\ \text{sent}_{i,t-1} + s\ \overline{\text{sent}}_{t-1} + \gamma_i + \sum_{k=-2}^{2} \left(\eta_k^{\text{agg}} \Delta \log Y_{t+k} + \eta_k^{\text{ind}} \Delta \log Y_{j(i),t+k} + \eta_k^{\text{firm}} \Delta \log \theta_{i,t+k}\right) + \varepsilon_{it}$$

	Outcome is sentiment$_{it}$						
Aggregate lag, $\overline{\text{sentiment}}_{t-1}$	0.253	0.385	0.410	0.340			
	(0.0519)	(0.0651)	(0.1103)	(0.1785)			
Ind. lag, $\overline{\text{sentiment}}_{j(i),t-1}$					0.175	0.151	0.21
					(0.0360)	(0.0409)	(0.065
Time FE					✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Own lag, opt$_{i,t-1}$	✓	✓	✓	✓	✓	✓	✓
$(\Delta \log Y_{t+k})_{k=-2}^{2}$		✓	✓	✓			
$(\Delta \log Y_{j(i),t+k})_{k=-2}^{2}$			✓	✓		✓	✓
$(\Delta \log \hat{\theta}_{i,t+k})_{k=-2}^{2}$				✓			✓
N	63,881	48,889	37,643	13,112	51,555	37,643	13,11
R^2	0.568	0.578	0.599	0.640	0.599	0.601	0.64

The Effects of Other Relevant Narratives

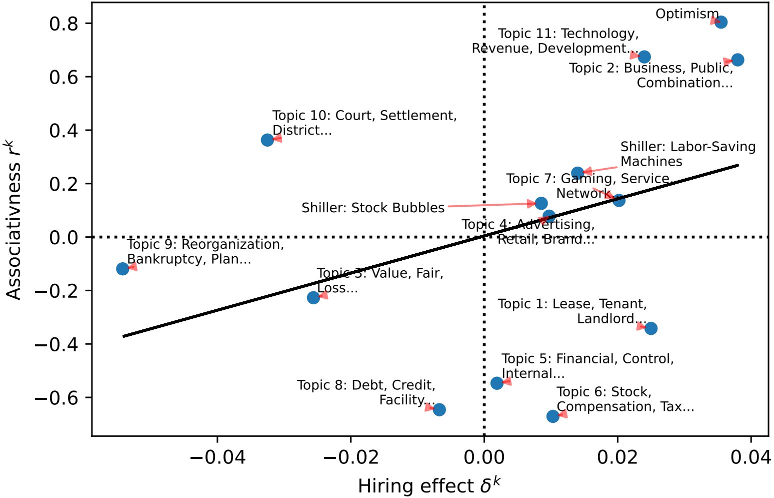
Back

$$\Delta \log L_{it} = \delta_k \{\hat{\lambda}_{k,it} > \text{med}[\hat{\lambda}_{k,it}]\} + \gamma_i + \chi_{j(i),t} + \tau' X_{it} + \varepsilon_{it}$$



Hiring and Associativeness

Back



Words for Shiller Narratives

Back

Panic	Frugality	Gold Standard	Labor-Saving Machines	Automation and AI	Real Estate	Stock Market	Boycotts	Wage-Price Spiral
bank	help	standard	replac	replac	price	chapter	price	countri
consum	hous	book	produc	appear	appear	peopl	profit	labor
appear	buy	money	technolog	show	real	specul	good	union
show	home	run	appear	question	find	drop	consum	ask
forecast	famili	paper	book	suggest	hous	play	start	wage
economi	lost	peopl	power	labor	estat	depress	fall	inflat
suggest	display	metal	save	ask	buy	warn	buy	strong
run	job	depress	problem	run	home	peak	wage	world
concept	peopl	eastern	labor	worker	citi	great	inflat	mile
peopl	explain	almost	innov	vacat	land	today	world	peopl
grew	phrase	depositor	run	autom	movement	get	cut	happen
around	depress	young	wage	human	world	decad	shop	depress
weather	postpon	today	worker	univers	tend	reaction	peopl	war
figur	car	want	electr	world	peopl	newspap	explain	tri
confid	justifi	went	mechan	machin	never	news	campaign	wrote
wall	cultur	decad	human	job	search	storm	play	peak
happen	fashion	idea	world	peopl	specul	saw	depress	great
depress	unemploy	man	machin	answer	explain	memori	behavior	recess
tri	great	newspap	job	around	popul	interview	postpon	went
unemploy	fault	popular	invent	figur	phrase	watch	war	get

