Predictable Forecast Errors in Full-Information Rational Expectations Models with Regime Shifts

Ina Hajdini
Federal Reserve Bank of Cleveland

André Kurmann
Drexel University

NBER Summer Institute

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Introduction

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- Many studies based on survey expectations of macro aggregates find that forecast errors are systematically predictable.
- Typically interpreted as evidence to reject the FIRE hypothesis
- Large literature introduces information frictions and/or departures from rational expectations to explain observed predictability of forecast errors.

This paper

- We study forecast error in FIRE models with regime shifts
  - structural changes in the economic environment
  - changes in the stance of monetary or fiscal policy

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- We study forecast errors in FIRE models with regime shifts
- **Result 1:** Regime shifts imply ex-post predictable, regime-dependent forecast errors
  - Similar to "peso problem", but analyzed in modern macroeconometric context
  - Implies **waves of over- and under-reaction** across rolling window samples, depending on sequence of ex-post realized regimes relative to agents' ex-ante expectations
  - We confirm this implication with data from Survey of Professional Forecasters (SPF)

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- We study forecast errors in FIRE models with regime shifts
- **Result 1:** Regime shifts imply ex-post predictable, regime-dependent forecast errors
- **Result 2:** Regime-robust test of FIRE
  - Assume FIRE model with regime shifts as data-generating process = the null
  - Simulate distribution of predictability regression coefficients, incorporating uncertainty about sequence of realized regimes
  - Compare to predictability coefficients estimated in data = t-test of the null

This paper

- We study forecast errors in FIRE models with regime shifts
- **Result 1:** Regime shifts imply ex-post predictable, regime-dependent forecast errors
- **Result 2:** Regime-robust test of FIRE
- **Result 3:** Medium-scale DSGE-RS model implies that null of FIRE cannot be rejected
  - CEE / SW / JPT type model with monetary policy regime shifts as in Bianchi (2013)
  - Estimated on post-WW2 U.S. data

This paper

- We study forecast errors in FIRE models with regime shifts
- **Result 1:** Regime shifts imply ex-post predictable, regime-dependent forecast errors
- **Result 2:** Regime-robust test of FIRE
- **Result 3:** Medium-scale DSGE-RS model implies that null of FIRE cannot be rejected
- **Lessons:**
  - Predictability of forecast errors is not sufficient to reject FIRE
  - Neither an endorsement of FIRE nor a rejection of alternative expectations theories
  - Different expectations theories should be evaluated as part of fully specified model that incorporates plausible regime shifts

Roadmap

- **Reduced-form forecast error regressions**
- A simple univariate example
- Generalized framework
- Application with estimated medium-scale DSGE-RS model

Forecast error regressions

- Survey-based forecasts of macro aggregates are often biased and forecast errors are autocorrelated (Mincer and Zarnowitz, 1969; Nordhaus, 1987; Croushore, 1998;...)

- Recent focus: forecast error regressions (Coibion and Gorodnichenko (2015); Kohlhas and Walther (2021))

$$y_{t+h} - F_t y_{t+h} = \alpha + \underset{<0}{\gamma} y_t + e_{t+h}$$

$$y_{t+h} - F_t y_{t+h} = \alpha + \underset{>0}{\delta} (F_t y_{t+h} - F_{t-1} y_{t+h}) + e_{t+h}$$

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$$y_{t+h} - F_t y_{t+h} = \alpha + \underbrace{\gamma}_{<0} y_t + e_{t+h}$$

$$y_{t+h} - F_t y_{t+h} = \alpha + \underbrace{\delta}_{>0} (F_t y_{t+h} - F_{t-1} y_{t+h}) + e_{t+h}$$

