Intrinsic Expectations Persistence

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Disclaimer

This paper does not necessarily represent the official views of

- The Federal Reserve System
- The Federal Reserve Bank of Boston
- Although it might

General Motivation

- Expectations are probably quite important to economic decision-making.
- We assume a lot about expectations.
- We know less.
- A good idea to learn more.
- Quite a few researchers are looking into this now. Good!

Macro Model Motivation

- DSGE models employ a number of features to explain persistence in macroeconomic data
  - Indexation or rule-of-thumb behavior in pricing
  - Habit formation in consumption/output
  - Autocorrelated structural shocks
- These features add lags/persistence to the models
  - Empirical basis for these features?
- In earlier work (JME 2017), I find that intrinsic persistence in expectations may provide a better explanation of macroeconomic persistence
- What is the source of such persistence? Look at micro data.

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Three surveys

- Survey of professional forecasters (SPF)
- European SPF
- Michigan survey of consumers

About these sources:

- SPF: Long sample, panel data, many variables, rolling quarter-by-quarter
- ESPF: Shorter sample (1999), panel data, fixed endpoints by year, several variables
- Michigan: Long sample, a few quantitative variables, limited and imperfect panel aspect
  - Consumers are a pretty interesting group. But focus less on them today.
- A key shortcoming for US data: We do not have quantitative data for firms' expectations.

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Key findings from micro data: Forecast inefficiency I

- All forecast revisions *appear* to be inefficient
  - Notation: forecast for $t+k$ made in $t-j$ is $x_{t+k,t-j}$
- Recall that an efficient forecast (absent information frictions) should satisfy:

$$X^i_{t+1,t} = X^i_{t+1,t-1} + News_t$$

$$R_t \equiv X^i_{t+1,t} - X^i_{t+1,t-1} = News_t$$

- This paper finds that *a* never close to 1 in these regressions:

$$X^i_{t+1,t} = aX^i_{t+1,t-1} + News_t$$

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$$a \neq 1, a << 1, (a-1) << 0$$

- True for households, professionals in US and Euro area

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Forecast inefficiency II

- Forecast errors can be predicted using revisions, and the individual forecasters' own forecasts

$$Error_t \equiv x_{t+1} - x_{t+1,t} = a[x_{t+1,t} - x_{t+1,t-1}] + bx^i_{t+k,t-j}$$

$$a, b \neq 0, R^2 >> 0$$

- Revisions enter significantly (could be "diagnostic expectations"), but $x^i_{t+k,t-j}$ includes lagged and current idiosyncratic forecasts, all forecaster-provided information.
- This runs counter to noisy information stories: all these forecasts should already be optimally filtered, so forecast errors should not be predicted by them.
- If they're filtering, they're doing so sub-optimally.

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Implications of revision inefficiency, without information frictions

- Forecast revisions are always inefficiently tied to previous forecast

$$R^i_{t+1,t} \equiv X^i_{t+1,t} - X^i_{t+1,t-1} = (a-1)X^i_{t+1,t-1} + News_t + 1, t$$

- Solve for forecasts in terms of news:

$$X^i_{t+1,t} = aX^i_{t+1,t-1} + News_{t+1,t} + (1-a)\mu$$

$$X_{t+1,t} = \sum_{i=0}^{\infty} a^i N_{t-i,t+1} + \mu$$

- When $a = 1$, $\mu = 0$, efficient forecast = sum of news
- When $a < 1$, $\mu \neq 0$, news is down-weighted, increasingly into the past (short "memory" $\rightarrow a \approx 0.5$)
- Forecast reverts to μ (initial estimate of x, other anchor)
- Similar to Tversky and Kahneman "Adjustment and Anchoring?"

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Results explained by information frictions?

- Consider the information frictions in standard models
  - **Sticky**: Agents update information sets when they get a Calvo draw. Upon update, they form rational expectations.
  - **Noisy**: Agents update all the time, efficiently filtering out the noise in information and combining with their previous forecast.
  - **Diagnostic Expectations:** Agents over-react at the micro level, under-react in the aggregate.
- Key empirical questions for these theories
  - How often do agents update information sets?
  - Do individual forecasts for signal-processors use all available information efficiently (i.e., efficiently filtering out noise)?
  - Do forecasters under- or over-react to news?

