Monetary-Based Asset Pricing: A Mixed-Frequency Structural Approach

Francesco Bianchi[1] Sydney C. Ludvigson[2] Sai Ma[3]

[1]Johns Hopkins University, CEPR, and NBER

[2]New York University, CEPR, and NBER

[3]Federal Reserve Board

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Truism: Stock market is highly attuned to monetary news. Empirical evidence is consistent. Why?

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  1. **Classic view**: surprise announcements proxy for **Taylor rule shocks** that have short-run effects on real economy as in canonical New Keynesian models (creates a puzzle)
  2. **Return premia** fluctuate b/c MP shocks cause effective risk aversion, shifts in wealth distribution, or sentiment to change.
  3. Announcements impart information about economic state **"Fed information effect"**
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  3. Announcements impart information about economic state **"Fed information effect"**
  4. Markets surprised by **Fed's** *reaction* to recent economic data.
- **Empirical facts** largely established from **high-frequency event studies in tight windows** around **Fed communications** & **reduced-form** empirical specifications
- **Interpretations** of facts largely follow from carefully **calibrated theoretical models** designed to show that **one explanation fits** some aspects of reduced-form evidence.

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1. Theories focused on single channel are useful for elucidating its marginal effects, but may reveal only part of picture. **To what extent are several competing explanations or others entirely playing a role simultaneously?**
2. Monetary announcements cover range of topics: interest rate policy, forward guidance, quantitative interventions, macroeconomic outlook. **How do these varied communications affect investor perceptions of primitive economic sources of risk hitting the economy?**
3. High-frequency event studies only capture the causal effects of the *surprise* component of monetary policy, potentially a gross underestimate of overall causal impact. **How much of causal influence of shifting monetary policy occurs *outside* of tight windows around Fed announcements?**

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- We examine **Fed communications** alongside high- and lower-frequency data through lens of a **structural equilibrium asset pricing model** with New Keynesian style macro dynamics.
- Model & estimation allow for **jumps in investor beliefs** about latent **economic state**, the perceived sources of **economic risk**, and the future **conduct of monetary policy (MP)** in response to Fed announcements.
- **Structural approach** allows to investigate a **variety of possible explanations** for why markets respond strongly to central bank actions and announcements...
- ...not merely by delineating which expectations are revised, but also by providing **granular detail on** *perceived sources of risk* **responsible for forecast revisions**
- **Structural estimation** permits us to quantify the causal **impact of MP** ***outside*** **of tight windows** around Fed news events.