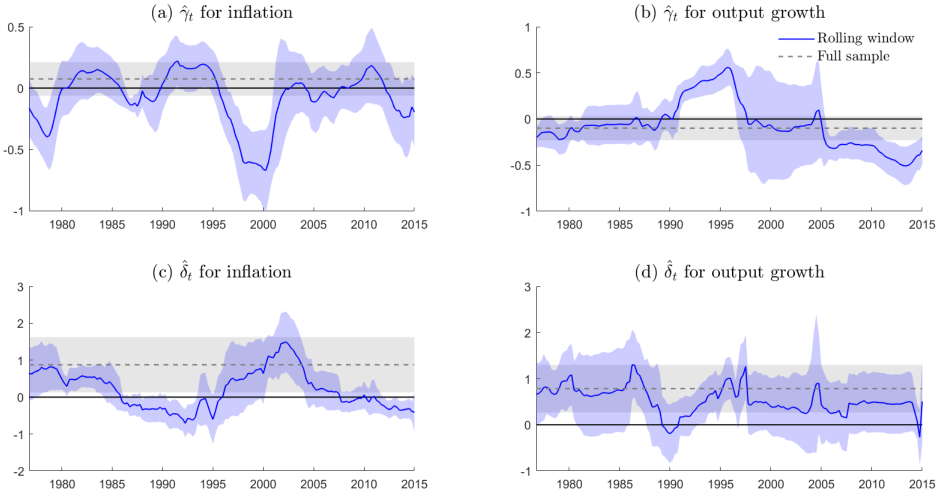
- Used as motivation / benchmark for prominent theories of information frictions and/or departures from rational expectations.
  - Mankiw and Reis (2002); Bordalo et al. (2020), Angeletos et al. (2021); Kohlhas and Walther (2021)

Forecast error regression estimates depend importantly on sample period

- Example: U.S. SPF data for inflation and output growth (Kohlhas and Walther, 2021)

	Inflation forecast error		Output growth forecast error	
	1970:4-2020:1	1982:3-2020:1	1970:4-2020:1	1982:3-2020:1
Current value (γ)	0.075	-0.131^{**}	-0.099	-0.075
	(0.070)	(0.061)	(0.067)	(0.098)
Forecast revision (δ)	0.876^{**}	0.104	0.784^{***}	0.557^{*}
	(0.382)	(0.210)	(0.264)	(0.310)

Waves of over- and under-reaction in 40 quarter rolling window samples



Taking stock

- Forecast error predictability varies substantially and non-systematically across subsamples

- One interpretation: small sample uncertainty

- Alternative interpretation: regime shifts

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Univariate example without regime shifts

$$y_t = \beta \mathbb{E}_t y_{t+1} + \psi x_t \tag{1}$$

$$x_t = \phi x_{t-1} + \varepsilon_t \tag{2}$$

Univariate example without regime shifts

$$y_t = \beta \mathbb{E}_t y_{t+1} + \psi x_t \tag{1}$$

$$x_t = \phi x_{t-1} + \varepsilon_t \tag{2}$$

- Full-information rational expectations solution

$$y_t = \frac{\psi}{1-\beta\phi} x_t = a x_t$$

- *h*-period ahead forecast error

$$y_{t+h} - \mathbb{E}_t y_{t+h} = a\phi^h x_t + a\sum_{\tau=1}^{h} \phi^{h-\tau}\varepsilon_{t+\tau} - a\phi^h x_t = a\sum_{\tau=1}^{h} \phi^{h-\tau}\varepsilon_{t+\tau}$$

$\Rightarrow$ Forecast errors are just accumulated i.i.d innovations = unpredictable

Univariate example with Markov regime shifts

- Suppose $\{\beta, \psi\}$ switch values across regimes $s_t \in \{1, 2\}$ with transition matrix

$$P = \begin{bmatrix} p_{11} & 1 - p_{11} \\ 1 - p_{22} & p_{22} \end{bmatrix}$$

where $p_{s_{t-1} s_t} = Pr(s_t | s_{t-1})$

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- Full-information rational expectations solution

$$y_t = a_{s_t} x_t$$

$$a_{s_t} = \begin{cases} a_1 & \text{if } s_t = 1 \\ a_2 & \text{if } s_t = 2 \end{cases}$$

with $\begin{bmatrix} a_1 & a_2 \end{bmatrix}' = (I_2 - \phi\beta P)^{-1} \begin{bmatrix} \psi_1 & \psi_2 \end{bmatrix}'$