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Incorporation of news in forecasts

- An interesting source of news: Median$[X^i_{t+k,t-1}]$
  - Not known to participants in period $t-1$, but known ("news") in period t
  - A good aggregator of lagged information?
- In many cases, can express as a "forecast discrepancy" in regressions:

$$X^i_{t+1,t} - X^i_{t+1,t-1} = (a-1)[X^i_{t+1,t-1} - Median(X^i_{t+1,t-1})]$$

  - Estimated $a-1 \cong -0.5$, p-value = 0.000
- No particular reason forecasts should correct toward the lagged discrepancy between their own forecast at $t-1$ and the median of $t-1$ forecasts
- Don't impose this restriction (include lagged medians), but may be interesting to look at it that way

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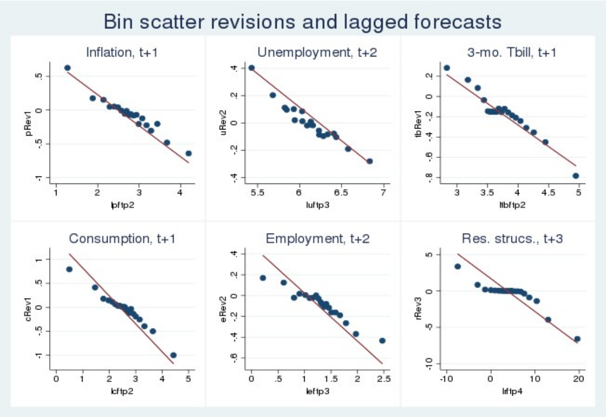
The basic result

Revisions to individual forecasts, various horizons, plotted against t-1 individual forecasts



$$R^i_{t+1} \equiv X^i_{t+1,t} - X^i_{t+1,t-1} = (a-1)X^i_{t+1,t-1}$$
$$(\hat{a}-1) \cong -0.5$$

Inflation revisions: Other forecast horizons, control variables

$$\pi^i_{t+1,t} - \pi^i_{t+1,t-1} = (a-1)[\pi^i_{t+1,t-1} - \pi^{Median}_{t+1,t-1}] + b\pi^i_{t-1} + c\pi^{Median}_{t+1,t-1} + dZ^i_t + \delta_i$$

Variable	t+1 revision					t+2	t+3
$\pi^i_{t+1,t-1} - Med(\pi^i_{t+1,t-1})$	-0.56	-0.56	-0.57	-0.55	-0.57	-0.52	-0.59
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged inflation		0.02	0.04	0.04	-0.04	0.05	0.06
		(0.116)	(0.026)	(0.033)	(0.001)	(0.000)	(0.000)
Lagged median			-0.21	-0.29	-0.20	-0.16	-0.20
			(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Lagged unemployment, T-bill, output				Y	Y		
Additional controls					Y		
Adjusted R-squared	0.16	0.16	0.18	0.17	0.34	0.23	0.28
Observations	3999	3988	3988	3717	3540	3971	3883
Estimation sample: 1981:Q3-2018:Q1							

Other variables: Unemployment

$$U^i_{t+1,t} - U^i_{t+1,t-1} = (a-1)[U^i_{t+1,t-1} - Med(U_{t+1,t-1})] + bU^i_{t-1} + cZ^i_t + \delta_i + \mu$$

Variable	$t+1$ revision				$t+2$	$t+3$
$[U^i_{t+1,t-1} - Med(U_{t+1,t-1})]$	-0.67	-0.68	-0.74	-0.71	-0.56	-0.49
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged unemployment		0.08	0.08	0.13	-0.03	-0.05
		(0.428)	(0.707)	(0.000)	(0.759)	(0.570)
Lagged median		-0.08	-0.07	-0.13	0.04	0.07
		(0.508)	(0.752)	(0.000)	(0.759)	(0.524)
Lagged inflation, t-bill, output			Y	Y		
Additional controls				Y		
Adjusted R-squared	0.21	0.21	0.23	0.78	0.16	0.15
Observations	5817	5807	3796	3542	5764	5503
Estimation sample: 1981:Q3-2018:Q1						

More variables (financial)

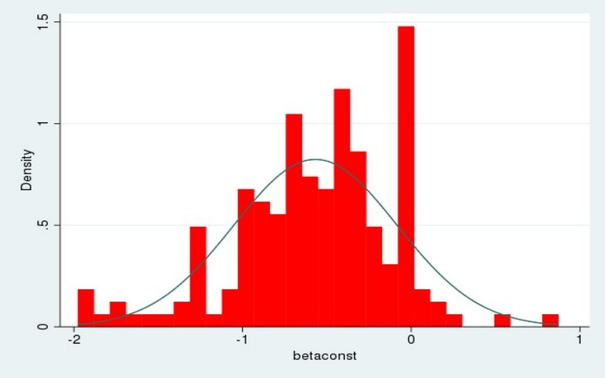
Financial variables

10-year Treasury Yield					
Variable	t+1			t+2	t+3
$[x^i_{t+1,t-1} - Med(x_{t+1,t-1})]$	-0.67	-0.68	-0.67	-0.59	-0.53
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged median		-0.04	-0.06	-0.03	-0.02
		(0.058)	(0.002)	(0.123)	(0.288)
Other controls	N	N	Y	N	N
R-squared	0.19	0.19	0.21	0.17	0.17
Observations	3176	3176	3045	3160	3047
BAA Corporate Bond Yield					
Variable	t+1			t+2	t+3
$[x^i_{t+1,t-1} - Med(x_{t+1,t-1})]$	-0.69	-0.66	-0.66	-0.56	-0.57
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged median		-0.15	-0.27	-0.18	-0.19
		(0.000)	(0.006)	(0.000)	(0.000)
Other controls	N	N	Y	N	N
R-squared	0.27	0.30	0.33	0.26	0.26
Observations	771	771	735	771	761

- Revisions always strongly correlated with lagged-viewpoint forecast.
- Absent information frictions, implies very inefficient incorporation of news.
- Lots more results in paper.