Words for Topic Narratives

Back

Topic 1		Topic 2		Topic 3		Topic 4		Topic 5		Topic 6	
Lem. Word	Weight	Lem. Word	Weight	Lem. Word	Weight	Lem. Word	Weight	Lem. Word	Weight	Lem. Word	We
lease	0.047	business	0.052	value	0.088	advertising	0.029	financial	0.051	stock	0.0
tenant	0.042	public	0.025	fair	0.082	retail	0.028	control	0.02	compensation	0.0
landlord	0.03	combination	0.024	loss	0.024	brand	0.018	internal	0.019	tax	0.0
lessee	0.017	merger	0.023	investment	0.024	credit	0.018	material	0.013	share	0.0
rent	0.016	class	0.015	asset	0.022	consumer	0.017	affect	0.012	income	0.0
lessor	0.014	offer	0.014	debt	0.02	distribution	0.016	officer	0.011	average	0.0
property	0.012	share	0.013	gain	0.019	card	0.015	base	0.01	expense	0.0
term	0.011	account	0.011	credit	0.019	marketing	0.015	information	0.01	asset	0.0
day	0.009	ordinary	0.01	level	0.017	food	0.013	make	0.01	outstanding	0.0
provide	0.008	private	0.01	financial	0.016	store	0.013	business	0.01	weight	0.0

Topic 7		Topic 8		Topic 9		Topic 10		Topic 11	
Lem. Word	Weight	Lem. Word	Weight	Lem. Word	Weight	Lem. Word	Weight	Lem. Word	Weight
gaming	0.035	debt	0.039	reorganization	0.048	court	0.038	technology	0.018
service	0.029	credit	0.039	bankruptcy	0.047	settlement	0.027	revenue	0.017
network	0.022	facility	0.037	plan	0.044	district	0.021	development	0.015
wireless	0.021	senior	0.028	predecessor	0.036	certain	0.019	business	0.013
local	0.019	interest	0.026	successor	0.027	litigation	0.016	customer	0.012
cable	0.015	agreement	0.021	chapter	0.021	action	0.016	stock	0.012
provide	0.014	cash	0.019	asset	0.019	complaint	0.012	product	0.012
equipment	0.013	rate	0.016	court	0.018	damage	0.011	support	0.009
access	0.013	term	0.016	cash	0.016	approximately	0.011	market	0.009
video	0.012	certain	0.014	certain	0.014	case	0.01	service	0.008

Placebo Test and Validation for Other Narratives

Back

- Are the selected narratives reasonable?

- Shiller: "The Gold Standard" and "Boycotts and Evil Businesses" describe episodes in history that are unlikely to be relevant over our sample. Results are consistent with this "placebo test."

- Topics: we find that the "Advertising, Retail, Brand" narrative predicts SG&A expenditure growth ($\delta = 0.0076$, SE: 0.0022) and that the "Technology, Revenue, Development" narrative predicts growth in R&D spending ($\delta = 0.0402$, SE: 0.0044).

Interactions Between Other Narratives and Optimism

Back

- We study if optimism has different effects when it coincides with more intense discussion of other narratives.
- For each of the thirteen hiring-relevant Shiller and topic narratives, we take our baseline regression with controls for lagged labor and current and lagged TFP and add both the non-optimism narrative and its interaction with optimism
- Out of our thirteen estimated regressions, the smallest p-value for an interaction coefficient that is different from zero is 0.039
- Applying a Bonferroni correction for multiple hypothesis testing, we would not reject the null that all interactions are zero at any significance level less than 50%
- Find no evidence that optimism acts differently when it interacts with other, more specific narratives

Model with Continuous Levels of Optimism

Back

- Levels of optimism $\mu \in [\mu_P, \mu_O]$ and the distribution of narratives is $Q_t \in \Delta([\mu_P, \mu_O])$.
- The probabilistic transition between models is now given by a Markov kernel

$$P : [\mu_P, \mu_O] \times \mathcal{Y} \times \Delta^2([\mu_P, \mu_O]) \to \Delta([\mu_P, \mu_O])$$

where $P_{\mu'}(\mu, \log Y, Q)$ is the density of agents who have model μ who switch to μ' when aggregate output is Y and the distribution of narratives is Q.

Proposition (Equilibrium Characterization with Continuous Narratives)

There exists a quasi-linear equilibrium:

$$\log Y(\log \theta_t, Q_t) = a_0 + a_1 \log \theta_t + f(Q_t)$$

Moreover, the density of narratives evolves according to the following difference equation:

$$\mathrm{d}Q_{t+1}(\mu') = \int_{\mu_P}^{\mu_O} P_{\mu'}(\mu, a_0 + a_1 \log \theta_t + f(Q_t), Q_t) \mathrm{d}Q_t(\mu)$$

GE Feedback with Continuous Levels of Optimism

Back

- Define the cumulant generating function (CGF) of the cross-sectional distribution of narratives as:

$$K_Q(\tau) = \log\left(\mathbb{E}_Q[\exp\{\tau\tilde{\mu}\}]\right)$$

- We have that:

$$f(Q) = \frac{\frac{\epsilon}{\epsilon-1}}{1-\omega}\left[K_Q\left(\frac{\epsilon-1}{\epsilon}\alpha\delta^{OP}\frac{1}{\mu_O-\mu_P}\right) - \frac{\epsilon-1}{\epsilon}\alpha\delta^{OP}\frac{\mu_P}{\mu_O-\mu_P}\right]$$

- By Maclaurin expansion, we express the CGF to first-order as $K_Q(\tau) = \mu_Q\tau + O(\tau^2)$ and obtain:

$$f(Q) = \frac{1}{1-\omega}\alpha\delta^{OP}\frac{\mu_Q-\mu_P}{\mu_O-\mu_P} + O\left(\left(\frac{\epsilon-1}{\epsilon}\alpha\delta^{OP}\frac{1}{\mu_O-\mu_P}\right)^2\right)$$