Forecast errors

- h-period ahead expectations

$$\mathbb{E}_t y_{t+h} = \phi^h (P^{(h)}_{s_t,1} a_1 x_t + P^{(h)}_{s_t,2} a_2 x_t)$$

$\Rightarrow \mathbb{E}_t y_{t+h}$ is a weighted average of regime-conditional forecasts

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- h-period ahead forecast error

$$y_{t+h} - \mathbb{E}_t y_{t+h} = \underbrace{\frac{(-1)^{s_{t+h}-1}(a_1 - a_2)(1 - P^{(h)}_{s_t,s_{t+h}})\phi^h}{a_{s_t}}}_{\gamma^{(h)}_{s_t,s_{t+h}} \neq 0} y_t + \underbrace{a_{s_{t+h}} \sum_{\tau=1}^{h} \phi^{h-\tau} \varepsilon_{t+\tau}}_{\xi_{t+h}}$$

$\Rightarrow$ assume $a_1 > a_2$ w.l.o.g.: $\gamma^{(h)}_{s_t,1} > 0$ and $\gamma^{(h)}_{s_t,2} < 0$ for $s_t \in \{1, 2\}$

Implications for reduced-form regressions

- Consider sample $\{y_t\}_{t=1}^{T+1}$ conditional on regime sequence $\{s_t\}_{t=1}^{T+1}$ and estimate

$$y_{t+1} - F_t y_{t+1} = \gamma y_t + e_{t+1}$$

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- Expected regression coefficient implied by univariate model (absent small sample bias)

$$\mathbb{E}\left[\gamma \mid \{s_t\}_{t=1}^{T+1}\right] = \frac{\mathbb{E}\left[(y_{t+1} - \mathbb{E}_t y_{t+1}) y_t | \{s_t\}_{t=1}^{T+1}\right]}{\mathbb{E}\left[y_t^2 | \{s_t\}_{t=1}^{T}\right]}$$

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$$= \underbrace{\frac{\phi(a_1 - a_2)}{a_1^2(1-f_{22}) + a_2^2(1-f_{11})}}_{(+)} \underbrace{(a_1(1-f_{22})({\color{red}f_{11} - p_{11}}) - a_2(1-f_{11})({\color{red}f_{22} - p_{22}}))}_{g(f_{11},f_{22})}$$

where conditional sample frequencies $f_{ii} = \frac{\sum_{t=1}^{T} \mathbf{1}(s_t = i, s_{t+1} = i)}{\sum_{t=1}^{T} \mathbf{1}(s_{t+1} = i)} \gtreqless p_{ii}$

Implications for reduced-form regressions

1. For finite sequence $\{s_t\}_{t=1}^{T+1}$ characterized by f_{11} and f_{22} such that

$$g(f_{11}, f_{22}) > 0 \Leftrightarrow \mathbb{E}\left[\gamma \mid \{s_t\}_{t=1}^{T+1}\right] > 0 \Rightarrow \text{agents look like they under-react to } y_t$$

$$g(f_{11}, f_{22}) < 0 \Leftrightarrow \mathbb{E}\left[\gamma \mid \{s_t\}_{t=1}^{T+1}\right] < 0 \Rightarrow \text{agents look like they over-react to } y_t$$

Illustration

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Illustration

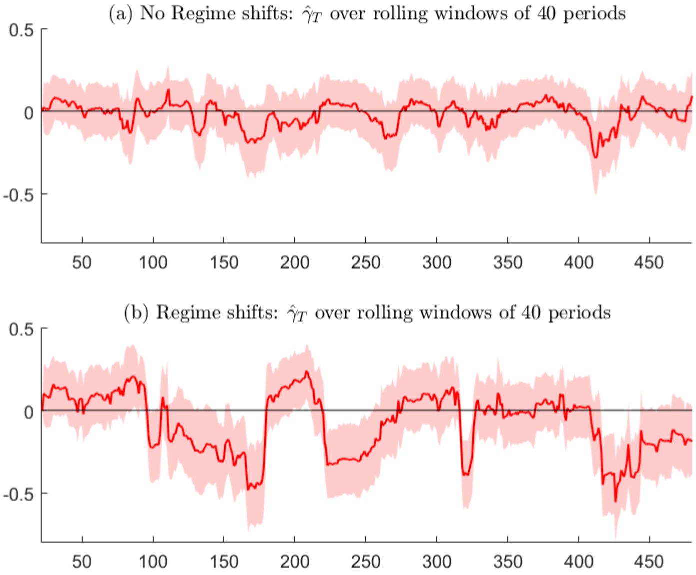
2. For $T \to \infty$ and $f_{ii} \to p_{ii}$ for any $i \in \{1, 2\}$