Heterogeneity in coefficient *a*

Distribution of forecaster-specific revision coefficients



Noticeable heterogeneity, but strong centering on significant negative values.

Euro SPF results (note: different information structure)

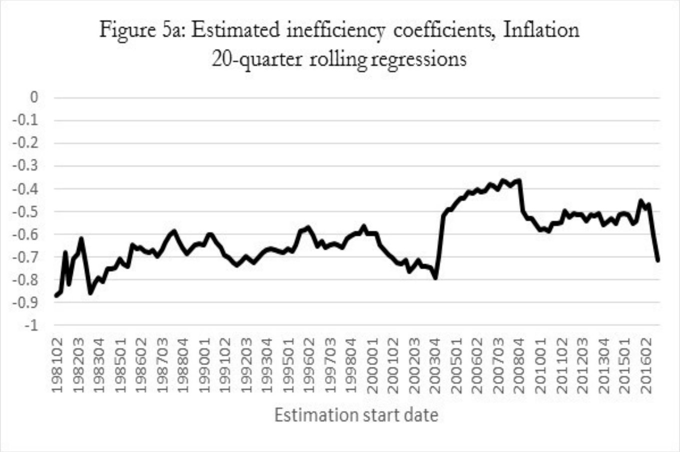
Inflation Results, Euro SPF, 1999-2018

Variable	Y1	Y2	Y1	Y2	Y1	Y2
Lagged discrepancy	-0.56	-0.48	-0.59	-0.49	-0.52	-0.51
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged inflation	0.17	0.06	0.16	0.06	0.20	0.07
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged median			Y	Y	Y	Y
Other controls					Y	Y
R-squared	0.19	0.24	0.28	0.25	0.44	0.32
Observations	3405	1054	3200	1025	2162	739

p-values in parentheses

Time-variation in the *a* coefficient, SPF

20-quarter rolling estimates



Time-variation, other variables

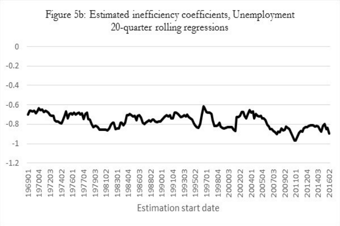


Figure 5b: Estimated inefficiency coefficients, Unemployment
20-quarter rolling regressions

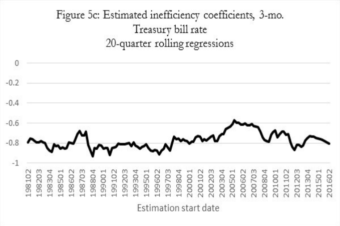


Figure 5c: Estimated inefficiency coefficients, 3-mo. Treasury bill rate
20-quarter rolling regressions

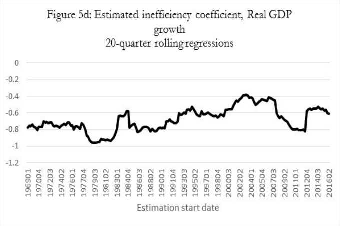


Figure 5d: Estimated inefficiency coefficient, Real GDP growth
20-quarter rolling regressions

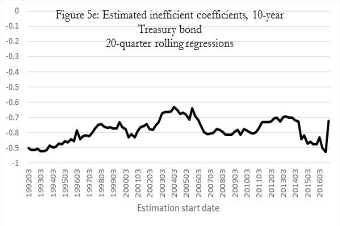


Figure 5e: Estimated inefficient coefficients, 10-year Treasury bond
20-quarter rolling regressions

Could these results be construed as evidence in favor of learning?

- No. (See the paper)
- Some evidence of least-squares learning.
- Relatively small changes in estimated coefficients over time.
- Does not substitute for inefficient revisions.

learning

Is this evidence simply a reflection of a standard information problem?

1. Sticky information? (Mankiw and Reis 2002)
2. Noisy information? (Maćkowiak and Wiederholt 2009)
3. Diagnostic expectations (Bordalo, Gennaioli, Ma and Shleifer 2018)

- Really nice paper by Coibion and Gorodnichenko (2015) provides this insight:
  - Under first two frameworks, forecast errors in the aggregate should be correlated only with forecast revisions.
  - The micro implications of these models are different. We will examine.
- Their aggregate results can be interpreted as pointing in the direction of information frictions

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Sticky information (Mankiw and Reis 2002)

- Recall that agents update with probability λ, form RE, or
- Don't update, no change in expectations.
- Implies that on average, forecast errors a function of revisions (Coibion and Gorodnichenko, 2015)

$$x_{t+1} - x_{t+1,t} = \nu_{t+1,t} + \frac{\lambda}{1-\lambda}[x_{t+1,t} - x_{t+1,t-1}]$$

- G&C get estimates of λ of about 0.5
- Micro data: this equation doesn't hold (some update, some don't)
- How many are not updating?
- For those who update, forecasts should be efficient–are they?