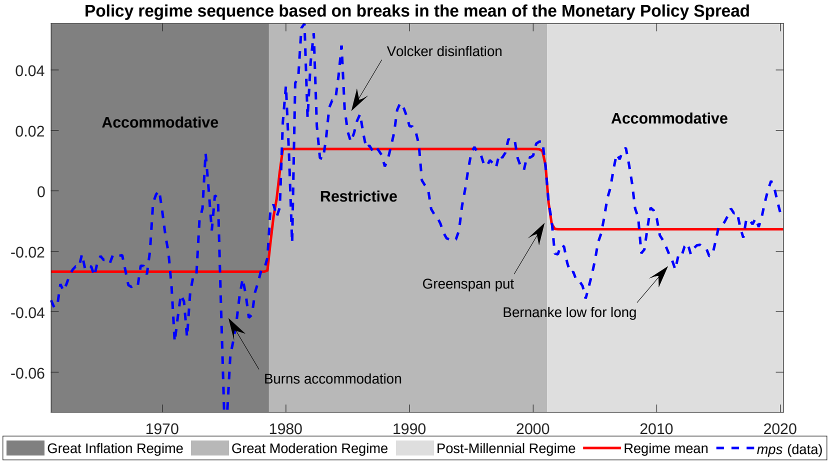
Related Literature on Fed and Markets

1. Real values of LT assets & return premia: Cochrane and Piazzesi (2002), Piazzesi (2005), Bernanke and Kuttner (2005), Hanson and Stein (2015), Gertler and Karadi (2015), Gilchrist, López-Salido, and Zakrajšek (2015), Boyarchenko, Haddad, and Plosser (2016), Pflueger and Rinaldi (2020), Kekre and Lenel (2021), Brooks, Katz, and Lustig (2018)
2. High-freq reactions proxy for monetary policy *shocks*: e.g., Cochrane and Piazzesi (2002), Piazzesi (2005), Hanson and Stein (2015), Kekre and Lenel (2021); Pflueger and Rinaldi (2020)
3. "Fed information effects"channel: Jarocinski and Karadi (2020), Cieslak and Schrimpf (2019), Romer and Romer (2000), Campbell, Evans, Fisher, Justiniano, Calomiris, and Woodford (2012), Melosi (2017), Nakamura and Steinsson (2018), Hillenbrand (2021)
4. Markets surprised by Fed's *response* to data Bauer and Swanson (2021), Bauer et. al., (2022)
5. Crisis episodes: Krishnamurthy and Vissing-Jorgensen (2011), Cox, Greenwald, and Ludvigson (2020), Haddad, Moreira, and Muir (2020)
6. Model builds on Bianchi, Lettau, and Ludvigson (2022) (BLL) with key differences:
   - Much larger mixed-frequency dataset
   - Explicitly model and estimate jumps in beliefs around announcements
   - More plausible *nonrecurrent* regime switching & **forward-looking data** to extract beliefs about the nature of future policy regimes.

Preliminary Evidence

Model-Free Evidence of Breaks in Monetary Policy Conduct

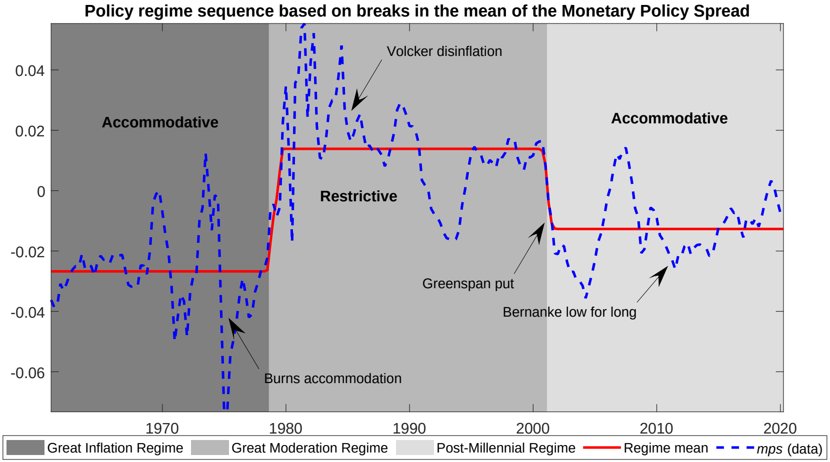
- Define: $mps_t \equiv FFR_t - Expected\ Inflation_t - r_t^*$



Note: Monetary policy spread $mps_t \equiv FFR_t - \text{Expected Inflation}_t - r_t^*$. r^* is from Laubach and Williams (2003). Accommodative regimes have $\overline{mps}_t < 0$; Restrictive regimes have $\overline{mps}_t > 0$. **GI regime: 1961:Q1-1978:Q3. GM regime: 1978:Q4-2001:Q3. PM regime: 2001:Q4-2020:Q1.** The full sample spans 1961:Q1-2020:Q1.

Model-Free Evidence of Breaks in Monetary Policy Conduct

- N-state *nonrecurrent* regime-switching Markov process, i.e., "structural breaks" for $\overline{mps}_t$