$$g(f_{11}, f_{22}) \to 0 \Leftrightarrow \mathbb{E}\left[\gamma \mid \{s_t\}_{t=1}^{T+1}\right] \to \mathbb{E}[\gamma] = 0$$

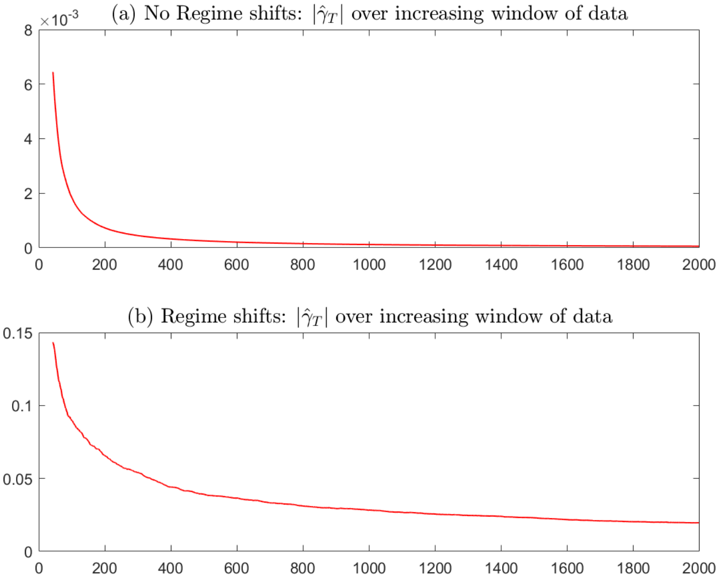
Waves of over- and under-reaction across rolling window samples

1. Set $a_1 = 2$, $a_2 = 0.5$ and $p_{11} = p_{22} = 0.7$
2. Simulate univariate model for $T = 500$ periods and compute implied 1-period ahead forecast
3. Estimate $y_{t+1} - F_t y_{t+1} = \alpha + \gamma y_t + e_{t+1}$ for rolling windows of 40 periods
4. Bias-correct OLS estimate $\hat{\gamma}_T$ for each rolling window

Waves of over- and under-reaction across rolling window samples



Average predictability of ex-post forecast errors by sample size



Regime-robust test of FIRE

- Assume FIRE model with regime shifts as data-generating process = the null
- Estimate data-generating process: parameters and smoothed regime probability evolution
- Simulate $i = 1, ..., N$ samples of size T and estimate $\hat{\gamma}_T^i$
  - T - sample size of SPF data being tested for FIRE
- Compute probability that $\hat{\gamma}_T^i$ exceeds $\hat{\gamma}_T$ = t-test of the null