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How do we know who updates?

- We don't
- How to estimate frequency of update?
  - *a priori*: Professional forecasters presumably update very frequently
  - Households probably less so–although re-interview may prompt updating
  - Revisions data: When revision$= 0$, *may not* have updated (Andrade *et al* use this for Euro SPF data)
- Probably an upper bound on the number of non-updaters

Percentage of forecasters whose revision equals zero

SPF(1981-2018)					Michigan	Euro SPF (1999-2018)			
One-quarter		Four-quarter			One-year	1,2,3 or 5-year			
Inflation	Unemp.	Infl.	Unemp.	All	Infl.	Infl.	Unemp.	Growth	All 3
18.7	20.2	6.2	6.9	1.0	9.4	33.6	29.2	9.2	3.3

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Do those who appear to update do so efficiently?

$$x_{t+1} - x^i_{t+1,t-1} = a[x^i_{t+1,t} - x^i_{t+1,t-1}] + bZ_{t-1} + \delta_i + e_{t+1}$$

	Inflation errors					Unemployment errors				
Variable	t	t+1	t+1	t+2	t+3	t	t+1	t+1	t+2	t+3
Lagged med.	-0.01	0.12	1.00	0.35	0.24	0.07	0.15	1.44	0.12	0.11
	(0.957)	(0.554)	(0.451)	(0.045)	(0.120)	(0.452)	(0.258)	(0.002)	(0.521)	(0.518)
Revision	-0.10	-0.79	-0.85	-0.90	-0.88	0.05	0.20	0.12	0.29	0.41
	(0.513)	(0.000)	(0.000)	(0.000)	(0.000)	(0.498)	(0.108)	(0.409)	(0.161)	(0.062)
$x^i_{t+k,t-1}$	-0.31	-0.78	-0.73	-0.99	-0.88	-0.08	-0.18	-0.24	-0.19	-0.24
	(0.024)	(0.000)	(0.000)	(0.000)	(0.000)	(0.389)	(0.154)	(0.021)	(0.245)	(0.088)
Additional $t-1$ info*			Y					Y		
R-squared	0.07	0.15	0.25	0.16	0.15	0.06	0.10	0.20	0.12	0.14
	Output growth errors					Treasury bill errors				
	t	t+1	t+1	t+2	t+3	t	t+1	t+1	t+2	t+3
Lagged med.	0.62	0.56	0.72	0.29	0.67	-0.02	0.23	-0.28	0.26	0.26
	(0.000)	(0.079)	(0.001)	(0.489)	(0.166)	(0.678)	(0.006)	(0.604)	(0.000)	(0.026)
Revision	-0.43	-0.51	-0.53	-0.73	-1.03	0.03	-0.10	-0.12	-0.06	0.00
	(0.000)	(0.000)	(0.0000)	(0.000)	(0.000)	(0.218)	(0.311)	(0.265)	(0.542)	(0.986)
$x^i_{t+k,t-1}$	-0.51	-0.64	-0.61	-0.83	-1.04	-0.00	-0.31	-0.34	-0.43	-0.49
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.987)	(0.000)	(0.000)	(0.000)	(0.000)
Additional $t-1$ info			Y					Y		
R-squared	0.11	0.08	0.21	0.15	0.24	0.01	0.05	0.10	0.10	0.12

* "Additional t-1 info"=lagged and current individual forecaster's forecasts

NO. (A bunch more results in the paper, all the same.)
True for Michigan survey, too.

Noisy information

- Simple motivating model from C & G

$$x_t = \rho x_{t-1} + \varepsilon_t$$
$$y_t^i = x_t + \omega_t^i$$

- Implies forecasts from viewpoint date t

$$x_{t,t}^i = G y_t^i + (1 - G) x_{t,t-1}^i$$
$$x_{t+h,t}^i = \rho^h x_{t,t}^i$$

- Individual forecasts should still efficiently use all information available to the forecaster
- Thus, forecaster errors should not be predictable using information available to the forecaster–especially not their own lagged and current forecasts, which by assumption have already filtered information efficiently.
- If they are, forecasters did not filter efficiently.