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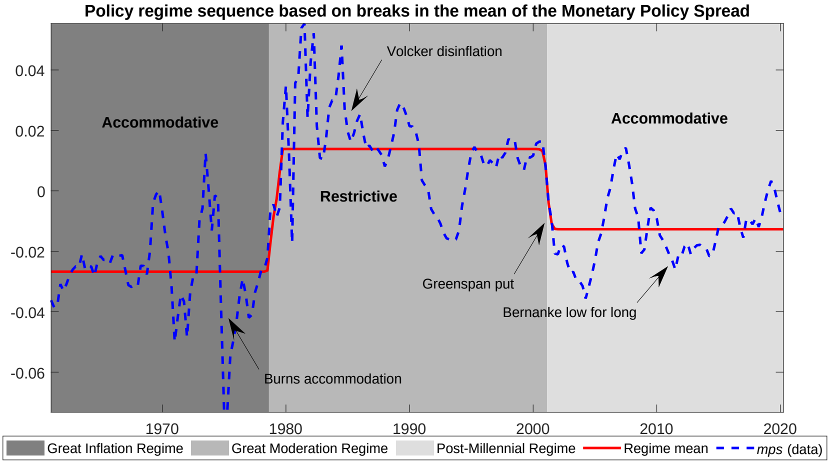
- Data: deviations in mps_t from 0 last *decades*



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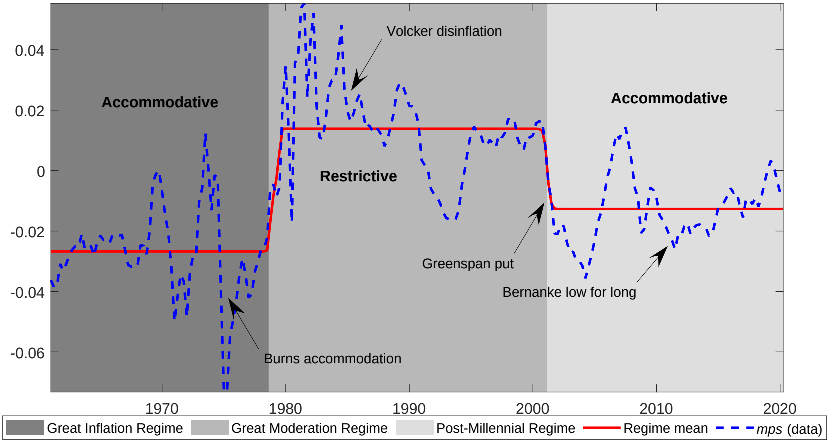
Model-Free Evidence of Breaks in Monetary Policy Conduct

- GI, PM regimes: extended accommodative episodes. GM: extended restrictive episode

Policy regime sequence based on breaks in the mean of the Monetary Policy Spread



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Preliminary Evidence: Dynamics of *mps*

- Take this as **model-free evidence** of breaks in the conduct of monetary policy over the sample.
- Use structural model to assess: did Fed's policy rule change across regime subperiods?
- Use breaks in $\overline{mps}_t$ to pin down *timing* of monetary regime changes in sample.
  - Avoids having to establish evidence on break dates that are **contingent on details** of structural model.
- Use Bayesian model comparison of different **structural models** to decide on $N_p = 3$ (number of regimes).

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  - **"Households":** workers invest in bonds only, whose **beliefs are key drivers of macro expectations**, i.e. expected π, Δgdp. HHs have "sticky"backward-looking expectations consistent with survey evidence (Malmendier and Nagel (2016)).

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- **Why 2 agents?**
  - **On one hand** Preliminary evidence suggests MP has persistent effects on real int. rate (RIR) => macro expectations subject to inertia (Bianchi, Lettau, and Ludvigson (2016) (BLL))
  - **On other hand** markets react swiftly to CB communications and actions, suggesting little inertia in expectations of market participants
  - **Reconcile** seemingly contradictory observations by considering 2 agents.

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  - **Reconcile** seemingly contradictory observations by considering 2 agents.
- **Decision interval and attentiveness**: both agents have monthly decision interval
  - Investors attend *within* a month to Fed announcements $\Rightarrow$ *jumps* in *investor* beliefs
- **Monetary Policy**: time-varying nominal int rate rule $\Rightarrow$ breaks in *conduct* of policy
  - Policy rule params treated as latent & freely estimated across nonrecurrent regimes ξ_t^P

Asset Pricing Dynamics

Representative investor:

- **Income only from 2 assets:** Stock market & nominal risk-free bond; consume agg. equity payout $D_t \equiv \exp(d_t)$. Assume $D_t = K_t Y_t$, with K_t **the payout** *share* **of** Y_t.

