

Imperfect Macroeconomic Expectations: Evidence and Theory

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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

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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)

$$(x_{t+k} - \bar{\mathbb{E}}_t x_{t+k}) = a + K_{CG} \cdot (\bar{\mathbb{E}}_t x_{t+k} - \bar{\mathbb{E}}_{t-1} x_{t+k}) + u_t$$

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variable sample	(1)	(2)	(3)	(4)
	Unemployment		Inflation	
	1968-2017	1984-2017	1968-2017	1984-2017
Revision _t (K _{CG})	0.741 (0.232)	0.809 (0.305)	1.528 (0.418)	0.292 (0.191)
R ²	0.111	0.159	0.278	0.016
Observations	191	136	190	135

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)

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

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	(1)	(2)	(3)	(4)
variable	Unemployment		Inflation	
sample	1968-2017	1984-2017	1968-2017	1984-2017
Revision $_{i,t}(K_{\text{BGMS}})$	0.321 (0.107)	0.398 (0.149)	0.143 (0.123)	-0.263 (0.054)
R ²	0.028	0.052	0.005	0.025
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.

BGMS argue that $K_{\text{BGMS}} < 0$ 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 $K_{\text{BGMS}} \approx 0$ “on average”

Facts 1 + 2 \Rightarrow Dispersed Info

variable sample	Unemployment		Inflation	
	1968-2017	1984-2017	1968-2017	1984-2017
K_{CG}	0.741	0.809	1.528	0.292
K_{BGMS}	0.321	0.398	0.143	-0.263
$K_{CG} > K_{BGMS}$	✓	✓	✓	✓

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

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

Evidence of dispersed private information

combined regression

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

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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)

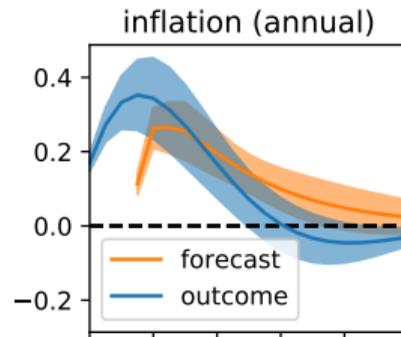
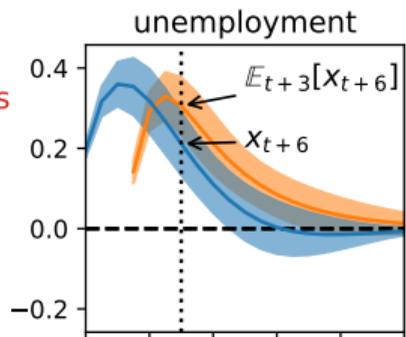
Estimation method: plain-vanilla linear projection; or big VARs; or **ARMA-IV** (novel approach) [details](#)

Moments of interest:

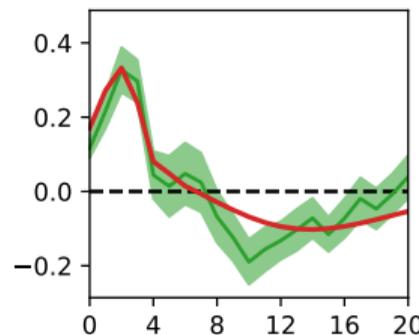
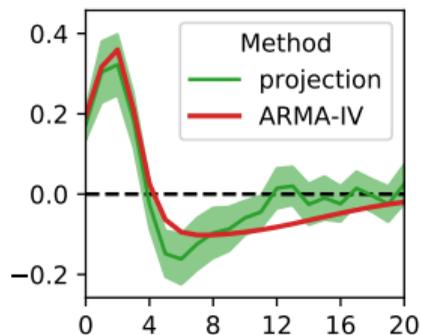
$$\left(\frac{\partial \text{ForecastError}_{t+k}}{\partial \text{BusinessCycleShock}_t} \right)_{k=0}^K = \text{Pattern of mistakes}$$