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Noisy info, test results

- Test: Predictable forecast errors? Yes (from previous table). From revisions, and from lots of other regressors.
    - All forecasts **dated t or t-1, as submitted by individual forecasters**

Test of noisy information (SPF $t+1$ forecasts)

	Inflation errors	Unemployment errors
Test, all vars. excl . revision=0	0.000 (0.000)	0.000 (0.000)
R-squared, all information	0.25	0.20
R-squared, revisions only	0.04	0.06
	Output growth errors	Treasury bill errors
Test, all vars. excl . revision=0	0.000 (0.000)	0.000 (0.000)
R-squared, all information	0.21	0.10
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- The significant inefficiency of forecast errors with respect to all of the forecaster-specific forecasts constitutes a strong rejection of any such theories.
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Contrast with Bordalo, Gennaioli, Ma, and Shleifer's (BGMS, 2018) results

- They use the C-G test regression, linking forecast errors to revisions in micro data, to assess over- or under-reaction

$$\varepsilon^i_{t+h,t} \equiv x_{t+h} - x^i_{t+h,t} = \beta(x^i_{t+h,t} - x^i_{t+h,t-1}) + e$$

  - If receive positive news and *under*-react in revision, causes an under-forecast (= negative forecast error A-F); similar for negative news $\rightarrow$ positive coefficient
  - Opposite if *over*-react (receive positive news, over-react, over-forecast) $\rightarrow$ negative coefficient
  - In most cases, they find a negative relationship
  - Appears consistent with *over*-reaction to news
  - Consistent with "diagnostic expectations"–over-react at micro level, and under-react in aggregate.
- Quite different from my findings on under-reaction
- Why?

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Digging into BGMS's results

- Test regression: Split revision into two terms:

$$\begin{aligned}\varepsilon^i_{t+h,t} \equiv x_{t+h} - x^i_{t+h,t} &= \beta(x^i_{t+h,t} - x^i_{t+h,t-1}) + e^i_{t+h} \\ &= \beta_1 x^i_{t+h,t} + \beta_2 x^i_{t+h,t-1} + e^i_{t+h}\end{aligned}$$

Un-packing the test regression: p-value for test $\beta_1 + \beta_2 = 0$

Variable	t	t+1	t+2	t+3	Variable	t	t+1	t+2	t+3
Inflation	0.000	0.000	0.000	0.000	Unemp.	.036	.015	0.0062	0.0033*
GDP growth	0.040	0.0063	0.000	0.000	T-bill	.012	.0045	0.000*	0.000*
GDP defl.	0.000*	0.000	0.000	0.000	dEmp	.001*	.0047	0.091*	0.333
dConsump	0.002	0.000*	0.000	0.000	dRes.	0.000*	0.012	0.000	0.000

* indicates $x^i_{t+h,t-1}$ coefficient (β_2) significant at .01 level or better

- Thus the error is associated with t–period forecast, not revision per se
- In most cases, the lagged viewpoint date forecast does not enter significantly at all (note *s)

Digging into BGMS's results

- Test regression: Split revision into two terms:

$$\varepsilon^i_{t+h,t} \equiv x_{t+h} - x^i_{t+h,t} = \beta(x^i_{t+h,t} - x^i_{t+h,t-1}) + e^i_{t+h}$$
$$= \beta_1 x^i_{t+h,t} + \beta_2 x^i_{t+h,t-1} + e^i_{t+h}$$

Un-packing the test regression:
p-value for test $\beta_1 + \beta_2 = 0$

Variable	t	t+1	t+2	t+3	Variable	t	t+1	t+2	t+3
Inflation	0.000	0.000	0.000	0.000	Unemp.	.036	.015	0.0062	0.0033*
GDP growth	0.040	0.0063	0.000	0.000	T-bill	.012	.0045	0.000*	0.000*
GDP defl.	0.000*	0.000	0.000	0.000	dEmp	.001*	.0047	0.091*	0.333
dConsump	0.002	0.000*	0.000	0.000	dRes.	0.000*	0.012	0.000	0.000

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Digging into BGMS's results

- Test regression: Split revision into two terms:

$$\varepsilon^i_{t+h,t} \equiv x_{t+h} - x^i_{t+h,t} = \beta(x^i_{t+h,t} - x^i_{t+h,t-1}) + e^i_{t+h}$$
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Un-packing the test regression: p-value for test $\beta_1 + \beta_2 = 0$

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- One possibility: Bias in forecasters' estimates of the *persistence* of macro variables
- Much simplified:

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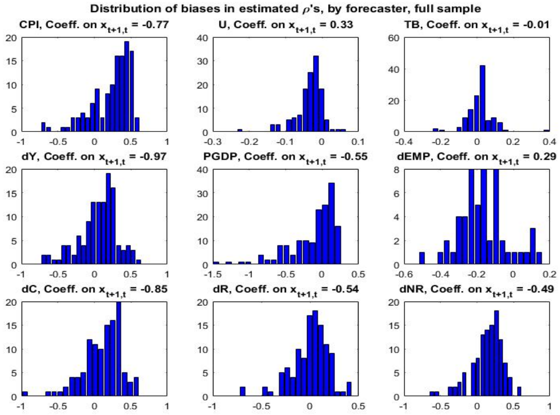
Biases in estimated autocorrelation



Yes we do. Distributions that skew positive generate negative test coefficients, and vice versa. 1998-2018 binscatter

Conclusions from examination of sticky and noisy information models

- Micro data reject sticky, noisy information, and diagnostic expectations
  - Sticky information:
    - Professionals update all the time, but inefficiently
    - Households update less frequently, but not at all efficiently
  - Noisy information
    - Individual forecast errors highly predictable
    - Which they shouldn't be if agents are filtering information efficiently. They're not.
  - Diagnostic expectations
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Building blocks of a model of expectations formation

- Agents are not naïve–they use a fair amount of information
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  - But not a trivial information set
- They do not use information efficiently→hard to explain with a rational filtering story.
  - They under-react to news at the micro level.
  - Their forecast errors are correlated with their own lagged and current forecasts→ inefficient filtering.
  - They smooth through news. The consistency with which they smooth–across agents, variables and time–is striking.
- A related implication is that they forget earlier news at a much more rapid rate than is optimal.

