Imperfect Macroeconomic Expectations: Evidence and Theory

George-Marios Angeletos, Zhen Huo, and Karthik A. Sastry
MIT and NBER, Yale, and MIT

35th NBER Macro Annual (1st Ever on Zoom)
April 3, 2020
State of The Art

Lots of lessons outside representative agent, rational expectations benchmark

But also a “wilderness” of alternatives

- Rational inattention, sticky info, etc. (Sims, Mankiw & Reis, Mackowiak & Wiederholt)
- Higher-order uncertainty (Morris & Shin, Woodford, Nimark, Angeletos & Lian)
- Level-K thinking (Garcia-Schmidt & Woodford, Farhi & Werning)
- Cognitive discounting (Gabaix)
- Over-extrapolation (Gennaioli, Ma & Shleifer, Fuster, Laibson & Mendel, Guo & Wachter)
- Over-confidence (Kohlhas & Broer, Scheinkman & Xiong)
- Representativeness (Bordalo, Gennaioli & Shleifer)
- Undue effect of historical experiences (Malmendier & Nagel)
- ...
This Paper

Contributions:

- Use a parsimonious framework to organize existing theories and evidence
- Provide new evidence
- Clarify which evidence is most relevant for the theory
- Identify the “right” model of expectations for business cycle context

Main lessons:

- Little support for FIRE, cognitive discounting, level-k
- Mixed support for over-confidence or representativeness
- Best model: dispersed info + over-extrapolation
- Best way to connect theory and data: IRFs of average forecasts (and their term structure)
This Paper

Contributions:

- Use a parsimonious framework to organize existing theories and evidence
- Provide new evidence
- Clarify which evidence is most relevant for the theory
- Identify the “right” model of expectations for business cycle context

Main lessons:

- Little support for FIRE, cognitive discounting, level-k
- Mixed support for over-confidence or representativeness
- Best model: dispersed info + over-extrapolation
- Best way to connect theory and data: IRFs of average forecasts (and their term structure)
Outline

The Facts

Facts Meet Theory (without/with GE)

Conclusion
Fact 1: Aggregate Forecast Errors are Predictable
Coibion and Gorodnichenko (2015)

\[(x_{t+k} - \overline{E}_t x_{t+k}) = a + K_{CG} \cdot (\overline{E}_t x_{t+k} - \overline{E}_{t-1} x_{t+k}) + u_t\]
Fact 1: Aggregate Forecast Errors are Predictable

Coibion and Gorodnichenko (2015)

\[(x_{t+k} - \hat{E}_{t}x_{t+k}) = a + K_{CG} \cdot (\hat{E}_{t}x_{t+k} - \hat{E}_{t-1}x_{t+k}) + u_{t}\]

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Revision (<em>t(K</em>{CG}))</td>
<td>0.741 (0.232)</td>
<td>0.809 (0.305)</td>
<td>1.528 (0.418)</td>
<td>0.292 (0.191)</td>
<td></td>
</tr>
<tr>
<td>R(^2)</td>
<td>0.111</td>
<td>0.159</td>
<td>0.278</td>
<td>0.016</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>191</td>
<td>136</td>
<td>190</td>
<td>135</td>
<td></td>
</tr>
</tbody>
</table>

Notes: The dataset is the Survey of Professional Forecasters and the observation is a quarter between Q4-1968 and Q4-2017. The forecast horizon is 3 quarters. Standard errors are HAC-robust, with a Bartlett (“hat”) kernel and lag length equal to 4 quarters. The data used for outcomes are first-release.
Fact 1: Aggregate Forecast Errors are Predictable

Coibion and Gorodnichenko (2015)

\[
(x_{t+k} - \overline{E}_t x_{t+k}) = a + K_{CG} \cdot (\overline{E}_t x_{t+k} - \overline{E}_{t-1} x_{t+k}) + u_t
\]