- Note: can express in terms of higher cumulants as wished

Dynamics with Continuous Levels of Optimism

Back

- Assume $P_{\mu'}(\mu, \log Y, Q) = P_{\mu'}(\mu'', \log Y, \mu_Q)$ for all $Q \in \Delta^2([\mu_P, \mu_O])$ and all $\mu, \mu', \mu'' \in [\mu_P, \mu_O]$.
- Tantamount to assuming no stubbornness (all agents update the same regardless of the model they start with) and that contagiousness only matters via the mean.
- We can express the difference equation as:

$$\mu_{Q,t+1} = T(\mu_{Q,t}, \theta_t) = \int_{\mu_P}^{\mu_O} \mu' P_{\mu'}(a_0 + a_1 \log \theta_t + f(\mu_{Q,t}), \mu_{Q,t}) \mathrm{d}\mu'$$

- Continuous state analog of the baseline difference equation expressed in terms of average beliefs
- Easy to obtain analogs of previous results

Hysteresis with Continuous Levels of Optimism

Back

- Define functional generalized inverses in this setting:

$$\hat{P}^{-1}(x; \mu_Q) = \sup\{Y : P(Y, Q) = \delta_x\}$$
$$\check{P}^{-1}(x; \mu_Q) = \inf\{Y : P(Y, Q) = \delta_x\}$$

where δ_x denotes the Dirac delta function on x.

Proposition (Steady State Multiplicity with Continuous States)

Extreme optimism and pessimism are simultaneously deterministic steady states for θ if and only if $\theta \in [\theta_O, \theta_P]$, which is non-empty if and only if

$$\check{P}^{-1}(\mu_O; \mu_O) - \hat{P}^{-1}(\mu_P; \mu_P) \leqslant f(1)$$

Characterizing the Equilibrium Impact of Narratives: Details

Back 1 Back 2

- Demand curve (from final goods firm's profit max.) and wage curve (from intratemporal Euler condition):

$$x_{it} = Y_t p_{it}^{-\epsilon} \qquad\qquad L_{it}^{\psi} = w_{it} C_t^{-\gamma}$$

- When priced according to household marginal utility, face problem:

$$\max_{x_{it}} \mathbb{E}_{it}\left[Y_t^{-\gamma} \left(Y_t^{\frac{1}{\epsilon}} x_{it}^{1-\frac{1}{\epsilon}} - Y_t^{\gamma} \theta_{it}^{-\frac{1+\psi}{\alpha}} x_{it}^{\frac{1+\psi}{\alpha}} \right) \right]$$

with FOC

$$\left(1 - \frac{1}{\epsilon}\right) \mathbb{E}_{it}\left[Y_t^{\frac{1}{\epsilon}-\gamma} \right] x_{it}^{-\frac{1}{\epsilon}} = \frac{1+\psi}{\alpha} \mathbb{E}_{it}\left[\theta_{it}^{-\frac{1+\psi}{\alpha}} \right] x_{it}^{\frac{1+\psi-\alpha}{\alpha}}$$

- Solving problem and aggregating yields fixed point equation for aggregate output:

$$\log Y_t = \frac{\epsilon}{\epsilon - 1} \log \mathbb{E}_t \Bigg[\exp \Bigg\{ \frac{\frac{\epsilon-1}{\epsilon}}{\frac{1+\psi-\alpha}{\alpha} + \frac{1}{\epsilon}} \Bigg(\log \left(\frac{1 - \frac{1}{\epsilon}}{\frac{1+\psi}{\alpha}} \right) - \log \mathbb{E}_{it}\left[\exp\left\{ -\frac{1+\psi}{\alpha} \log \theta_{it} \right\} \right] + \log \mathbb{E}_{it}\left[\exp\left\{ \left(\frac{1}{\epsilon} - \gamma \right) \log Y_t \right\} \right] \Bigg) \Bigg\} \Bigg]$$

Defining and Bounding Complementarity

Back

- The composite complementarity parameter is given by:

$$\omega = \frac{\frac{1}{\epsilon} - \gamma}{\frac{1+\psi-\alpha}{\alpha} + \frac{1}{\epsilon}}$$

- Indexes the strength of aggregate demand externalities in generating strategic complementarities

- Assumption: $\omega \in [0, 1)$.

"Essential" Uniqueness of Equilibrium

Back

- Result only proves uniqueness within *quasi-linear class*, but is *essentially unique*
- Define family of truncated models in which fundamentals are bounded by some $M \in \mathbb{R}$, *i.e.*, $\log \theta_t \in [-M, M]$, $\log \gamma_i \in [-M, M]$, $\log \tilde{\theta}_{it} \in [-M, M]$, and $\varepsilon_{it} \in [-M, M]$.