$$m_{t+1} = \log(\beta_p) + \vartheta_{pt} - \sigma_p(\Delta d_{t+1})$$ Log SDF

$$pd_t = \kappa_0 + \mu + \mathbb{E}_t^b[m_{t+1} + \Delta d_{t+1} + \kappa_1 pd_{t+1}] + .5\mathbb{V}_t^b[m_{t+1} + \Delta d_{t+1} + \kappa_1 pd_{t+1}]$$ Log price-payout ratio

$$i_t - \mathbb{E}_t^b[\pi_{t+1}] = -\mathbb{E}_t^b[m_{t+1}] - .5\mathbb{V}_t^b[m_{t+1} + i_t - \pi_{t+1}] - \underbrace{lp_t}_{\textbf{pref. bonds}}$$ Log Euler equation for bonds

$$\underbrace{\mathbb{E}_t^b[r_{t+1}^D] - \left(i_t - \mathbb{E}_t^b[\pi_{t+1}]\right)}_{\textbf{equity premium}} = \underbrace{\begin{bmatrix} -.5\mathbb{V}_t^b[r_{t+1}^D] - \mathbb{COV}_t^b[m_{t+1}, r_{t+1}^D] \\ +.5\mathbb{V}_t^b[\pi_{t+1}] - \mathbb{COV}_t^b[m_{t+1}, \pi_{t+1}] \end{bmatrix}}_{\textbf{subj risk premium}} + \underbrace{lp_t}_{\textbf{liquidity Premium}},$$ Perceived Equity Premium

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Macro Dynamics: Households and the Central Bank

Let $\tilde{y}_t \equiv \ln(Y_t/A_t)$ w/ $g_t \equiv \ln(A_t/A_{t-1})$ is **stochastic trend growth** $=>$ $\tilde{y}_t$ is output gap.

$$\widetilde{y}_t = \varrho \widetilde{y}_{t-1} - \sigma \left[i_t - \phi \pi_t - (1-\phi)\overline{\pi}_t - r_{ss} \right] + \underbrace{f_t}_{\text{demand shock}}$$

Real activity

$$\pi_t = \overline{\pi}_t + \frac{\kappa_0}{1-\beta\phi}\widetilde{y}_t + \frac{\kappa_1}{1-\beta\phi}\widetilde{y}_{t-1} + \sigma_\mu \underbrace{\varepsilon_{\mu,t}}_{\text{markup shock}}$$

Phillips curve

$$i_t - \left(\bar{r} + \pi^T_{\xi^p_t}\right) = \left(1 - \rho_{i_1,\xi^p_t} - \rho_{i_2,\xi^p_t}\right)\left[\psi_{\pi,\xi^p_t}\left(\pi_{t,t-3} - 3\pi^T_{\xi^p_t}\right) + \psi_{\Delta y,\xi^p_t}\left(\Delta y_{t,t-3}\right)\right]$$

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Monetary Policy Rule

$$\overline{\pi}_t = \left[1 - \gamma^T\right] \underbrace{\left[\overline{\pi}_{t-1} + \gamma (1-\phi)^{-1} \left(\pi_t - \phi\pi_{t-1} - (1-\phi)\overline{\pi}_{t-1}\right)\right]}_{\textbf{constant gain learning}} + \underbrace{\gamma^T \pi^T_{\xi^P_t}}_{\textbf{inflation target signal}}$$

Perceived trend inflation

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- Prototypical New Keynesian Model w/ 4 Gaussian shocks but w/ 3 modifications:

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- Prototypical New Keynesian Model w/ 4 Gaussian shocks but w/ 3 modifications:
  1. **Policy rule changes:** Regime Shifts in $\pi^T_{\xi^P_t}$ and activism coefficients.
  2. **Learning and adaptive expectations:** Agent learns about *trend* inflation $\overline{\pi}_t$ using constant-gain learning (Malmendier and Nagel (2016)) + backward-looking rule to form expectations of y_{t+i}.
  3. **Perceived $\overline{\pi}_t \neq \pi^T_{\xi^P_t}$:** Agents don't directly observe $\pi^T_{\xi^P_t}$ and/or CB announcements not viewed as fully credible or informative. Magnitude of γ^T related to **CB credibility**