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>sample</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Unemployment</td>
<td>Inflation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Revision\textsubscript{t}(K\textsubscript{CG})</td>
<td>0.741 (0.232)</td>
<td>0.809 (0.305)</td>
<td>1.528 (0.418)</td>
<td>0.292 (0.191)</td>
</tr>
<tr>
<td>R\textsuperscript{2}</td>
<td>0.111</td>
<td>0.159</td>
<td>0.278</td>
<td>0.016</td>
</tr>
<tr>
<td>Observations</td>
<td>191</td>
<td>136</td>
<td>190</td>
<td>135</td>
</tr>
</tbody>
</table>

Notes: The dataset is the Survey of Professional Forecasters and the observation is a quarter between Q4-1968 and Q4-2017. The forecast horizon is 3 quarters. Standard errors are HAC-robust, with a Bartlett (“hat”) kernel and lag length equal to 4 quarters. The data used for outcomes are first-release.

Bad news for: RE + common information

Good news for: (i) RE + dispersed noisy information

(ii) under-confidence, under-extrapolation, cognitive discounting, level-K
Fact 2: Individual Forecast Errors are Predictable

Bordalo, Gennaioli, Ma, and Shleifer (2018); Kohlhas and Broer (2018); Fuhrer (2018)

\[ (x_{t+k} - \mathbb{E}_{i,t}x_{t+k}) = a + K_{BGMS} \cdot (\mathbb{E}_{i,t}x_{t+k} - \mathbb{E}_{i,t-1}x_{t+k}) + u_t \]
Fact 2: Individual Forecast Errors are Predictable

Bordalo, Gennaioli, Ma, and Shleifer (2018); Kohlhas and Broer (2018); Fuhrer (2018)

\[
(x_{t+k} - \mathbb{E}_{i,t} x_{t+k}) = a + K_{BGMS} \cdot (\mathbb{E}_{i,t} x_{t+k} - \mathbb{E}_{i,t-1} x_{t+k}) + u_t
\]

<table>
<thead>
<tr>
<th>variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>sample</td>
<td>Unemployment</td>
<td>Inflation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Revision\textsubscript{i,t} (\textit{K}\textsubscript{BGMS})</td>
<td>0.321 (0.107)</td>
<td>0.398 (0.149)</td>
<td>0.143 (0.123)</td>
<td>-0.263 (0.054)</td>
</tr>
<tr>
<td>R\textsuperscript{2}</td>
<td>0.028</td>
<td>0.052</td>
<td>0.005</td>
<td>0.025</td>
</tr>
<tr>
<td>Observations</td>
<td>5383</td>
<td>3769</td>
<td>5147</td>
<td>3643</td>
</tr>
</tbody>
</table>

Notes: The observation is a forecaster by quarter between Q4-1968 and Q4-2017. The forecast horizon is 3 quarters. Standard errors are clustered two-way by forecaster ID and time period. Both errors and revisions are winsorized over the sample to restrict to 4 times the inter-quartile range away from the median. The data used for outcomes are first-release.

BGMS argue that $K_{BGMS} < 0$ is more prevalent in other forecasts. If so, then:

**Bad news for:** under-extrapolation, cognitive discounting, and level-K thinking

**Good news for:** over-extrapolation and over-confidence (or “representativeness”)

But: perhaps $K_{BGMS} \approx 0$ “on average”
Facts $1 + 2 \Rightarrow$ Dispersed Info

<table>
<thead>
<tr>
<th>variable</th>
<th>Unemployment</th>
<th>Inflation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_{CG}$</td>
<td>0.741</td>
<td>0.809</td>
</tr>
<tr>
<td>$K_{BGMS}$</td>
<td>0.321</td>
<td>0.398</td>
</tr>
<tr>
<td>$K_{CG} &gt; K_{BGMS}$</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

Q: What does $K_{CG} > K_{BGMS}$ mean?