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Lemma

In the truncated model, for any M, there exists a unique equilibrium

- Define truncated map $V_M : \mathcal{B} \to \mathcal{B}$ as fixed point map, endow with sup norm
- Can verify Blackwell's conditions (monotonicity, discounting)

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- Define truncated map $V_M : \mathcal{B} \to \mathcal{B}$ as fixed point map, endow with sup norm
- Can verify Blackwell's conditions (monotonicity, discounting)

Definition

$\hat{Y}$ is a ε-equilibrium if $||\hat{Y} - V_M(\hat{Y})||_p < \varepsilon$

Lemma

For every $\varepsilon > 0$, there exists an $M \in \mathbb{N}$ such that $\log Y^*$ is a ε-equilibrium.

Narratives Can Generate Hysteresis

Back

- Define two generalized inverses:

$$P_P^{-1}(x;Q) = \sup\{Y : P_P(Y,Q) = x\} \quad \text{and} \quad P_O^{-1}(x;Q) = \inf\{Y : P_O(Y,Q) = x\}$$

Proposition (Characterization of Extremal Multiplicity)

Extreme optimism ($Q = 1$) and pessimism ($Q = 0$) are simultaneously deterministic steady states for θ if and only if $\theta \in [\theta_O, \theta_P]$, which is non-empty if and only if

$$P_O^{-1}(1;1) - P_P^{-1}(0;0) \leqslant f(1)$$

Narratives and Hysteresis: Main Result

Back

Proposition (Steady State Existence, Multiplicity, and Stability)

The following statements are true:

1. *There exists a deterministic steady state level of optimism for every* $\theta \in \Theta$
2. *There exist thresholds* θ_P *and* θ_O *such that:* $Q = 0$ *is a deterministic steady state for* θ *if and only if* $\theta \leqslant \theta_P$ *and* $Q = 1$ *is a deterministic steady state for* θ *if and only if* $\theta \geqslant \theta_O$*. Moreover, these thresholds are given by:*

$$\theta_P = \exp\left\{\frac{P_P^{-1}(0;0) - a_0}{a_1}\right\} \quad \textit{and} \quad \theta_O = \exp\left\{\frac{P_O^{-1}(1;1) - a_0 - f(1)}{a_1}\right\}$$

   where $P_P^{-1}(x;Q) = \sup\{Y : P_P(Y,Q) = x\}$ *and* $P_O^{-1}(x;Q) = \inf\{Y : P_O(Y,Q) = x\}$.
3. *Extreme pessimism is stable if* $\theta < \theta_P$ *and* $P_O(P_P^{-1}(0;0), 0) < 1$ *and extreme optimism is stable if* $\theta > \theta_O$ *and* $P_P(P_O^{-1}(1;1), 1) > 0$.

Impulse Responses – "Stable" (SSC-A) case

Back

Proposition (SSC-A Impulse Response Functions)

In the SSC-A case, suppose that $Q_0 = \hat{Q}_1 \in (0,1)$. The impulse response to a one-time fundamental shock is given by:

$$\log Y_t = \begin{cases} a_0 + f(\hat{Q}_1), & t = 0, \\ a_0 + a_1 \log \hat{\theta} + f(\hat{Q}_1), & t = 1, \\ a_0 + f(Q_t), & t \geqslant 2 \end{cases} \qquad Q_t = \begin{cases} \hat{Q}_1, & t \leqslant 1, \\ Q_2, & t = 2, \\ T_1(Q_{t-1}), & t \geqslant 3. \end{cases}$$

Moreover, $Q_2 = \hat{Q}_1 P_O(a_0 + a_1 \log \hat{\theta} + f(\hat{Q}_1), \hat{Q}_1) + (1 - \hat{Q}_1) P_P(a_0 + a_1 \log \hat{\theta} + f(\hat{Q}_1), \hat{Q}_1) > \hat{Q}_1$, Q_t *is monotonically declining forin* $t \geqslant 2$, *and* $Q_t \to \hat{Q}_1$. *The IRF is hump-shaped if and only if* $\hat{\theta} < \exp\left\{\frac{f(\hat{Q}_2) - f(\hat{Q}_1)}{a_1}\right\}$.

Impulse Responses – "Hysteresis" (SSC-B) case

Back

Proposition (SSC-B Impulse Response Functions)

In the SSC-B case, suppose that $\theta_O < 1 < \theta_P$ and that $Q_0 = 0$. The impulse response of the economy to a one-time fundamental shock is given by:

$$\log Y_t = \begin{cases} a_0, & t = 0, \\ a_0 + a_1 \log \hat{\theta}, & t = 1, \\ a_0 + f(Q_t), & t \geqslant 2 \end{cases} \qquad Q_t = \begin{cases} 0, & t \leqslant 1, \\ P_P(a_0 + a_1 \log \hat{\theta}, 0), & t = 2, \\ T_1(Q_{t-1}), & t \geqslant 3. \end{cases}$$

These impulse responses fall into the following four exhaustive cases:

1. $\hat{\theta} \leqslant \theta_P$, *No Lift-Off:* $Q_t = 0$ *for all* $t \in \mathbb{N}$.
2. $\hat{\theta} \in (\theta_P, \theta^*)$, *Transitory Impact:* Q_t *is monotonically declining for all* $t \geqslant 2$ *and* $Q_t \to 0$.
3. $\hat{\theta} = \theta^*$, *Permanent (Knife-edge) Impact:* $Q_t = \hat{Q}_1$ *for all* $t \geqslant 1$
4. $\hat{\theta} > \theta^*$, *Permanent Impact, :* Q_t *is monotonically increasing for all* $t \geqslant 2$ *and* $Q_t \to 1$