Fact 3: Dynamic Over-Shooting in Response to Business Cycle Shocks

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



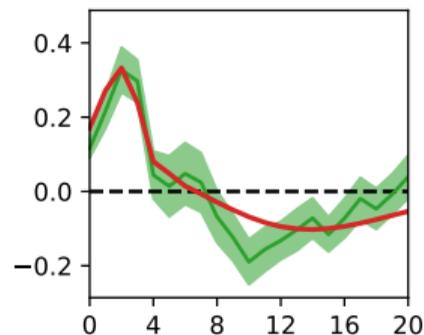
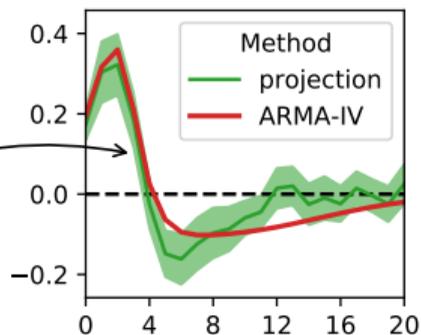
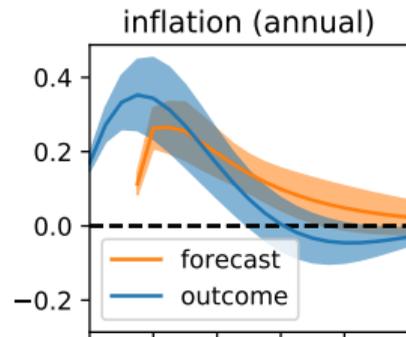
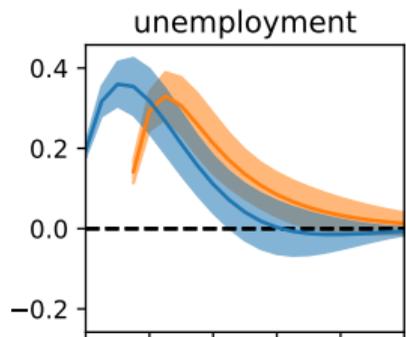
forecast and outcome