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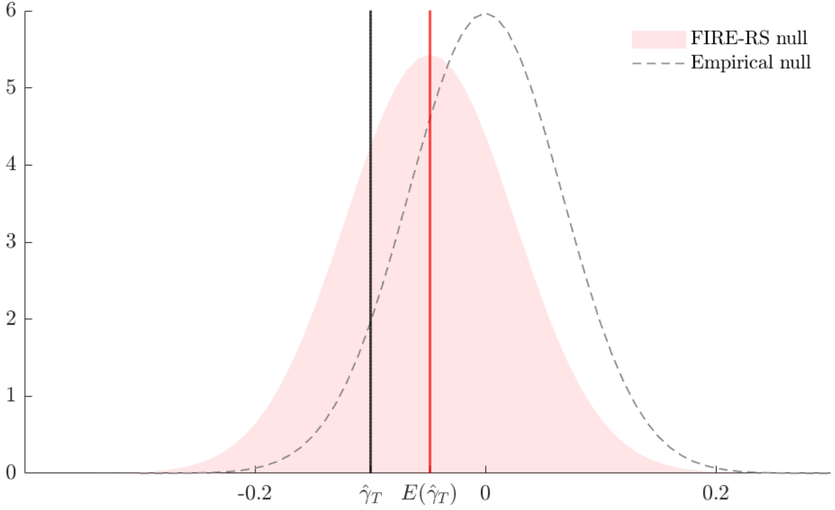
- Two important features:
  1. Incorporate uncertainty about regime realizations by drawing regimes $\left\{s_t^i\right\}_{t=1}^{T+h}$ from $\hat{P}r(s_t \mid \mathcal{Y}_T)$ implied by model and observed data $\mathcal{Y}_T$ Output growth volatility regimes
  2. Naturally delivers robust standard error of finite sample distribution of $\hat{\gamma}_T$

Test for γ with univariate model estimated on output growth data



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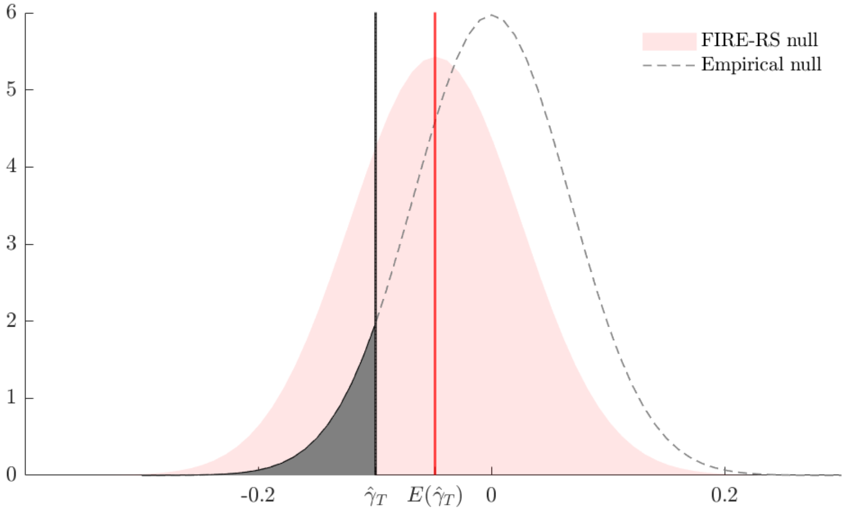

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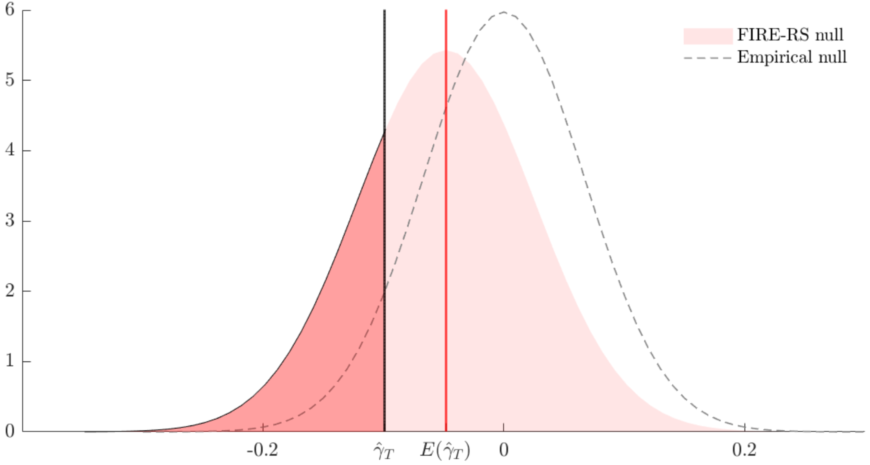
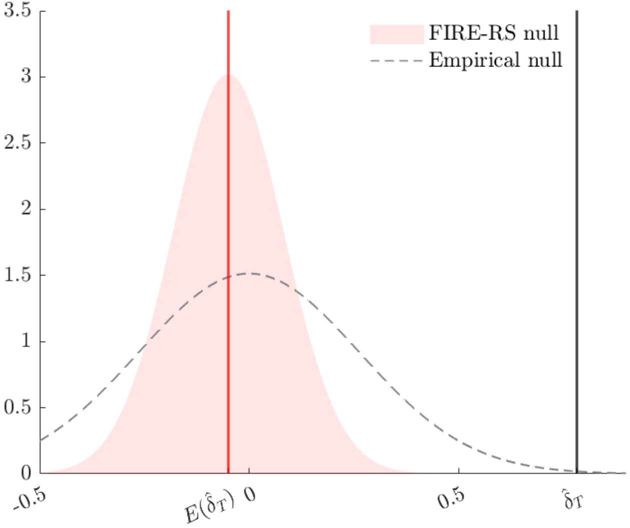