Endogenous Boom-Bust Cycles

Back

- Study stochastic properties of the economy: the period of fluctuations

$$T_{PO} = \mathbb{E}_H \left[\min\{\tau \in \mathbb{N} : Q_\tau = 1\} | Q_0 = 0\right], \quad T_{OP} = \mathbb{E}_H \left[\min\{\tau \in \mathbb{N} : Q_\tau = 0\} | Q_0 = 1\right]$$

Proposition (Period of Boom-Bust Cycles)

The expected regime-switching times satisfy the following inequalities:

$$T_{PO} \leqslant \frac{1}{1 - H\left(\exp\left\{\frac{P_P^\dagger(1;0) - a_0}{a_1}\right\}\right)}$$

$$T_{OP} \leqslant \frac{1}{H\left(\exp\left\{\frac{P_O^\dagger(0;1) - a_0 - f(1)}{a_1}\right\}\right)}$$

where $P_P^\dagger(x;Q) = \inf\{Y : P_P(Y,Q) = x\}$ *and* $P_O^\dagger(x;Q) = \sup\{Y : P_O(Y,Q) = x\}$*. Moreover, when* $P_O^\dagger(0;1) - P_P^\dagger(1;0) \leqslant f(1)$*, these bounds are tight in the sense that they are attained for some* H*.*

Proof Sketch of Proposition

Back

1. Consider the case where we seek to bound $\tau_{PO} = \min\{t \in \mathbb{N} : Q_\tau = 1, Q_0 = 0\}$.
2. Fix a path of fundamentals $\{\theta_t\}_{t\in\mathbb{N}}$ and define the fictitious $\overline{Q}$ process as:

$$\overline{Q}_{t+1} = \mathbb{I}[T_{\theta_t}(\overline{Q}_t, \theta_t) = 1], \quad \overline{Q}_0 = 0$$

3. Prove by induction that $\overline{Q}_t \leqslant Q_t$ for all $t \in \mathbb{N}$. Follows that $\overline{\tau}_{PO} \succeq_{FOSD} \tau_{PO}$.
4. The possible sample paths for $\{\overline{Q}_t\}_{t\in\mathbb{N}}$ until stopping are given by the set:

$$\mathcal{G}_{PO} = \{(0^{(n-1)}, 1)\} : n \geqslant 1\}$$

5. Thus, $\overline{\tau}_{PO}$ has a geometric distribution with parameter given by $\mathbb{P}[Q_{t+1} = 1 | Q_t = 0]$
6. Use structure of updating equation to find probability and obtain:

$$\tau_{PO} \preceq_{FOSD} \overline{\tau}_{PO} \sim \text{Geo}\left(1 - H\left(\exp\left\{\frac{P_P^\dagger(1;0) - a_0}{a_1}\right\}\right)\right)$$

7. Construct H that attain this bound by "hollowing out" shock distribution

The Bayesian Benchmark

Back 1 Back 2

- Each agent believes optimistic model w.p. $\lambda_{i0} \in (0,1)$
- Aggregate belief in optimism follows:

$$Q_{t+1} = \int_{[0,1]} \mathbb{P}_i[\mu = \mu_O | \{\log Y_j\}_{j=0}^t] \, \mathrm{d}i$$

- Define log-odds ratio of agent's belief as $\Omega_{it} = \frac{\lambda_{it}}{1-\lambda_{it}}$

Proposition (Dynamics under the Bayesian Benchmark)

Each agent's log-odds ratio follows a random walk with drift, $\Delta\Omega_{i,t+1} = a + \xi_t$, where $a = \mathbb{E}_H\left[\frac{(\log\theta_t - \mu_P)^2 - (\log\theta_t - \mu_O)^2}{\sigma^2}\right]$ and ξ_t is an IID, mean-zero random variable. The economy converges almost surely to either extreme optimism ($a > 0$) or extreme pessimism ($a < 0$). Thus, the economy does not feature steady state multiplicity, hump-shaped or discontinuous IRFs, or the possibility for boom-bust cycles.

Contrarianism, Endogenous Cycles and Chaos

Back 1 Back 2

- Define $\tilde{P}_O(Q)$, $\tilde{P}_P(Q)$ as the *equilibrium* updating probabilities

Proposition

The following statements are true:

1. *When $\tilde{P}_O \geqslant \tilde{P}_P$ and both are monotone, there are neither cycles of any period nor chaotic dynamics.*
2. *When $\tilde{P}_O$ and $\tilde{P}_P$ are linear, cycles of period 2 are possible, cycles of any period $k > 2$ are not possible, and chaotic dynamics are not possible.*
3. *Without further restrictions on $\tilde{P}_O$ and $\tilde{P}_P$, cycles of any period $k \in \mathbb{N}$ and chaotic dynamics are possible.*