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$$\pi_t = \overline{\pi}_t + \frac{\kappa_0}{1-\beta\phi}\widetilde{y}_t + \frac{\kappa_1}{1-\beta\phi}\widetilde{y}_{t-1} + \sigma_\mu \underbrace{\varepsilon_{\mu,t}}_{\text{markup shock}} \qquad \text{Phillips curve}$$

$$i_t - \left(\overline{r} + \pi^T_{\xi^p_t}\right) = \left(1 - \rho_{i_1,\xi^p_t} - \rho_{i_2,\xi^p_t}\right)\left[\psi_{\pi,\xi^p_t}\left(\pi_{t,t-3} - 3\pi^T_{\xi^p_t}\right) + \psi_{\Delta y,\xi^p_t}\left(\Delta y_{t,t-3}\right)\right]$$

$$+ \rho_{i_1,\xi^p_t}\left[i_{t-1} - \left(\overline{r} + \pi^T_{\xi^p_t}\right)\right] + \rho_{i_2,\xi^p_t}\left[i_{t-2} - \left(\overline{r} + \pi^T_{\xi^p_t}\right)\right] + \sigma_i \underbrace{\varepsilon_{i,t}}_{\text{monetary policy shock}} \qquad \text{Monetary Policy Rule}$$

$$\overline{\pi}_t = \left[1 - \gamma^T\right]\underbrace{\left[\overline{\pi}_{t-1} + \gamma(1-\phi)^{-1}\left(\pi_t - \phi\pi_{t-1} - (1-\phi)\overline{\pi}_{t-1}\right)\right]}_{\text{constant gain learning}} + \underbrace{\gamma^T \pi^T_{\xi^P_t}}_{\text{inflation target signal}} \qquad \text{Perceived trend inflation}$$

Macro Dynamics: Households and the Central Bank

Let $\tilde{y}_t \equiv \ln(Y_t/A_t)$ w/ $g_t \equiv \ln(A_t/A_{t-1})$ is **stochastic trend growth** $=>$ $\tilde{y}_t$ is output gap.

- Prototypical New Keynesian Model w/ 4 Gaussian shocks but w/ 3 modifications:
  1. **Policy rule changes:** Regime Shifts in $\pi^T_{\xi^p_t}$ and activism coefficients.
  2. **Learning and adaptive expectations:** Agent learns about *trend* inflation $\overline{\pi}_t$ using constant-gain learning (Malmendier and Nagel (2016)) + backward-looking rule to form expectations of y_{t+i}.
  3. **Perceived $\overline{\pi}_t \neq \pi^T_{\xi^p_t}$:** Agents don't directly observe $\pi^T_{\xi^p_t}$ and/or CB announcements not viewed as fully credible or informative. Magnitude of γ^T related to **CB credibility**
- Exogenous: f_t, g_t follow AR(1) LOMs; 4 Gaussian shocks: $\varepsilon_{f,t}, \varepsilon_{\mu,t}, \varepsilon_{g,t}, \varepsilon_{i,t}$
- Investors take below as given, form beliefs about regime shifts in MP.

$$\widetilde{y}_t = \varrho \widetilde{y}_{t-1} - \sigma\left[i_t - \phi\pi_t - (1-\phi)\overline{\pi}_t - r_{ss}\right] + \underbrace{f_t}_{\text{demand shock}} \qquad \text{Real activity}$$

$$\pi_t = \overline{\pi}_t + \frac{\kappa_0}{1-\beta\phi}\widetilde{y}_t + \frac{\kappa_1}{1-\beta\phi}\widetilde{y}_{t-1} + \sigma_\mu \underbrace{\varepsilon_{\mu,t}}_{\text{markup shock}} \qquad \text{Phillips curve}$$