Test for δ with with univariate model estimated on output growth data



Roadmap

- Reduced-form forecast error regressions
- A simple univariate example
- **Generalized framework**
- Application with estimated medium-scale DSGE-RS model

Generalized framework

- Consider multivariate regime-shift FIRE model with minimum state variable solution

$$\underbrace{X_t}_{n_x \times 1} = A_{s_t} X_{t-1} + B_{s_t} \underbrace{\epsilon_t}_{n_\epsilon \times 1}$$

$$\underbrace{Y_t}_{n_y \times 1} = \Psi_0 + \Psi_1 \underbrace{X_t}_{n_x \times 1}$$

- As in univariate case, suppose that A_{s_t}, B_{s_t} switch values across regimes $s_t \in \{1, 2\}$
- Important: A_{s_t} is generally not a diagonal matrix

Relation of ex-post forecast errors with current information

- As in univariate example, h-period ahead forecast errors are predictable

$$Y_{t+h} - \mathbb{E}_t Y_{t+h} = \underbrace{\Gamma_{t,t+h}}_{\neq \mathbf{0}} X_t + \xi_{t+h}$$

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- **Two key differences to univariate example**

  1. $\Gamma_{t,t+h}$ is complicated function of entire sequence of regime realizations $\{s_\tau\}_{\tau=t}^{t+h}$
  2. $\Gamma_{t,t+h}$ is not diagonal $\Leftrightarrow$ elements of $Y_{t+h} - \mathbb{E}_t Y_{t+h}$ are related to entire vector X_t

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$\Rightarrow y_{t+h} - F_t y_{t+h} = \alpha + \gamma y_t + e_{t+h}$ does not have structural counterpart $\Rightarrow$ reduced-form

regression is subject to omitted variable bias

Relation of ex-post forecast errors with ex-ante forecast revisions

- Recall that

$$y_{t+h} - F_t y_{t+h} = \alpha + \underset{<0}{\gamma} y_t + e_{t+h}$$

$$y_{t+h} - F_t y_{t+h} = \alpha + \underset{>0}{\delta} (F_t y_{t+h} - F_{t-1} y_{t+h}) + e_{t+h}$$

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- General regime-shift FIRE model implies

$$Y_{t+h} - \mathbb{E}_t Y_{t+h} = \underbrace{\Delta_{t,t+h}}_{\neq \mathbf{0}} (\mathbb{E}_t X_{t+h} - \mathbb{E}_{t-1} X_{t+h}) + \underbrace{\Lambda_{t,t+h}}_{\neq \mathbf{0}} X_{t-1} + \xi_{t+h}$$

Relation of ex-post forecast errors with ex-ante forecast revisions

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$$y_{t+h} - F_t y_{t+h} = \alpha + \underset{<0}{\gamma}\, y_t + e_{t+h}$$

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$\Rightarrow y_{t+h} - F_t y_{t+h} = \alpha + \delta(F_t Y_{t+h} - F_{t-1} Y_{t+h}) + e_{t+h}$ is s.t omitted variable bias

$\Rightarrow$ No guarantee that $sign(\mathbb{E}\left[\hat{\gamma}_T | \{s_t\}_{t=1}^{T+1}\right]) = sign(\mathbb{E}\left[\hat{\delta}_T | \{s_t\}_{t=1}^{T+1}\right])$