- Approach allows empirical test of conditions for cycles and chaos

Testing for Endogenous Cycles and Chaos

Back 1 Back 2

Run regression

$$\text{opt}_{it} = \gamma_i + \alpha_1 \text{opt}_{i,t-1} + \beta_1 \text{opt}_{i,t-1} \cdot \overline{\text{opt}}_{i,t-1} + \beta_2(1 - \text{opt}_{i,t-1}) \cdot \overline{\text{opt}}_{i,t-1} + \tau \left(\overline{\text{opt}}_{i,t-1}\right)^2 + \varepsilon_{it}$$

Define logistic parameter

$$\hat{\eta} = 1 + \sqrt{(\hat{\alpha}_1 + \hat{\beta}_2 - 1)^2 + 4\hat{\alpha}_1(\hat{\tau} + \hat{\beta}_2 - \hat{\beta}_1)}$$

Cases:

- $\eta < 3$: there are neither cycles of any period nor chaotic dynamics
- $\eta \geqslant 3$: there can be cycles of period 2 or more and/or chaos
- $\eta > 3.57$: chaotic dynamics obtain.

Our 95% CI: $(0.076, 2.810)$

α: Constant	-0.051
	(0.244)
α_1: $\text{opt}_{i,t-1}$	0.655
	(0.062)
β_1: $\text{opt}_{i,t-1} \cdot \overline{\text{opt}}_{i,t-1}$	0.052
	(1.021)
β_2: $(1 - \text{opt}_{i,t-1}) \cdot \overline{\text{opt}}_{i,t-1}$	0.952
	(1.006)
τ: $(\overline{\text{opt}}_{i,t-1})^2$	-0.062
	(1.034)
η: Logistic parameter	1.443
	(0.698)
Firm FE?	✓
N	67,648
R^2	0.480

Notes: Standard errors are two-way clustered by firm ID and

Contagious Narratives Can Be Good for Welfare

Back

- What are the welfare effects of misspecified optimism (i.e., when pessimism is correctly specified)?

Proposition (Narratives and Welfare)

When the pessimistic narrative is correctly specified, extreme optimism is welfare-equivalent to an ad valorem price subsidy for intermediate goods producers of:

$$\tau^* = \exp\left\{(1-\omega)\left(\frac{1+\psi-\alpha}{\alpha}+\frac{1}{\epsilon}\right)f(1)\right\}-1$$

- Intuition: optimism increases output $\implies$ undoes distortions arising from market power
- Quantitatively: extreme optimism is equivalent to 2.6% subsidy. Dynamics of optimism welfare equivalent to 1.3% subsidy

Multi-Dimensional Narratives and Persistent Fundamentals

Back 1 Back 2

- Perceived data-generating processes (DGP) for fundamentals

$$\log \theta_t = (1-\rho)\mu + \rho \log \theta_{t-1} + \sigma \nu_t$$

  with $\nu_t \sim N(0,1)$ and IID
- True DGP denoted by H
- Set of *narratives* $\{(\mu_k, \rho_k, \sigma_k)\}_{k \in \mathcal{K}}$
- We write π_t^k as the associated transition density for $\theta_t \mid \theta_{t-1}$ under parameters $(\mu_k, \rho_k, \sigma_k)$
- Each agent i, at time t, believes in narrative k, *i.e.*,

$$\pi_{it} = \sum_{k \in \mathcal{K}} \lambda_{it} \pi_t^k$$

  where $\lambda_{it} \in \Lambda = \{e_k\}_{k \in \mathcal{K}}$

Multi-Dimensional Narratives and Persistent Fundamentals: Result

Back 1

Back 2

- Can obtain analogous quasi-linear equilibrium representation

Proposition (Equilibrium Characterization with Multi-Dimensional Narratives)

There exists a quasi-linear equilibrium:

$$\log Y(\log \theta_t, \log \theta_{t-1}, Q_t) = a_0 + a_1 \log \theta_t + a_2 \log \theta_{t-1} + f(Q_t, \theta_{t-1})$$

for some $a_1 > 0$, $a_2 \geqslant 0$, *and* f.

Persistent Idiosyncratic Shocks and Narrative Updating

Back

- Let updating probabilities also depend on $\tilde{\theta}_{it}$
- Allow $\tilde{\theta}_{it}$ to follow a Gaussian AR(1) process
- New state variable: joint distribution of narratives and productivity $\check{Q}_t \in \Delta(\Lambda \times \mathbb{R})$
- Intuition: need to keep track of correlation between narrative and firm size

Proposition (Equilibrium Characterization with Multi-Dimensional Narratives, Aggregate and Idiosyncratic Persistence, and Idiosyncratic Narrative Updating)

There exists a quasi-linear equilibrium:

$$\log Y(\log \theta_t, \log \theta_{t-1}, \check{Q}_t) = a_0 + a_1 \log \theta_t + a_2 \log \theta_{t-1} + f(\check{Q}_t, \theta_{t-1})$$

for some $a_1 > 0$, $a_2 \geqslant 0$, and f.