A: *My* forecast revision today predicts *your* forecast error tomorrow

Evidence of dispersed private information
The Missing Piece: Conditional Moments

So far: unconditional correlations of forecasts, outcomes, and errors

What we really want to know: conditional responses to the ups and downs of the business cycle
The Missing Piece: Conditional Moments

So far: unconditional correlations of forecasts, outcomes, and errors

What we really want to know: conditional responses to the ups and downs of the business cycle

Solution: estimate IRFs of forecasts to shocks

Shocks: usual suspects; or DSGE shocks; or “main BC shocks” (Angeletos, Collard & Dellas, 2020)

Estimation method: plain-vanilla linear projection; or big VARs; or ARMA-IV (novel approach)

Moments of interest:

\[ \left( \frac{\partial \text{ForecastError}_{t+k}}{\partial \text{BusinessCycleShock}_t} \right)^K_{k=0} = \text{Pattern of mistakes} \]
Fact 3: Dynamic Over-Shooting in Response to Business Cycle Shocks

Each "slice" compares 3-Q-ahead forecasts with outcome

Shaded area = ± 1 SE forecast error
Fact 3: Dynamic Over-Shooting in Response to Business Cycle Shocks

Slow recognition, big forecast errors

Forecast error
Shaded area = ± 1 SE
**Fact 3: Dynamic Over-Shooting in Response to Business Cycle Shocks**

![Graphs showing unemployment and inflation response to business cycle shocks]

- **Unemployment**
  - Delayed over-shooting, smaller but persistent forecast errors

- **Inflation (Annual)**
  - Forecast and outcome
  - Method: projection, ARMA-IV

Shaded area = ± 1 SE forecast error
Fact 3 [Over-shooting]: Same Pattern with Other Identified Shocks

Gali (1999): Technology → Inflation

Outcome
Forecast
Forecast Error


Outcome
Forecast
Forecast Error
Fact 3 [Over-shooting]: Same Pattern in a Structural VAR

13-Variable Model: macro “usual suspects” + unemployment and inflation forecasts (SPF)

ACD, 2020 (max-share for BC)

Cholesky (one-step-ahead Error)
Fact 3 [Over-shooting]: Over-persistence in the “Term Structure”

\[
\bar{E}_t[x_{t+k}] = \alpha_k + \beta_k^f \cdot \epsilon_t + \gamma' W_t + u_{t+k}
\]

\[
x_{t+k} = \alpha_k + \beta_k^o \cdot \epsilon_t + \gamma' W_t + u_{t+k}
\]

Expectation from \( t = 0 \)

Reality from \( t = 0 \)
Outline

The Facts

Facts Meet Theory (without/with GE)

Conclusion
### Need to Combine Frictions to Explain Facts

<table>
<thead>
<tr>
<th>Theory</th>
<th>Fact 1</th>
<th>Fact 2</th>
<th>Fact 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Information</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Noisy common information</td>
<td>No</td>
<td>No*</td>
<td>No</td>
</tr>
<tr>
<td>Noisy dispersed information</td>
<td>Yes</td>
<td>No*</td>
<td>No</td>
</tr>
</tbody>
</table>
## Need to Combine Frictions to Explain Facts

<table>
<thead>
<tr>
<th>Theory</th>
<th>Fact 1</th>
<th>Fact 2</th>
<th>Fact 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Information</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Noisy common information</td>
<td>No</td>
<td>No*</td>
<td>No</td>
</tr>
<tr>
<td>Noisy dispersed information</td>
<td>Yes</td>
<td>No*</td>
<td>No</td>
</tr>
<tr>
<td><strong>Confidence</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Over-confidence or representativeness heuristic</td>
<td>No</td>
<td>Maybe</td>
<td>No</td>
</tr>
<tr>
<td>Under-confidence or “timidness”</td>
<td>No</td>
<td>Maybe</td>
<td>No</td>
</tr>
</tbody>
</table>
## Need to Combine Frictions to Explain Facts

<table>
<thead>
<tr>
<th>Theory</th>
<th>Fact 1</th>
<th>Fact 2</th>
<th>Fact 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Information</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Noisy common information</td>
<td>No</td>
<td>No*</td>
<td>No</td>
</tr>
<tr>
<td>Noisy dispersed information</td>
<td>Yes</td>
<td>No*</td>
<td>No</td>
</tr>
<tr>
<td><strong>Confidence</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Over-confidence or representativeness heuristic</td>
<td>No</td>
<td>Maybe</td>
<td>No</td>
</tr>
<tr>
<td>Under-confidence or “timidness”</td>
<td>No</td>
<td>Maybe</td>
<td>No</td>
</tr>
<tr>
<td><strong>Foresight</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Over-extrapolation</td>
<td>No</td>
<td>Maybe</td>
<td>Yes</td>
</tr>
<tr>
<td>Under-extrapolation or cognitive discounting or level-K</td>
<td>Yes</td>
<td>Maybe</td>
<td>No</td>
</tr>
</tbody>
</table>
Need to Combine Frictions to Explain Facts:  A Winning Combination