forecast error

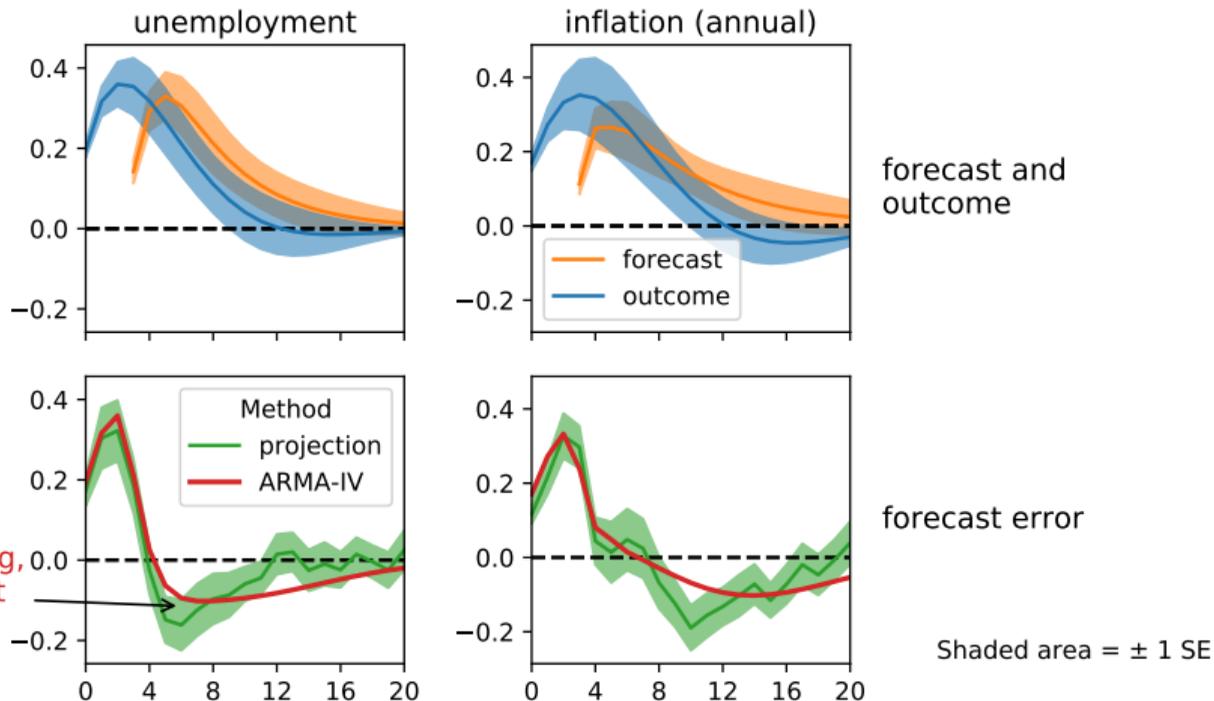
Shaded area = ± 1 SE

Fact 3: Dynamic Over-Shooting in Response to Business Cycle Shocks



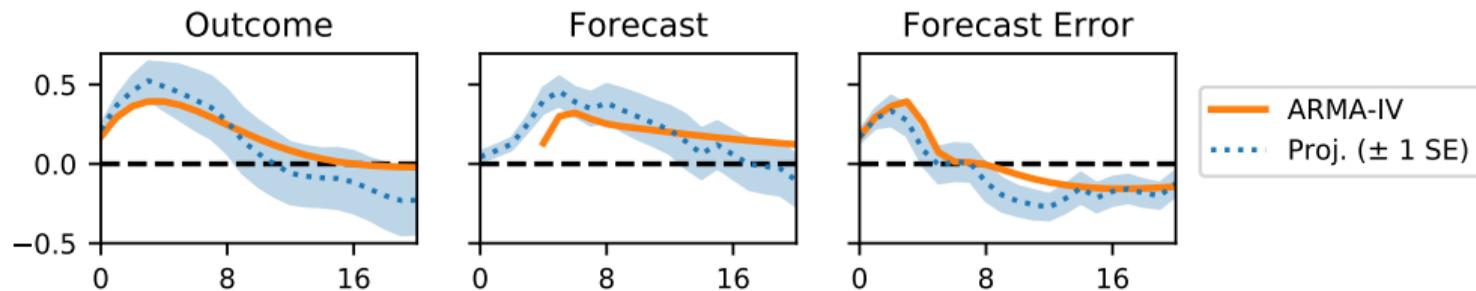
Slow recognition,
big forecast errors

Fact 3: Dynamic Over-Shooting in Response to Business Cycle Shocks

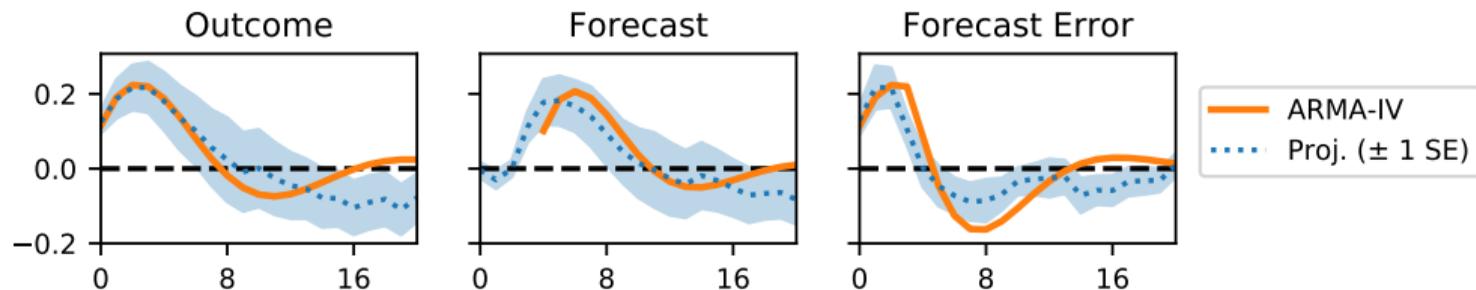


Fact 3 [Over-shooting]: Same Pattern with Other Identified Shocks

Gali (1999): Technology \rightarrow Inflation



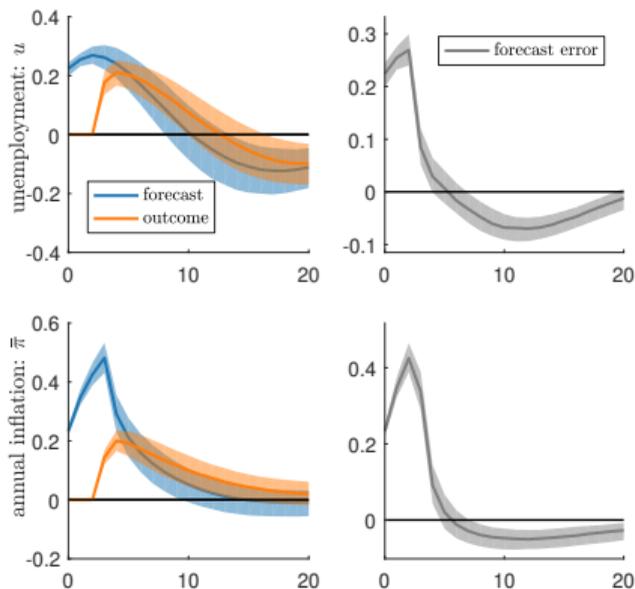
Justiniano, Primiceri, and Tambalotti (2010): Investment Shock \rightarrow Unemployment