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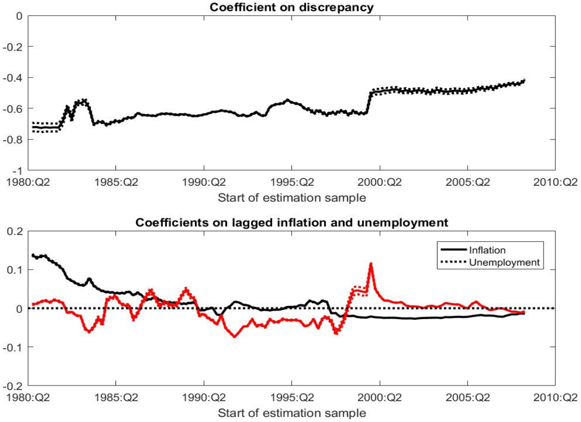
Appendix Materials

Learning vs. inefficient updating



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Common information

The effect of common information

Response of forecast revisions to lagged discrepancies between individual forecasts and central tendency measures, controlling for revision in aggregate forecast, 1981-2018:Q1

$$\pi^{i,SPF}_{t+1,t} - \pi^{i,SPF}_{t+1,t-1} = \gamma[\pi^{Median}_{t+1,t-2} - \pi^{Median}_{t+1|t-1}] + \delta[\pi^{i,SPF}_{t+1,t-1} - C(\pi_{t+1,t-1})] + a\pi^{i}_{t-1} + cZ^{i}_{t} + \delta_i + \mu_t + \varepsilon^{i}_{t}$$

Inflation results

Variable	Lagged revision				Contemporaneous revision			
$\pi^{i}_{t+1,t-1} - \pi^{Median}_{t+1\|t-1}$	-0.56	-0.55	-0.56	-0.53	-0.58	-0.58	-0.56	-0.56
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\pi^{Median}_{t+1,t-1} - \pi^{Median}_{t+1\|t-2}$		0.11	0.16	0.19				
		(0.386)	(0.204)	(0.172)				
$\pi^{Median}_{t+1,t} - \pi^{Median}_{t+1\|t-1}$					0.91	0.88	0.87	0.62
					(0.000)	(0.000)	(0.000)	(0.006)
π^{i}_{t-1}	0.02	0.02	0.03	0.03	-0.01	0.00	0.00	
	(0.116)	(0.337)	(0.093)	(0.153)	(0.506)	(0.963)	(0.917)	
$\pi^{Median}_{t+1,t-1}$			-0.24	-0.36		-0.07	-0.07	
			(0.000)	(0.000)		(0.007)	(0.060)	
Additional forecast variables	N	N	N	Y	N	N	Y	Instrumented
Adjusted R^2	0.16	0.15	0.17	0.17	0.29	0.29	0.28	
Observations	3988	3952	3952	3685	3988	3988	3717	3962

* "Additional forecast variables" include real-time estimates of lagged unemployment, Treasury bill rate.

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Common information, cont'd.

Unemployment results								
Variable	Lagged revision				Contemporaneous revision			
$U^i_{t+1,t-1} - U^{Median}_{t+1\|t-1}$	-0.68	-0.65	-0.67	-0.72	-0.66	-0.66	-0.70	-0.67
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$U^{Median}_{t+1,t-1} - U^{Median}_{t+1\|t-2}$		0.44	0.53	0.61				
		(0.000)	(0.000)	(0.000)				
$U^{Median}_{t+1,t} - U^{Median}_{t+1\|t-1}$					0.96	0.96	0.99	0.99
					(0.000)	(0.000)	(0.000)	(0.000)
U^i_{t-1}	0.01	-0.01	0.26	0.41	0.00	-0.01	-0.00	
	(0.471)	(0.401)	(0.000)	(0.000)	(0.606)	(0.139)	(0.935)	
$U^i_{t+1,t-1}$			-0.29	-0.44		0.02	0.00	
			(0.000)	(0.000)		(0.091)	(0.986)	
Additional forecast variables	N	N	N	Y	N	N	Y	Instrumented
Adjusted R-squared	0.21	0.37	0.41	0.45	0.77	0.77	0.79	–
Observations	5807	5363	5363	3764	5807	5807	3796	5371
*"Additional forecast variables" includes real-time estimates of lagged inflation, Treasury bill rate.								

back

The effect of integer rounding (Michigan survey)

- Michigan responses are rounded to nearest integer
  - Dependent variable (revision) thus truncated
- Could cause problems with OLS regression
- How bad is it?
- Setup:
  - 10,000 observations, $x = RN(0,1)$
  - $y = -ax + b + 0.5RN(0,1)$
  - $a = .5, b = 2$

Coefficient	Raw data	Rounded to 0.1	Integers
$-a$	-0.50	-0.50	-0.460
	(0.005)	(0.005)	(0.006)
b	2.00	2.00	2.00
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Similar to modest classical measurement error?