<table>
<thead>
<tr>
<th>Theory</th>
<th>Fact 1</th>
<th>Fact 2</th>
<th>Fact 3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Information</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Noisy common information</td>
<td>No</td>
<td>No*</td>
<td>No</td>
</tr>
<tr>
<td>Noisy dispersed information</td>
<td>Yes</td>
<td>No*</td>
<td>No</td>
</tr>
<tr>
<td><strong>Confidence</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Over-confidence or representativeness heuristic</td>
<td>No</td>
<td>Maybe</td>
<td>No</td>
</tr>
<tr>
<td>Under-confidence or “timidness”</td>
<td>No</td>
<td>Maybe</td>
<td>No</td>
</tr>
<tr>
<td><strong>Foresight</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Over-extrapolation</td>
<td>No</td>
<td>Maybe</td>
<td>Yes</td>
</tr>
<tr>
<td>Under-extrapolation or cognitive discounting or level-K</td>
<td>Yes</td>
<td>Maybe</td>
<td>No</td>
</tr>
</tbody>
</table>
Tractable NK Model with Imperfect Expectations

Familiar Ingredients

Euler equation/DIS

\[ c_t = \mathbb{E}_t^*[c_{t+1}] - \varsigma r_t + \epsilon_t \]

Market clearing

\[ c_t = y_t \]

Demand shock

\[ \xi_t \equiv -\varsigma r_t + \epsilon_t = (1 - \rho \Pi) \eta_t \]

Prices fully rigid (relax later on)
Tractable NK Model with Imperfect Expectations

Familiar Ingredients

Euler equation/DIS

\[ c_t = \mathbb{E}_t^*[c_{t+1}] - \varsigma r_t + \epsilon_t \]

Market clearing

\[ c_t = y_t \]

Demand shock

\[ \xi_t \equiv -\varsigma r_t + \epsilon_t = (1 - \rho L)\eta_t \]

New Ingredients: noise + irrationality

Prices fully rigid (relax later on)
Tractable NK Model with Imperfect Expectations

**Familiar Ingredients**

Euler equation/DIS

\[ c_t = E^*_t[c_{t+1}] - \varsigma r_t + \epsilon_t \]

Market clearing

\[ c_t = y_t \]

Demand shock

\[ \xi_t \equiv -\varsigma r_t + \epsilon_t = (1 - \rho L) \eta_t \]

Prices fully rigid (relax later on)

**New Ingredients:** noise + irrationality

Noisy signal

\[ s_{i,t} = \xi_t + u_{i,t}/\sqrt{\tau} \]

Perception of signal

\[ s_{i,t} = \xi_t + u_{i,t}/\sqrt{\hat{\tau}} \]

Perception of demand process

\[ \xi_t = (1 - \hat{\rho} L) \eta_t \]

over- or under-confidence?

\[ \hat{\rho} < \rho \] in GE

≈ cognitive discounting, level-K
Tractable NK Model with Imperfect Expectations

**Familiar Ingredients**

Euler equation/DIS

\[ c_t = \mathbb{E}_t^*[c_{t+1}] - \varsigma r_t + \epsilon_t \]

Market clearing

\[ c_t = y_t \]

Demand shock

\[ \xi_t \equiv -\varsigma r_t + \epsilon_t = (1 - \rho L) \eta_t \]

Prices fully rigid (relax later on)

**New Ingredients:** noise + irrationality

Noisy signal

\[ s_{i,t} = \xi_t + u_{i,t}/\sqrt{\tau} \]