Persistent Idiosyncratic Shocks and Narrative Updating

Back

- Can express the effect as a time-varying covariance between optimism and productivity:

$$f(\check{Q}_t) = \frac{\frac{\epsilon}{\epsilon-1}}{1-\omega} \log \left(\left[\exp\left\{ \frac{\epsilon-1}{\epsilon} \alpha \delta_{OP} \right\} - 1 \right] \exp\left\{ \frac{1}{2} \left(\frac{\epsilon-1}{\epsilon} \xi \right)^2 \frac{\sigma_\zeta^2}{1-\rho_{\tilde{\theta}}^2} \right\} Q_t \right.$$
$$\left. + \, \mathrm{Cov}_t \left(Q_{t|\tilde{\theta}}, \tilde{\theta}^{\frac{\epsilon-1}{\epsilon}\xi} \right) + \exp\left\{ \frac{1}{2} \left(\frac{\epsilon-1}{\epsilon} \xi \right)^2 \frac{\sigma_\zeta^2}{1-\rho_{\tilde{\theta}}^2} \right\} \right)$$

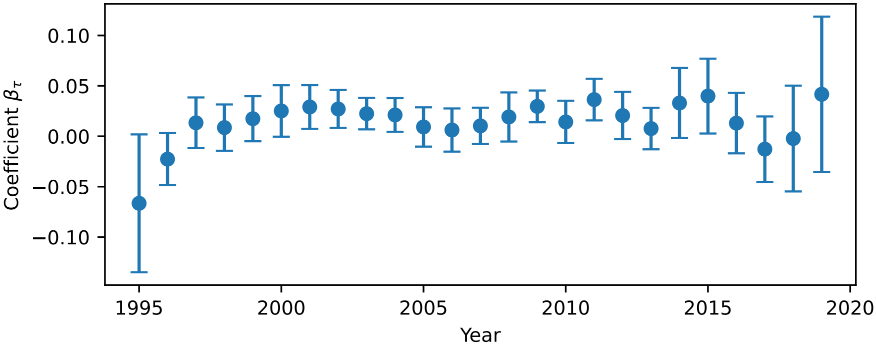
where $\xi = \frac{\frac{1+\psi}{\alpha}}{\frac{1+\psi-\alpha}{\alpha} + \frac{1}{\epsilon}} \rho_{\tilde{\theta}}$, $\rho_{\tilde{\theta}}$ is the AR(1) parameter, and σ_ζ^2 is the variance of the innovation

- To test if this is relevant, we see how much this covariance moves over time in the data

Persistent Idiosyncratic Shocks and Narrative Updating

Back

Figure: Time-Varying Relationship Between Optimism and TFP



Notes: The outcome variable is firm-level log TFP, $\log \theta_{it}$, and the regressors are indicators for binary optimism interacted with year dummies, with coefficients β_τ. In the regression, we trim the 1% and 99% tails of the outcome variable. Error bars are 95% confidence intervals, based on standard errors clustered by firm and industry-time.

Narratives in Games and the Role of Higher-Order Beliefs

Back

- Focused on a specific macro model, but general idea is portable
- Consider a linear beauty contest game (Morris and Shin, 2002):

$$x_{it} = \alpha \mathbb{E}_{it}[\theta_t] + \beta \mathbb{E}_{it}[Y_t]$$

- Define average expecations operators:

$$\overline{\mathbb{E}}_t[\theta_t] = \int_{[0,1]} \mathbb{E}_{it}\left[\theta_t\right] \mathrm{d}i \quad \text{and} \quad \overline{\mathbb{E}}_t^k[\theta_t] = \int_{[0,1]} \mathbb{E}_{it}\left[\overline{\mathbb{E}}_t^{k-1}[\theta_t]\right] \mathrm{d}i$$

- Equilibrium output given by:

$$Y_t = \alpha \sum_{k=1}^{\infty} \beta^{k-1} \overline{\mathbb{E}_t}^k[\theta_t]$$

- Narratives affect hierarchy of higher-order beliefs

$$\overline{\mathbb{E}}_t^k[\theta_t] = \kappa^k \theta_t + (1-\kappa^k)(Q_t \mu_O + (1-Q_t)\mu_P)$$

Narratives in Games and the Role of Higher-Order Beliefs

Back

Proposition (Narratives and Higher-Order Beliefs)

There exists a unique equilibrium. In this unique equilibrium, aggregate output is given by:

$$Y_t = \frac{\alpha}{1-\beta}\left(\frac{(1-\beta)\kappa}{1-\beta\kappa}\theta_t + \frac{1-\kappa}{1-\beta\kappa}\left(Q_t\mu_O + (1-Q_t)\mu_P\right)\right)$$

Moreover, agents' actions follow:

$$x_{it} = \alpha\frac{1}{1-\beta\kappa}\left[\kappa\theta_t + \kappa\varepsilon_{it} + (1-\kappa)\left(\lambda_{it}\mu_O + (1-\lambda_{it})\mu_P\right)\right] + \beta\frac{\alpha}{1-\beta}\frac{1-\kappa}{1-\beta\kappa}\left(Q_t\mu_O + (1-Q_t)\mu_P\right)$$

Identification Details for the Quantitative Model

Back

1. Step 1: identify f

Corollary (Identification of Model Parameters)

Conditional on $(\alpha, \epsilon, \gamma, \psi)$, δ^{OP} uniquely identifies f, the equilibrium effect of optimism on aggregate output.