Taking stock

- FIRE models with regime shifts generate predictable, regime-dependent forecast errors
- In generalized linear framework, predictability of $y_{t+h} - F_t y_{t+h}$ depends on (i) entire sequence of regime realizations $\{s_\tau\}_{\tau=t}^{t+h}$; and (ii) entire state vector X_t
- In finite samples, regime shifts imply waves of (what appears like) over- and under-reaction to current information (y_t) and forecast revisions $(F_t Y_{t+h} - F_{t-1} Y_{t+h})$
- Can realistic FIRE model with regime shifts generate forecast errors predictability consistent with reduced-form evidence?

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- **Application with estimated medium-scale DSGE-RS model**

Medium-scale DSGE-RS model

- Model a la Christiano et al. (2005), Smets and Wouters (2007), Justiniano et al. (2011)
  - Habit persistence in consumption
  - Investment adjustment cost and variable capital utilization
  - Staggered nominal price and wage contracts
  - Monetary policy rule
  - Several real and nominal shocks

Regime-robust test of FIRE with medium-scale DSGE-RS model

- Model a la Christiano et al. (2005), Smets and Wouters (2007), Justiniano et al. (2011)
- Regime shifts in monetary policy rule as in Bianchi (2013)

$$R_t = \phi^R_{s_t} R_{t-1} + (1 - \phi^R_{s_t}) \left(\phi^{\Delta y}_{s_t} \Delta y_t + \phi^{\pi}_{s_t} \pi_t \right) + v_t$$

- Estimate model on post-war US macro data Policy rule parameters estimates
- Simulate N data samples of size T, taking into account uncertainty about sequence of regime realizations Evolution of monetary regimes
- Estimate distribution of forecast error regression estimates from simulated data
- Compute t-test of null that observed estimates were generated by DSGE-RS model

Null of DSGE-RS model cannot be rejected at high significance levels

Panel A: $y_{t+h} - F_t y_{t+h} = \alpha + \gamma y_t + e_{t+h}$

	$\hat{\gamma}_T$	$\mathbb{E}[\hat{\gamma}_T]$	$\sigma_{\hat{\gamma}_T}$	*p-value* $H_0 : \hat{\gamma}_T = \mathbb{E}[\hat{\gamma}_T]$
Inflation	0.086	−0.031	0.086	0.179
Output growth	−0.086	−0.005	0.058	0.166

Panel B: $y_{t+h} - F_t y_{t+h} = \alpha + \delta(F_t y_{t+h} - F_{t-1} y_{t+h}) + e_{t+h}$

	$\hat{\delta}_T$	$\mathbb{E}[\hat{\delta}_T]$	$\sigma_{\hat{\delta}_T}$	*p-value* $H_0 : \hat{\delta}_T = \mathbb{E}[\hat{\delta}_T]$
Inflation	0.925	0.754	0.088	0.052
Output growth	0.837	0.689	0.168	0.370

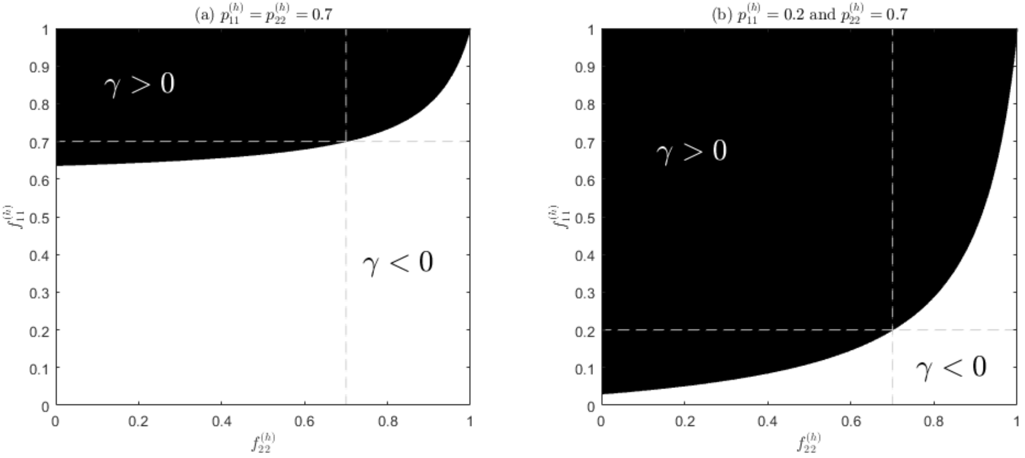
Concluding Remarks

- FIRE models with regime shifts imply predictable, regime-dependent forecast errors.

