Imperfect Macroeconomic Expectations: Evidence and Theory

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MIT and NBER, Yale, and MIT

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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)
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Outline

The Facts

Facts Meet Theory (without/with GE)

Conclusion
Fact 1: Aggregate Forecast Errors are Predictable

Coibion and Gorodnichenko (2015)

\[
(x_{t+k} - \bar{E}_t x_{t+k}) = a + K_{CG} \cdot (\bar{E}_t x_{t+k} - \bar{E}_{t-1} x_{t+k}) + u_t
\]
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<table>
<thead>
<tr>
<th>variable</th>
<th>sample</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
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<td>Revision_{t}(K_{CG})</td>
<td>0.741</td>
<td>0.809</td>
<td>1.528</td>
<td>0.292</td>
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<td></td>
<td>(0.232)</td>
<td>(0.305)</td>
<td>(0.418)</td>
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<td>R^2</td>
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<td>0.278</td>
<td>0.016</td>
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<tr>
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<td>191</td>
<td>136</td>
<td>190</td>
<td>135</td>
<td></td>
</tr>
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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.
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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)

\[(x_{t+k} - \mathbb{E}_{i,t}x_{t+k}) = a + K_{BGMS} \cdot (\mathbb{E}_{i,t}x_{t+k} - \mathbb{E}_{i,t-1}x_{t+k}) + u_t\]
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<tr>
<td>Revision (<em>{i,t}(K</em>{BGMS}) )</td>
<td>0.321</td>
<td>0.398</td>
<td>0.143</td>
<td>-0.263</td>
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<td>(0.107)</td>
<td>(0.149)</td>
<td>(0.123)</td>
<td>(0.054)</td>
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<td>0.028</td>
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<tr>
<td>Observations</td>
<td>5383</td>
<td>3769</td>
<td>5147</td>
<td>3643</td>
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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 ⇒ Dispersed Info

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<td>$K_{CG} &gt; K_{BGMS}$</td>
<td>✓</td>
<td>✓</td>
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<td>✓</td>
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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) details

Moments of interest:

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

Each "slice" compares 3-Q-ahead forecasts with outcome.
Fact 3: Dynamic Over-Shooting in Response to Business Cycle Shocks

- Slow recognition, big forecast errors

**Forecast and outcome**

**Forecast error**

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

Delayed over-shooting, smaller but persistent forecast errors

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

Gali (1999): Technology → Inflation

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”

\[ \begin{align*}
\hat{E}_t[x_{t+k}] &= \alpha_k + \beta_k^f \cdot \epsilon_t + \gamma' W_t + u_{t+k} \\
x_{t+k} &= \alpha_k + \beta_k^o \cdot \epsilon_t + \gamma' W_t + u_{t+k}
\end{align*} \]

Expectation from \( t = 0 \)
Reality from \( t = 0 \)

Unemployment

Inflation

\( \beta_k^o, \) outcomes
\( \beta_k^f, \) forecasts

horizon

0 1 2 3 4

0.05 0.10 0.15 0.20 0.25

0.05 0.10 0.15 0.20 0.25

Unemployment

Inflation
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Conclusion
## Need to Combine Frictions to Explain Facts

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<td>Noisy common information</td>
<td>No</td>
<td>No</td>
<td>No*</td>
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# Need to Combine Frictions to Explain Facts: A Winning Combination

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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)
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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

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

Over- or under-confidence?

Over- or under-extrapolation?

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

\[ \approx \text{cognitive discounting, level-K} \]
Tractable NK Model with Imperfect Expectations

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over- or under-confidence?
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- Euler equation/DIS
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- Market clearing
  \[ c_t = y_t \]
- Demand shock
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- Perception of demand process
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over- or under-confidence?
over- or under-extrapolation?
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over- or under-confidence?

over- or under-extrapolation?

\[ \hat{\rho} < \rho \text{ in GE } \approx \text{ cognitive discounting, level-K} \]
Proposition: Mapping to Forecast Data

Closed-form expressions:

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

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

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

\[
\begin{align*}
    c_t &= -r_t + \omega_f B^*_t[c_{t+1}] + \omega_b c_{t-1} \\
    (\omega_f, \omega_b) &= \Omega(\hat{\tau}, \rho, \hat{\rho}, \text{mpc})
\end{align*}
\]
**Theoretical Results: Transparent Mapping from Moments to Model**

**Proposition: Mapping to Forecast Data**

Closed-form expressions:

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

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

**Proposition: Equilibrium Outcomes**

As-if representative, rational agent with

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

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- **Actual dispersion** \( \tau \) only affects \( K_{BGMS} \); irrelevant for aggregate outcomes and main facts
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As-if representative, rational agent with

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

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

- 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 → 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

+ noise
+ over-extrapolation

Noise smooths and dampens IRF ("stickiness/inertia and myopia")
Over-extrapolation increases present value and amplifies initial response ("amplification and momentum")

0 5 10 15 20
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5

0 5 10 15 20
0
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0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5

output gap (minus)
forecast

output gap (minus)
forecast

output gap (minus)
forecast
Counterfactuals: Interaction of Forces Matters

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

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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>variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
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<tbody>
<tr>
<td>sample</td>
<td>Unemployment</td>
<td>Inflation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Revision$<em>{i,t} -$ Revision$</em>{t}$ ($-K_{\text{noise}}$)</td>
<td>-0.166</td>
<td>-0.162</td>
<td>-0.346</td>
<td>-0.410</td>
</tr>
<tr>
<td></td>
<td>(0.043)</td>
<td>(0.053)</td>
<td>(0.042)</td>
<td>(0.041)</td>
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<tr>
<td>Revision$<em>{t}$ ($K</em>{\text{agg}}$)</td>
<td>0.745</td>
<td>0.841</td>
<td>1.550</td>
<td>0.412</td>
</tr>
<tr>
<td></td>
<td>(0.173)</td>
<td>(0.210)</td>
<td>(0.278)</td>
<td>(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>
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<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

Figure 1: *

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>
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<tr>
<td>$\theta$</td>
<td>Calvo prob</td>
<td>0.6</td>
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<tr>
<td>$\kappa$</td>
<td>Slope of NKPC</td>
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</tr>
<tr>
<td>$\chi$</td>
<td>Discount factor</td>
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</tr>
<tr>
<td>mpc</td>
<td>MPC</td>
<td>0.3</td>
</tr>
<tr>
<td>$\varsigma$</td>
<td>IES</td>
<td>1.0</td>
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<tr>
<td>$\phi$</td>
<td>Monetary policy</td>
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</tbody>
</table>

### Table 2: Calibrated Parameters

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