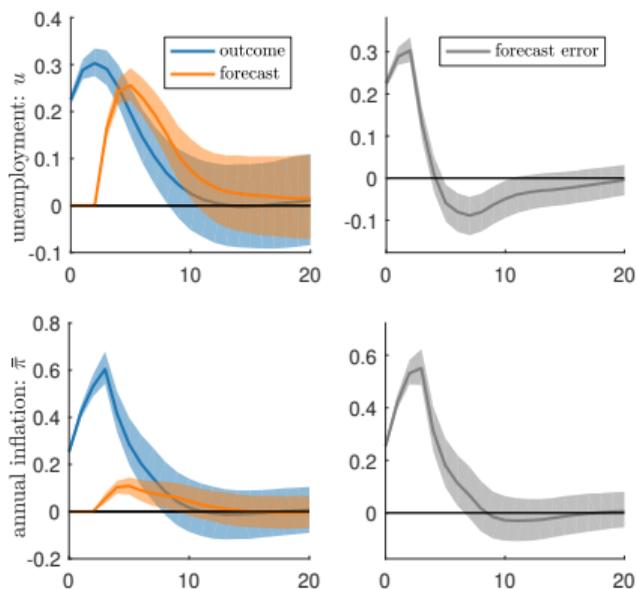
Fact 3 [Over-shooting]: Same Pattern in a Structural VAR

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

ACD, 2020 (max-share for BC)



Cholesky (one-step-ahead Error)



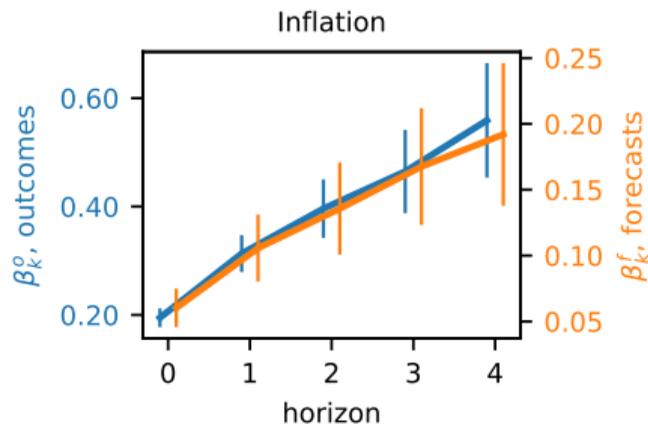
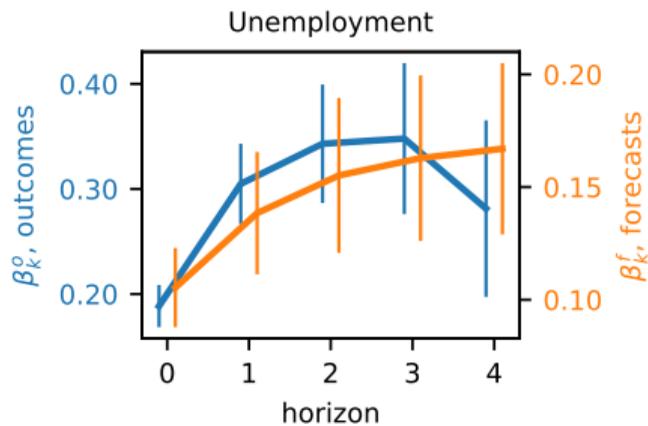
Fact 3 [Over-shooting]: Over-persistence in the “Term Structure”

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

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

Expectation from $t = 0$

Reality from $t = 0$



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Need to Combine Frictions to Explain Facts

	Theory	Fact 1	Fact 2	Fact 3
<i>Information</i>	Noisy common information	No	No*	No
	Noisy dispersed information	Yes	No*	No
<i>Confidence</i>	Over-confidence or representativeness heuristic	No	Maybe	No
	Under-confidence or “timidness”	No	Maybe	No