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Anchoring to long-run expectations

SPF inflation forecast revisions, varying horizons
Revision regressions with the revision in the long-term (10-year) forecast, full sample

	Revision				Revision			
	t	t+1	t+2	t+3	t	t+1	t+2	t+3
$\pi^i_{t,t-1} - \pi^{Median}_{t\|t-1}$	-0.59				-0.64			
	(0.000)				(0.000)			
$\pi^i_{t+1,t-1} - \pi^{Median}_{t+1\|t-1}$		-0.47				-0.48		
		(0.000)				(0.000)		
$\pi^i_{t+2,t-1} - \pi^{Median}_{t+2\|t-1}$			-0.43				-0.43	
			(0.000)				(0.000)	
$\pi^i_{t+3,t-1} - \pi^{Median}_{t+3\|t-1}$				-0.51				-0.52
				(0.000)				(0.000)
Lagged revision, 10-yr	-0.43	0.33	0.19	0.08	-0.64	0.31	0.10	-0.06
	(0.425)	(0.057)	(0.288)	(0.692)	(0.223)	(0.120)	(0.592)	(0.777)
Other controls	N	N	N	N	Y	Y	Y	Y
Adjusted R-squared	0.09	0.11	0.15	0.18	0.19	0.12	0.17	0.22
Observations	3252	3251	3239	3166	3000	2999	2991	2947

A quick check: Revision correlations in the SPF

Correlation of revision from viewpoint $t-1$ to t with revisions from $t-k$ to t for all k available in SPF dataset, for various terminal dates $t+j$

	Terminal dates								
	Inflation forecasts			Unemp. forecasts			T-bill forecasts		
Viewpoint	t	t+1	t+2	t	t+1	t+2	t	t+1	t+2
t-2	0.86	0.71	0.55	0.75	0.74	0.76	0.71	0.75	0.74
t-3	0.82	0.56	-	0.64	0.62	-	0.55	0.60	-
t-4	0.80	-	-	0.56	-	-	0.48	-	-
Observs.	2177	2523	3000	3003	3524	4250	2129	2478	2958

Null hypothesis is that these correlations are 0, as they reflect “news” (easily rejected)

What inefficient expectations revision looks like in a NKPC

- Consider a simple model

$$\pi_t = \beta E_t \pi_{t+1} + \gamma y_t + \varepsilon_t$$
$$y_t = \rho y_{t-1} + u_t$$

- RE solution implies the t and $t-1$ period expectations for $t+1$:

$$E_t \pi_{t+1} = \frac{\rho\gamma}{1-\rho\beta} y_t ; \; E_{t-1}\pi_{t+1} = \frac{\rho^2\gamma}{1-\rho\beta} y_{t-1}$$

- So the revision is $E_t\pi_{t+1} - E_{t-1}\pi_{t+1} = \frac{\rho\gamma}{1-\rho\beta} u_t$, which is just news
- But if revisions are inefficient as in paper, then this implies a smoothed/muted response to news
- Use $t-1$ efficient expectation, and update inefficiently

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$$F_t \pi_{t+1} = a E_{t-1}\pi_{t+1} + \frac{\rho\gamma}{1-\rho\beta} u$$

What inefficient expectations revision looks like in a NKPC

- Consider a simple model

$$\pi_t = \beta E_t \pi_{t+1} + \gamma y_t + \varepsilon_t$$
$$y_t = \rho y_{t-1} + u_t$$

- RE solution implies the t and $t-1$ period expectations for $t+1$:

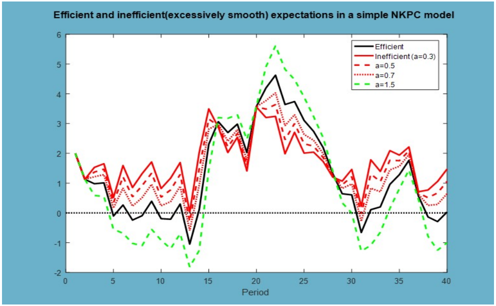
$$E_t \pi_{t+1} = \frac{\rho\gamma}{1-\rho\beta} y_t;\ E_{t-1}\pi_{t+1} = \frac{\rho^2\gamma}{1-\rho\beta} y_{t-1}$$

- So the revision is $E_t\pi_{t+1} - E_{t-1}\pi_{t+1} = \frac{\rho\gamma}{1-\rho\beta} u_t$, which is just news
- But if revisions are inefficient as in paper, then this implies a smoothed/muted response to news
- Use $t-1$ efficient expectation, and update inefficiently

$$F_t \pi_{t+1} = a E_{t-1}\pi_{t+1} + \frac{\rho\gamma}{1-\rho\beta} u$$

Expectations under-reaction in this simple example

Efficient and inefficient expectations in NKPC model



- Note: if a>1, implies over-reaction to news
- cf. to BGMS, who find over-reaction
- These are clearly different agents
- Note: a static exercise–no feedback from expectations to realizations.