2. Step 2: derive law-of-motion for fundamental output:

Corollary

Fundamental output follows an ARMA(1,1) process in equilibrium:

$$\log Y_t^f - \rho \log Y_{t-1}^f = a_1 \sigma \nu_t + a_2 \sigma \nu_{t-1}$$

3. Derive mapping from ARMA coefficients to κ, ρ, σ
4. Find (unique) $\kappa, \mu_O - \mu_P, \rho, \sigma$ that exactly match ARMA coefficients and δ^{OP}

Sensitivity Analysis of Quantitative Results

Back

Table: Sensitivity Analysis for the Quantitative Analysis

	Parameters						Results			
	α	γ	ψ	ϵ	ω	$\frac{1}{1-\omega}$	$\hat{c}_Q(0)$	$\hat{c}_Q(1)$	2000-02	2007-09
Baseline	1.0	0.0	0.4	2.6	0.490	1.962	0.192	0.335	0.316	0.181
High ψ	1.0	0.0	2.5	2.6	0.133	1.154	0.175	0.359	0.186	0.106
High γ	1.0	1.0	0.4	2.6	-0.784	0.560	0.041	0.184	0.090	0.052
Empirical Multiplier	1.0	0.0	1.15	2.6	0.250	1.333	0.167	0.329	0.215	0.123
Calibrated Multiplier	1.0	0.0	0.845	2.6	0.313	1.455	0.168	0.324	0.235	0.134
High ϵ	1.0	0.0	0.21	5.0	0.490	1.962	0.109	0.240	0.317	0.181
Decreasing RtS	0.75	0.0	0.05	2.6	0.490	1.962	0.125	0.238	0.237	0.135

Notes: This table summarizes the quantitative results under alternative calibrations of the macroeconomic parameters, which we report along side their implied complementarity ω and demand multiplier $\frac{1}{1-\omega}$. We report four statistics as the "results" in the last four columns. The first two are the fraction of output variance explained statically, $\hat{c}_Q(0)$, and at a one-year horizon, $\hat{c}_Q(1)$, by optimism. The second two are the fraction of output losses in the 2000-02 downturn and 2007-09 downturn explained by fluctuations in narrative optimism. Baseline corresponds to our main calibration. High ψ increases the inverse Frisch elasticity to 2.5, or decreases the Frisch elasticity to 0.4. High γ increases the curvature of consumption utility (indexing income effects in labor supply) from 0.0 to 1.0. Empirical Multiplier adjusts ψ to match an output multiplier in line with estimates from Flynn et al. (2021). Calibrated multiplier adjusts ψ to match our own calculation of the multiplier in our setting. High ϵ increases the elasticity of substitution from 2.6 to 5.0, with ψ adjusting

Implied Shock Series

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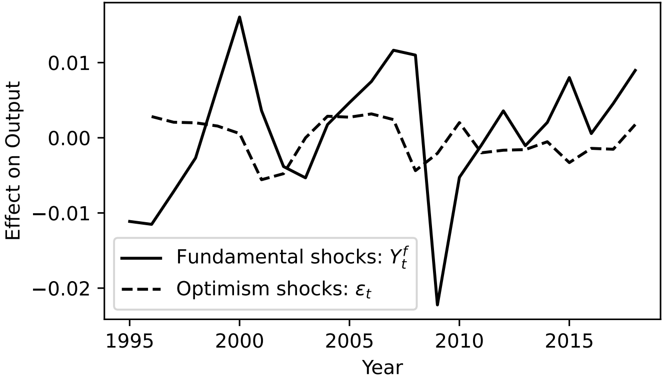
Figure: Fundamental and Optimism Shocks That Explain US GDP



- $\varepsilon_{2001} = -0.08$, or -1.8 standard deviations
- $\varepsilon_{2008} = -0.06$ or -1.4 standard deviations

Variance Contribution with No Shocks

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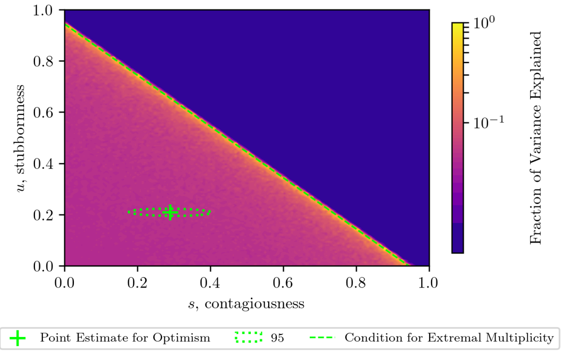

Notes: Variant model with no exogenous shocks to optimism.

Tendency Toward Extremes

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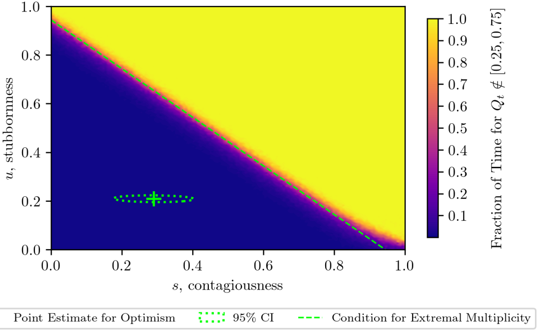

Notes: This Figure plots, in color, the fraction of time that optimism Q_t lies outside of the range $[0.25, 0.75]$ and therefore concentrates at extreme values.