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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

$$\xi_t \equiv -\varsigma r_t + \epsilon_t = (1 - \rho_{\mathbb{L}})\eta_t$$

Prices fully rigid (relax later on)

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over- or
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Perception of demand process

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over- or
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$\hat{\rho} < \rho$ in GE \approx cognitive
discounting, level-K

Theoretical Results: Transparent Mapping from Moments to Model

Proposition: Mapping to Forecast Data

Closed-form expressions:

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

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

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Proposition: Equilibrium Outcomes

As-if representative, rational agent with

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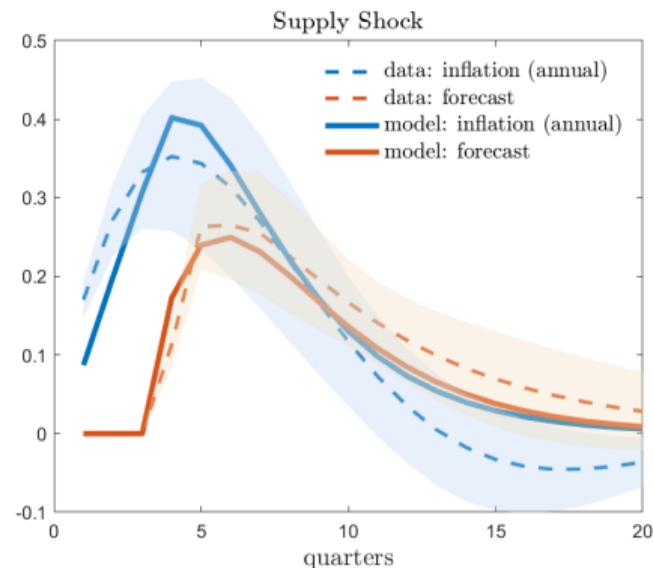
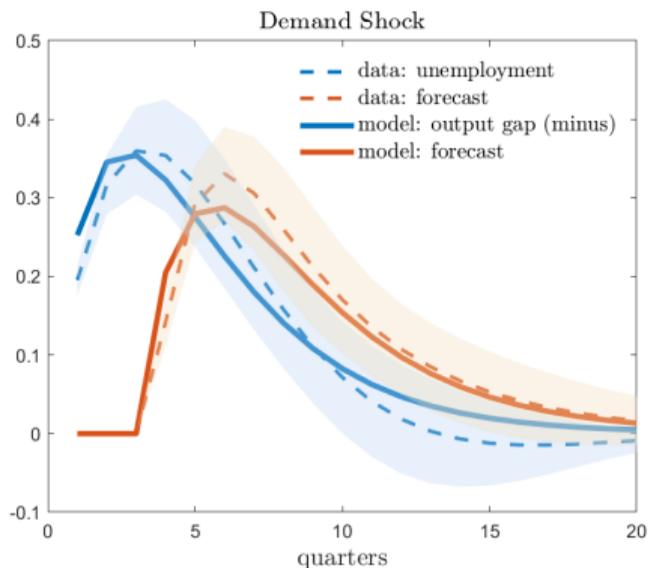
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- General equilibrium matters through mpc = slope of Keynesian cross
- Actual dispersion τ only affects K_{BGMS} ; irrelevant for aggregate outcomes and main facts
- **Key behavior** pinned down by $(\hat{\tau}, \rho, \hat{\rho})$
 - *Three parameters*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