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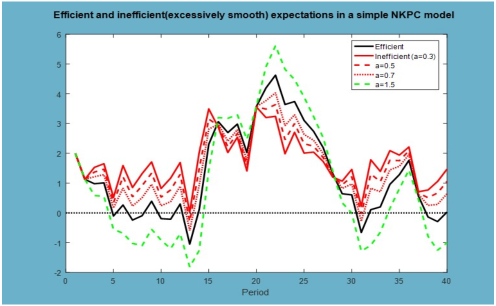

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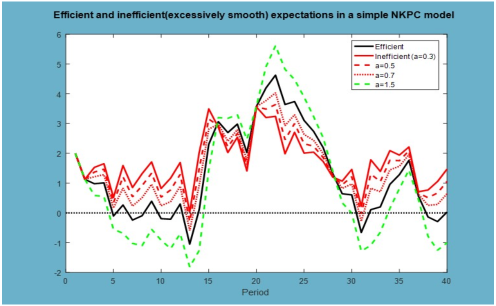

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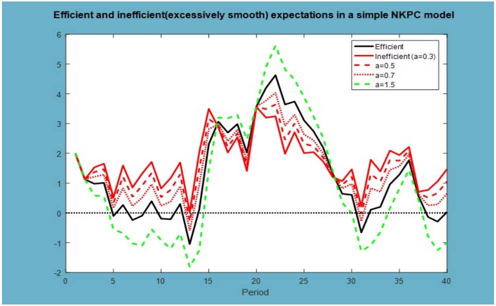

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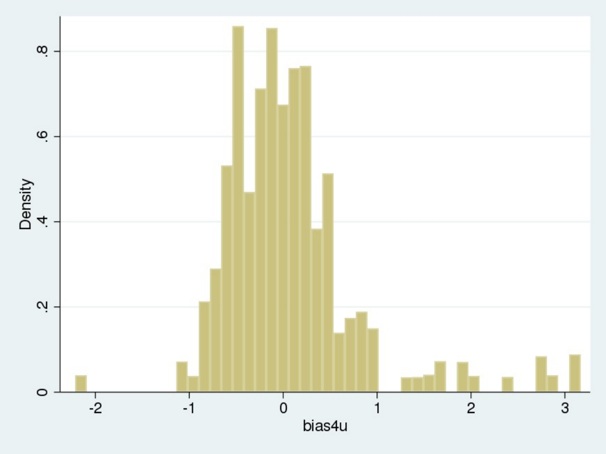
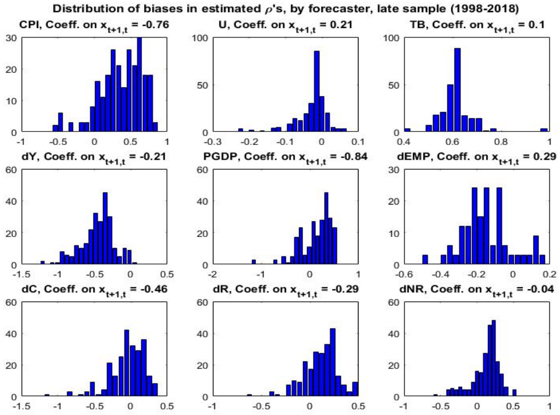
Bias by forecaster, 4-qtr. Unemployment rate

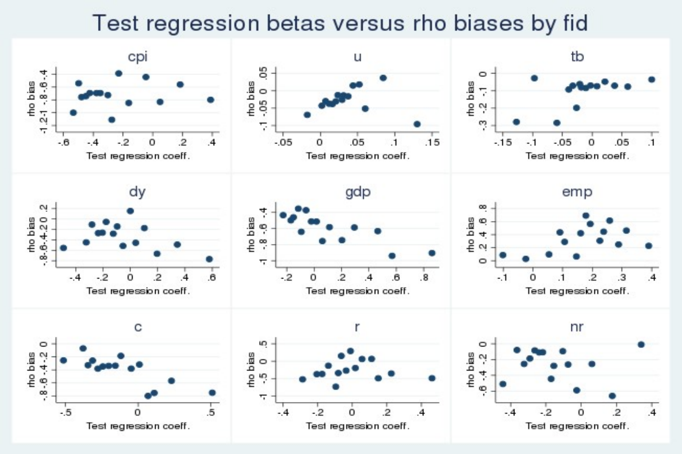


Biases in estimated autocorrelation, 1998-2018



Same result. Distributions that skew positive generate negative test coefficients, and vice versa. back

Bin scatter of ρ biases versus test regression β's



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