Perception of signal

\[ s_{i,t} = \xi_t + u_{i,t}/\sqrt{\hat{\tau}} \]

over- or under-confidence?
Tractable NK Model with Imperfect Expectations

**Familiar Ingredients**

Euler equation/DIS

\[ c_t = \mathbb{E}_t^*[c_{t+1}] - \varsigma r_t + \epsilon_t \]

Market clearing

\[ c_t = y_t \]

Demand shock

\[ \xi_t \equiv -\varsigma r_t + \epsilon_t = (1 - \rho L) \eta_t \]

Prices fully rigid (relax later on)

**New Ingredients:** noise + irrationality

Noisy signal

\[ s_{i,t} = \xi_t + u_{i,t}/\sqrt{\tau} \]

Perception of signal

\[ s_{i,t} = \xi_t + u_{i,t}/\sqrt{\hat{\tau}} \]

Perception of demand process

\[ \xi_t = (1 - \hat{\rho} L) \eta_t \]

over- or under-confidence?

over- or under-extrapolation?
Tractable NK Model with Imperfect Expectations

**Familiar Ingredients**

Euler equation/DIS

\[ c_t = \mathbb{E}_t^*[c_{t+1}] - \varsigma r_t + \epsilon_t \]

Market clearing

\[ c_t = y_t \]

Demand shock

\[ \xi_t \equiv -\varsigma r_t + \epsilon_t = (1 - \rho L)\eta_t \]

Prices fully rigid (relax later on)

**New Ingredients**: noise + irrationality

Noisy signal

\[ s_{i,t} = \xi_t + u_{i,t}/\sqrt{\tau} \]

Perception of signal

\[ s_{i,t} = \xi_t + u_{i,t}/\sqrt{\hat{\tau}} \]

Perception of demand process

\[ \xi_t = (1 - \hat{\rho} L)\eta_t \]

over- or under-confidence?

over- or under-extrapolation?

\( \hat{\rho} < \rho \) in GE \( \approx \) cognitive discounting, level-K
Theoretical Results: Transparent Mapping from Moments to Model

**Proposition: Mapping to Forecast Data**

Closed-form expressions:

F1. \( K_{CG} = K_{CG}(\hat{\tau}, \rho, \hat{\rho}; \text{mpc}) \)

F2. \( K_{BGMS} = K_{BGMS}(\tau, \hat{\tau}, \rho, \hat{\rho}; \text{mpc}) \)

F3. \( \left\{ \frac{\partial \text{Error}_{t+k}}{\partial \eta_t} \right\}_{k \geq 1} = F(\hat{\tau}, \rho, \hat{\rho}; \text{mpc}) \)

**Proposition: Equilibrium Outcomes**

As-if representative, rational agent with

\[ c_t = -r_t + \omega_f E_t^* [c_{t+1}] + \omega_b c_{t-1} \]

\( (\omega_f, \omega_b) = \Omega(\hat{\tau}, \rho, \hat{\rho}, \text{mpc}) \)
Theoretical Results: Transparent Mapping from Moments to Model

Proposition: Mapping to Forecast Data

Closed-form expressions:

F1. \( K_{CG} = K_{CG}(\hat{\tau}, \rho, \hat{\rho}; \text{mpc}) \)

F2. \( K_{BGMS} = K_{BGMS}(\tau, \hat{\tau}, \rho, \hat{\rho}; \text{mpc}) \)

F3. \( \left\{ \frac{\partial \text{Error}_{t+k}}{\partial \eta_t} \right\}_{k \geq 1} = F(\hat{\tau}, \rho, \hat{\rho}; \text{mpc}) \)

- **General equilibrium** matters through \( \text{mpc} = \) slope of Keynesian cross

Proposition: Equilibrium Outcomes

As-if representative, rational agent with

\[ c_t = -r_t + \omega_f \mathbb{E}_t^*[c_{t+1}] + \omega_b c_{t-1} \]

\( (\omega_f, \omega_b) = \Omega(\hat{\tau}, \rho, \hat{\rho}, \text{mpc}) \)
Proposition: Mapping to Forecast Data

Closed-form expressions:

F1. $K_{CG} = K_{CG}(\hat{\tau}, \rho, \hat{\rho}; \text{mpc})$

F2. $K_{BGMS} = K_{BGMS}(\tau, \hat{\tau}, \rho, \hat{\rho}; \text{mpc})$

F3. $\left\{ \frac{\partial \text{Error}_{t+k}}{\partial \eta_t} \right\}_{k \geq 1} = F(\hat{\tau}, \rho, \hat{\rho}; \text{mpc})$

Proposition: Equilibrium Outcomes

As-if representative, rational agent with

$$c_t = -r_t + \omega_f B_t^*[c_{t+1}] + \omega_b c_{t-1}$$

$$(\omega_f, \omega_b) = \Omega(\hat{\tau}, \rho, \hat{\rho}, \text{mpc})$$

- General equilibrium matters through $\text{mpc} = \text{slope of Keynesian cross}$
- **Actual dispersion** $\tau$ only affects $K_{BGMS}$; irrelevant for aggregate outcomes and main facts
Theoretical Results: Transparent Mapping from Moments to Model

Proposition: Mapping to Forecast Data

Closed-form expressions:

F1. \( K_{CG} = K_{CG}(\hat{\tau}, \rho, \hat{\rho}; \text{mpc}) \)

F2. \( K_{BGMS} = K_{BGMS}(\tau, \hat{\tau}, \rho, \hat{\rho}; \text{mpc}) \)

F3. \( \left\{ \frac{\partial \text{Error}_{t+k}}{\partial \eta_t} \right\}_{k \geq 1} = F(\hat{\tau}, \rho, \hat{\rho}; \text{mpc}) \)

Proposition: Equilibrium Outcomes

As-if representative, rational agent with

\[ c_t = -r_t + \omega_f \Pi_t^*[c_{t+1}] + \omega_b c_{t-1} \]

\( (\omega_f, \omega_b) = \Omega(\hat{\tau}, \rho, \hat{\rho}, \text{mpc}) \)

- General equilibrium matters through mpc = slope of Keynesian cross
- Actual dispersion \( \tau \) only affects \( K_{BGMS} \); irrelevant for aggregate outcomes and main facts
- Key behavior pinned down by \( (\hat{\tau}, \rho, \hat{\rho}) \)
  - Three parameters \( \rightarrow \) lots of phenomena!
  - Facts 1 and 3 are key; Fact 2 less so
New Keynesian Model Calibrated to Facts 1 and 3

Good fit for demand shock, mediocre for supply shock

Right qualitative ingredients but no abundance of free parameters
Counterfactuals: Interaction of Forces Matters

- Perfect Expectations
- Only Noise
- Noise and Over-Extrapolation

Graphs showing the impact of perfect expectations, only noise, and noise and over-extrapolation on output gap (minus) and forecast over time.
Counterfactuals: Interaction of Forces Matters

Noise smooths and dampens IRF
(“stickiness/inertia and myopia”)

+ noise
Counterfactuals: Interaction of Forces Matters

Noise smooths and dampens IRF ("stickiness/inertia and myopia")

Over-extrapolation increases present value and amplifies initial response ("amplification and momentum")

+ over-extrapolation
Outline

The Facts

Facts Meet Theory (without/with GE)

Conclusion
Conclusion

Contributions:

- Developed a simple framework to organize diverse theories and evidence
- Found little support for certain theories (FIRE, cognitive discounting, level-K)
- Argued that the “right” model combines dispersed info and over-extrapolation
- Clarified which moments of forecasts are most relevant in the theory
- Illustrated GE implications

Limitations/Future Work:

- Context: “regular business cycles” vs. crises or specific policy experiments
- Forecast data: ideally we would like expectations of firms and consumers, and for the objects that matter the most for their choices
Conclusion

Contributions:

- Developed a simple framework to organize diverse theories and evidence
- Found little support for certain theories (FIRE, cognitive discounting, level-K)
- Argued that the “right” model combines dispersed info and over-extrapolation
- Clarified which moments of forecasts are most relevant in the theory
- Illustrated GE implications

Limitations/Future Work:

- **Context**: “regular business cycles” vs. crises or specific policy experiments
- **Forecast data**: ideally we would like expectations of firms and consumers, and for the objects that matter the most for their choices
Facts 1 + 2: Showing Under-reaction and Dispersion

\[ \text{Error}_{i,t,k} = a - K_{\text{noise}} \cdot (\text{Revision}_{i,t,k} - \text{Revision}_{t,k}) + K_{\text{agg}} \cdot \text{Revision}_{t,k} + u_{i,t,k} \]

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Revisions</td>
<td>-0.166 (0.043)</td>
<td>-0.162 (0.053)</td>
<td>-0.346 (0.042)</td>
<td>-0.410 (0.041)</td>
</tr>
<tr>
<td>Revisions</td>
<td>0.745 (0.173)</td>
<td>0.841 (0.210)</td>
<td>1.550 (0.278)</td>
<td>0.412 (0.180)</td>
</tr>
<tr>
<td>R^2</td>
<td>0.103</td>
<td>0.152</td>
<td>0.211</td>
<td>0.072</td>
</tr>
<tr>
<td>Observations</td>
<td>5383</td>
<td>3769</td>
<td>5147</td>
<td>3643</td>
</tr>
</tbody>
</table>

Notes: The observation is a forecaster by quarter between Q4-1968 and Q4-2017. The forecast horizon is 3 quarters. Standard errors are clustered two-way by forecaster ID and time period. Both errors and revisions are winsorized over the sample to restrict to 4 times the inter-quartile range away from the median. The data used for outcomes are first-release.
Estimation Strategy

**Overall goal**: allow flexibility for dynamics to be “shock-specific”

**ARMA-IV**: two-stage-least-squares estimate of

\[
x_t = \alpha + \sum_{p=1}^{P} \gamma_p \cdot x_{t-p}^{IV} + \sum_{k=1}^{K} \beta_k \cdot \epsilon_{t-k} + u_t
\]

\[
X_{t-1} = \eta + \mathcal{E}_{t-1}' \Theta + e_t
\]

where \( X_{t-1} \equiv (x_{t-p})_{p=1}^{P} \), \( \mathcal{E}_{t-1} \equiv (\epsilon_{t-k-j})_{j=1}^{J} \) and \( J \geq P \). Main specification: \( P = 3, J = 6 \).

**Projection**: OLS estimation at each horizon \( h \) of

\[
x_{t+h} = \alpha_h + \beta_h \cdot \epsilon_t + \gamma'W_t + u_{t+h}
\]

where the controls \( W_t \) are \( x_{t-1} \) and \( \bar{E}_{t-k-1}[x_{t-1}] \).
Estimation Strategy

Forecast error estimation with projection method (grey) and ARMA-OLS(1,1) (green).
Variable List for SVAR

10 usual suspects: real GDP, real investment, real consumption, labor hours, the labor share, the Federal Funds Rate, labor productivity, and utilization-adjusted TFP

3 forecast variables: three-period-ahead unemployment forecast, three-period annual inflation forecast, one-period-ahead quarter-to-quarter inflation forecast
### Table 1: Exogenously Set Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta$</td>
<td>Calvo prob</td>
<td>0.6</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>Slope of NKPC</td>
<td>0.02</td>
</tr>
<tr>
<td>$\chi$</td>
<td>Discount factor</td>
<td>0.99</td>
</tr>
<tr>
<td>mpc</td>
<td>MPC</td>
<td>0.3</td>
</tr>
<tr>
<td>$\zeta$</td>
<td>IES</td>
<td>1.0</td>
</tr>
<tr>
<td>$\phi$</td>
<td>Monetary policy</td>
<td>1.5</td>
</tr>
</tbody>
</table>

### Table 2: Calibrated Parameters

<table>
<thead>
<tr>
<th></th>
<th>$\hat{\rho}$</th>
<th>$\rho$</th>
<th>$\tau$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Demand shock</td>
<td>0.94</td>
<td>0.80</td>
<td>0.38</td>
</tr>
<tr>
<td>Supply shock</td>
<td>0.82</td>
<td>0.57</td>
<td>0.15</td>
</tr>
</tbody>
</table>