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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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)

\[ (x_{t+k} - \bar{E}_t x_{t+k}) = a + K_{CG} \cdot (\bar{E}_t x_{t+k} - \bar{E}_{t-1} x_{t+k}) + u_t \]
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<tr>
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<td>sample</td>
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<tr>
<td>Unemployment</td>
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<tr>
<td>Unemployment</td>
<td>0.741</td>
<td>0.809</td>
<td>1.528</td>
<td>0.292</td>
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<tr>
<td>(0.232)</td>
<td>(0.305)</td>
<td>(0.418)</td>
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<td>Inflation</td>
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<tr>
<td>Revision (t(K_{CG}))</td>
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<td>R²</td>
<td>0.111</td>
<td>0.159</td>
<td>0.278</td>
<td>0.016</td>
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<tr>
<td>Observations</td>
<td>191</td>
<td>136</td>
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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)

\[ (x_{t+k} - \bar{E}_{i,t}x_{t+k}) = a + K_{BGMS} \cdot (\bar{E}_{i,t}x_{t+k} - \bar{E}_{i,t-1}x_{t+k}) + u_t \]
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<tbody>
<tr>
<td>Revision</td>
<td>(K_{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>R²</td>
<td></td>
<td>0.028</td>
<td>0.052</td>
<td>0.005</td>
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<tr>
<td>Observations</td>
<td></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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</tr>
<tr>
<td>$K_{CG} &gt; K_{BGMS}$</td>
<td>✓</td>
<td>✓</td>
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</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)

details

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.

- Unemployment: $E_{t+3}[x_{t+6}]$ and $x_{t+6}$
- Inflation (annual):
  - Forecast and outcome
  - Forecast error with shaded area $\pm 1$ SE
Fact 3: Dynamic Over-Shooting in Response to Business Cycle Shocks

Slow recognition, big forecast errors

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

Forecast and outcome

Forecast error

Method
projection
ARMA-IV

Forecast and outcome

Forecast error
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”

\[ \overline{E}_t[x_{t+k}] = \alpha_k + \beta^f_k \cdot \epsilon_t + \gamma' W_t + u_{t+k} \]

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

Expectation from \( t = 0 \)

Reality from \( t = 0 \)
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## Need to Combine Frictions to Explain Facts

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<tr>
<th>Information</th>
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<th>Fact 1</th>
<th>Fact 2</th>
<th>Fact 3</th>
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<tr>
<td>Noisy common information</td>
<td>No</td>
<td>No</td>
<td>No*</td>
<td>No</td>
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<tr>
<td>Noisy dispersed information</td>
<td>Yes</td>
<td>No*</td>
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<td><strong>Confidence</strong></td>
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<td>Over-confidence or representativeness heuristic</td>
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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

\[ \xi_t \equiv -\varsigma r_t + \epsilon_t = (1 - \rho \mathbb{I}) \eta_t \]

Prices fully rigid (relax later on)
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**New Ingredients**: noise + irrationality

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**New Ingredients:** noise + irrationality

Noisy signal

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

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  \[ c_t = y_t \]
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**New Ingredients**: noise + irrationality

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

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

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

over- or under-confidence?
over- or under-extrapolation?
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over- or under-confidence?

over- or under-extrapolation?

\[ \hat{\rho} < \rho \text{ in GE } \approx \text{cognitive discounting, level-K} \]
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

\[
\begin{align*}
    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})
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\( (\omega_f, \omega_b) = \Omega(\hat{\tau}, \rho, \hat{\rho}, \text{mpc}) \)

- **General equilibrium** matters through \( \text{mpc} = \) 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
### Theoretical Results: Transparent Mapping from Moments to Model

**Proposition: Mapping to Forecast Data**

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

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

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

![Graphs showing the interaction of forces in different scenarios.](image-url)
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")
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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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- Found little support for certain theories (FIRE, cognitive discounting, level-K)
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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

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

|-----------------|--------|-----------------------------|-----------------------------|--------------------------|--------------------------|
| Revision\text{
\_i,t - Revision\text{
\_t (-K}_{\text{noise})} | -0.166 | -0.162 | -0.346 | -0.410 |
| | (0.043) | (0.053) | (0.042) | (0.041) |
| Revision\text{
\_t (K}_{\text{agg}) | 0.745 | 0.841 | 1.550 | 0.412 |
| | (0.173) | (0.210) | (0.278) | (0.180) |
| R^2 | 0.103 | 0.152 | 0.211 | 0.072 |
| Observations | 5383 | 3769 | 5147 | 3643 |

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

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

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

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 \(\overline{E}_{t-k-1}[x_{t-1}]\).
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

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<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
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<tr>
<td>$\theta$</td>
<td>Calvo prob</td>
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<tr>
<td>$\kappa$</td>
<td>Slope of NKPC</td>
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<tr>
<td>$\chi$</td>
<td>Discount factor</td>
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<td>mpc</td>
<td>MPC</td>
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<td>$\varsigma$</td>
<td>IES</td>
<td>1.0</td>
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<td>$\phi$</td>
<td>Monetary policy</td>
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Table 2: Calibrated Parameters

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<th>$\hat{\rho}$</th>
<th>$\rho$</th>
<th>$\tau$</th>
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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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