New Keynesian Model Calibrated to Facts 1 and 3

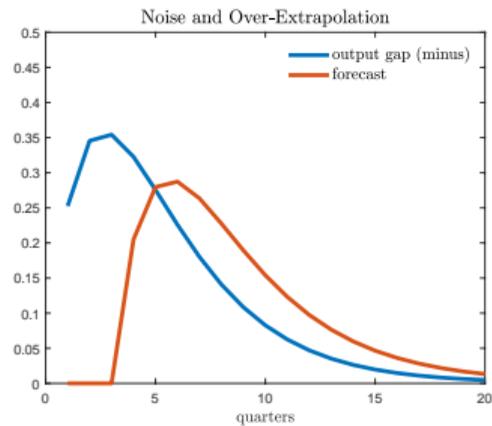
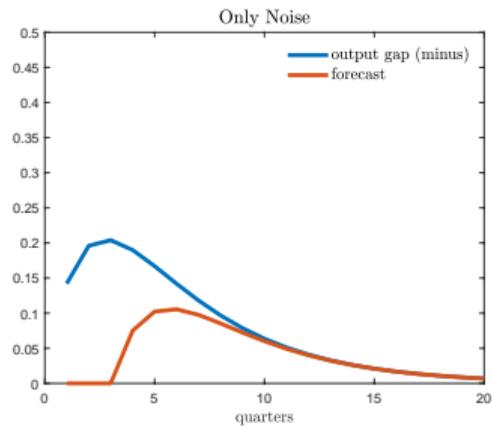
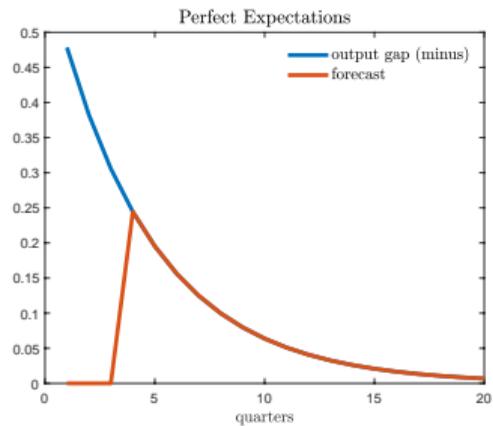


Good fit for demand shock, mediocre for supply shock

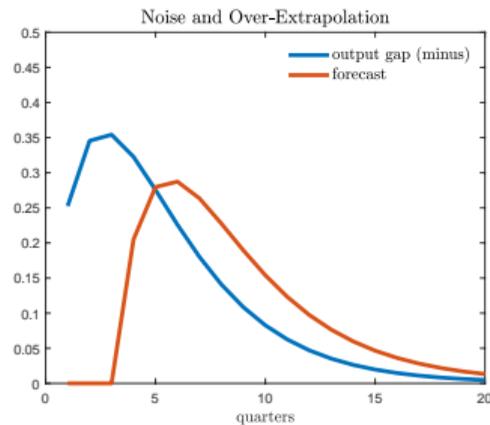
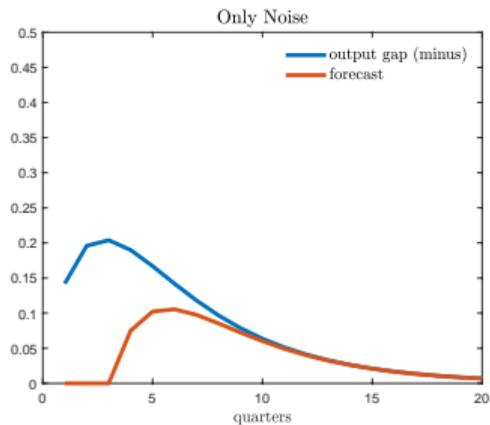
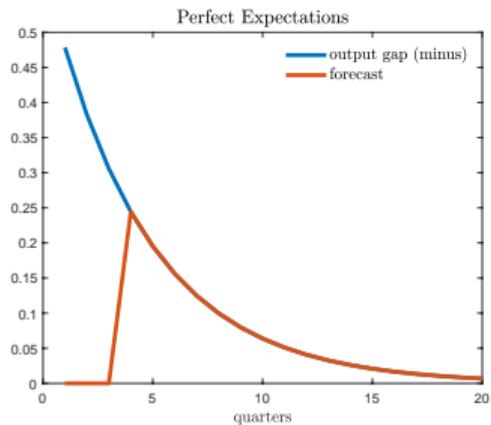
Right qualitative ingredients but no abundance of free parameters