$$i_t - \left(\bar{r} + \pi^T_{\xi^p_t}\right) = \left(1 - \rho_{i_1,\xi^p_t} - \rho_{i_2,\xi^p_t}\right)\left[\psi_{\pi,\xi^p_t}\left(\pi_{t,t-3} - 3\pi^T_{\xi^p_t}\right) + \psi_{\Delta y,\xi^p_t}\left(\Delta y_{t,t-3}\right)\right]$$
$$+ \rho_{i_1,\xi^p_t}\left[i_{t-1} - \left(\bar{r} + \pi^T_{\xi^p_t}\right)\right] + \rho_{i_2,\xi^p_t}\left[i_{t-2} - \left(\bar{r} + \pi^T_{\xi^p_t}\right)\right] + \sigma_i \underbrace{\varepsilon_{i,t}}_{\text{monetary policy shock}} \qquad \text{Monetary Policy Rule}$$

$$\overline{\pi}_t = \left[1 - \gamma^T\right]\underbrace{\left[\overline{\pi}_{t-1} + \gamma(1-\phi)^{-1}\left(\pi_t - \phi\pi_{t-1} - (1-\phi)\overline{\pi}_{t-1}\right)\right]}_{\textbf{constant gain learning}} + \underbrace{\gamma^T \pi^T_{\xi^p_t}}_{\textbf{inflation target signal}} \qquad \text{Perceived trend inflation}$$

Investor Beliefs

Investor beliefs key to how shifts in conduct of MP affect asset valuations, return premia

- Investors understand $\exists$ infrequent, **nonrecurrent regime** changes in policy rule.
- Requires model of how **expectations** are formed in presence of **structural breaks**.
- They **monitor** CB communications, can observe/estimate *current* rule.
- They are **uncertain** about *how long* any regime will last and what will come next.
- For each realized regime ξ_t^P they **contemplate an Alternative regime** ξ_t^A they perceive will come next:

$$
\begin{aligned}
i_t - \left(\bar{r} + \pi^T_{\xi_t^A}\right) \quad &= \quad \left(1 - \rho_{i_1,\xi_t^A} - \rho_{i_2,\xi_t^A}\right)\left[\psi_{\pi,\xi_t^A}\left(\pi_{t,t-3} - 3\pi^T_{\xi_t^A}\right) + \psi_{\Delta y,\xi_t^A}\left(\Delta y_{t,t-3}\right)\right] \\
&+\rho_{i_1,\xi_t^A}\left[i_{t-1} - \left(\bar{r} + \pi^T_{\xi_t^A}\right)\right] + \rho_{i_2,\xi_t^A}\left[i_{t-2} - \left(\bar{r} + \pi^T_{\xi_t^A}\right)\right] + \sigma_i \varepsilon_i
\end{aligned}
$$

- Investors form **beliefs about the probability of staying** in ξ_t^P versus switching to ξ_t^A.

Belief Regimes

- $\xi_t^b = 1, 2, ...B$: **grid** of *perceived probabilities* that current policy rule will *remain* in $t+1$
- $\xi_t^b = B+1$: a regime rep. the perceived probability of *staying* in ξ_t^A once there.

$$\mathbf{H}^b = \begin{bmatrix} p_{b1}p_s & p_{b2}p_{\Delta 1|2} & \cdots & p_{bB}p_{\Delta 1|B} & 0 \\ p_{b1}p_{\Delta 2|1} & p_{b2}p_s & & p_{bB}p_{\Delta 2|B} & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ p_{b1}p_{\Delta B|1} & & & p_{bB}p_s & 0 \\ 1-p_{b1} & 1-p_{b2} & \cdots & 1-p_{bB} & p_{B+1,B+1}=1 \end{bmatrix},$$

where $\mathbf{H}_{ij}^b \equiv p\left(\xi_t^b = i | \xi_{t-1}^b = j\right)$, $\sum_{i \neq j} p_{\Delta i|j} = 1 - p_s$. ξ_t^A is an absorbing state–a form of **bounded rationality**.