- We propose a regime-robust test and fail to reject FIRE at high significance levels.

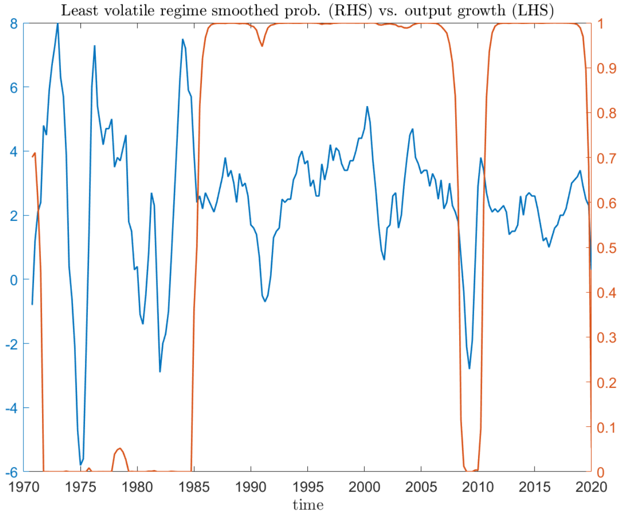
- Neither an endorsement of FIRE nor a rejection of alternative expectations theories.
  - Forecast error predictability regressions provide valuable moments
  - Apply regime-robust test for whatever is your favorite model
  - FIRE or non-FIRE; different assumptions about regime shifts and learning;...

Illustration



Back

Estimated output growth volatility regimes



Back to the test

Estimation and implied monetary policy regime

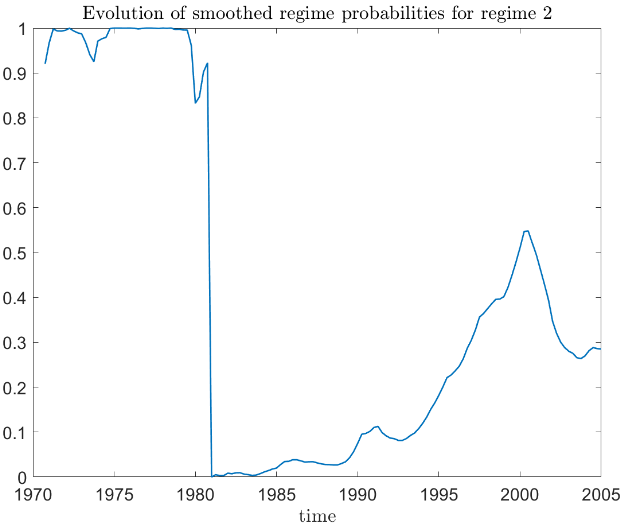
- Compute minimum state solution under FIRE
- Bayesian estimation on post-war U.S. data for (output growth, consumption growth, investment growth, wage growth, labor hours, inflation, Fed funds rate)
- Posterior mode estimates of monetary policy rule and transition matrix

	$\rho^R_{s_t}$	$\phi^{\Delta y}_{s_t}$	$\phi^{\pi}_{s_t}$	$P(1, s_t)$	$P(2, s_t)$
$s_t = 1$	0.68	0.29	2.07	0.979	0.034
$s_t = 2$	0.77	0.33	1.10	0.021	0.966

- Compute smoothed regime probabilities (Kim and Nelson, 1999) and infer implied regime $s_t = i$ if $Pr(s_t = i) > 0.5$

Back

Estimated monetary policy regimes (regime 2 = least aggressive regime)



Waves in simulated vs SPF forecast error regression coefficients