parameter values

Counterfactuals: Interaction of Forces Matters



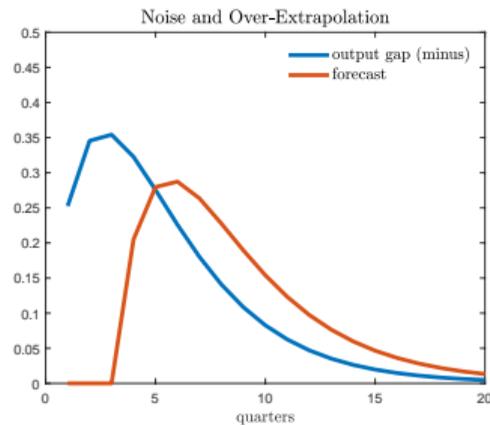
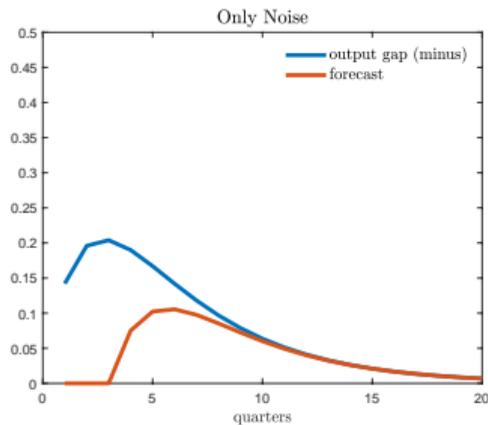
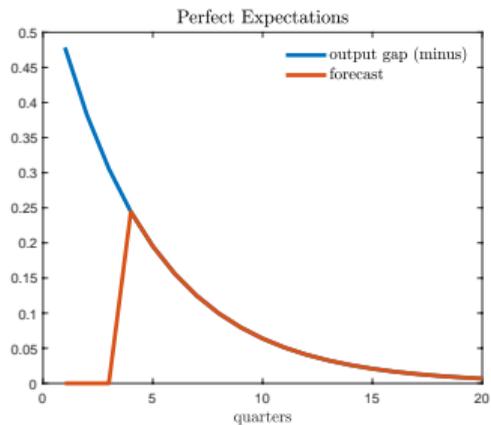
Counterfactuals: Interaction of Forces Matters



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

Counterfactuals: Interaction of Forces Matters

+ over-extrapolation



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

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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

back

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

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variable	Unemployment		Inflation	
sample	1968-2017	1984-2017	1968-2017	1984-2017
Revision _{i,t} - Revision _t (-K _{noise})	-0.166 (0.043)	-0.162 (0.053)	-0.346 (0.042)	-0.410 (0.041)
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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.

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Example

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 $\bar{\mathbb{E}}_{t-k-1}[x_{t-1}]$.

Estimation Strategy

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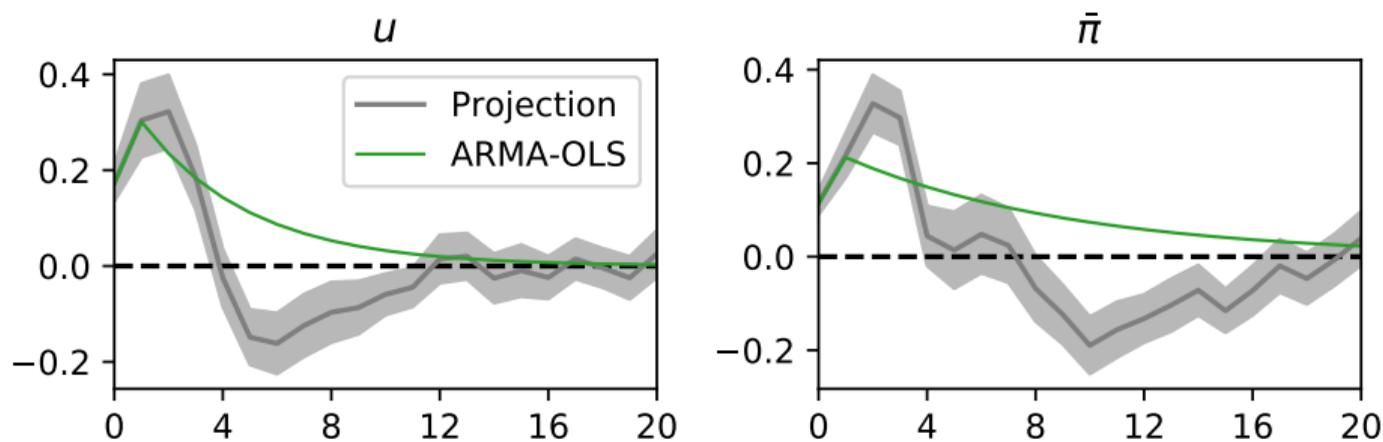


Figure 1: *

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

Variable List for SVAR

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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

Parameter	Description	Value
θ	Calvo prob	0.6
κ	Slope of NKPC	0.02
χ	Discount factor	0.99
mpc	MPC	0.3
ς	IES	1.0
ϕ	Monetary policy	1.5

Table 2: Calibrated Parameters

	$\hat{\rho}$	ρ	τ
Demand shock	0.94	0.80	0.38
Supply shock	0.82	0.57	0.15