- p_{b1}: subj prob of remaining in ξ_t^P under belief 1, e.g., $p_{b1} = 0.05$
- Non-zero **off-diagonal elements**: agents know they might *change their beliefs*
- $p_{\Delta i|j}$: prob agents assign to *changing their minds* due to new information
- p_s: probability investors assign to *not changing* their minds
- $p_{bj}p_s$: prob of belief j tomorrow, conditional on j today
- $p_{bj}p_{\Delta i|j}$: prob of any belief $i \neq j, i \in \{1, ..., B\}$ at $t+1$ conditional on j today
- $1 - p_{bj}$: prob of belief j today but exiting to ξ_t^A at $t+1$

Model Solution

- **Economic state**:
$$S_t = \left[S_t^M, m_t, pd_t, k_t, lp_t, \mathbb{E}_t^b\left(m_{t+1}\right), \mathbb{E}_t^b\left(pd_{t+1}\right)\right],$$
where $S_t^M \equiv [\widetilde{y}_t, g_t, \pi_t, i_t, \overline{\pi}_t, f_t]$
- **Solution in form of MS-VAR**:
$$S_t = \underbrace{C\left(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b\right)}_{\text{level}} + \underbrace{T\left(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b\right)}_{\text{propagation}} S_{t-1} + \underbrace{R\left(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b\right)}_{\text{amplification}} Q\varepsilon_t, \qquad \text{(State Eqn)}$$
where $\varepsilon_t = \left(\varepsilon_{f,t}, \varepsilon_{i,t}, \varepsilon_{g,t}, \varepsilon_{k,t}, \varepsilon_{lp,t}, \varepsilon_{\mu,t}\right)$ is the vector of Gaussian shocks.

Model Solution

- **Economic state**:

$$S_t = \left[S_t^M, m_t, pd_t, k_t, lp_t, \mathbb{E}_t^b\left(m_{t+1}\right), \mathbb{E}_t^b\left(pd_{t+1}\right)\right],$$

where $S_t^M \equiv [\tilde{y}_t, g_t, \pi_t, i_t, \overline{\pi}_t, f_t]$

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where $\varepsilon_t = \left(\varepsilon_{f,t}, \varepsilon_{i,t}, \varepsilon_{g,t}, \varepsilon_{k,t}, \varepsilon_{lp,t}, \varepsilon_{\mu,t}\right)$ is the vector of Gaussian shocks.

- **Beliefs about future conduct of MP & ξ_t^P** affect equilibrium economy three ways:

Model Solution

- **Economic state**:

$$S_t = \left[S_t^M, m_t, pd_t, k_t, lp_t, \mathbb{E}_t^b\left(m_{t+1}\right), \mathbb{E}_t^b\left(pd_{t+1}\right) \right],$$

  where $S_t^M \equiv [\widetilde{y}_t, g_t, \pi_t, i_t, \overline{\pi}_t, f_t]$

- **Solution in form of MS-VAR**:

$$S_t = \underbrace{C\left(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b\right)}_{\text{level}} + \underbrace{T\left(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b\right)}_{\text{propagation}} S_{t-1} + \underbrace{R\left(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b\right)}_{\text{amplification}} Q\varepsilon_t, \qquad \text{(State Eqn)}$$

  where $\varepsilon_t = \left(\varepsilon_{f,t}, \varepsilon_{i,t}, \varepsilon_{g,t}, \varepsilon_{k,t}, \varepsilon_{lp,t}, \varepsilon_{\mu,t}\right)$ is the vector of Gaussian shocks.

- **Beliefs about future conduct of MP & ξ_t^P** affect equilibrium economy three ways:
  1. **Level** $C(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b)$: moves with changes in CB's objectives and subj risk premium
  2. **Propagation** $T(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b)$: affect how today's state is related to tomorrow's
  3. **Amplification** $R(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b)$: **endogenous heteroskedasticity** of Gaussian shocks

Model Solution

- **Economic state**:

$$S_t = \left[S_t^M, m_t, pd_t, k_t, lp_t, \mathbb{E}_t^b\left(m_{t+1}\right), \mathbb{E}_t^b\left(pd_{t+1}\right)\right],$$

where $S_t^M \equiv [\widetilde{y}_t, g_t, \pi_t, i_t, \overline{\pi}_t, f_t]$

- **Solution in form of MS-VAR**:

$$S_t = \underbrace{C\left(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b\right)}_{\text{level}} + \underbrace{T\left(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b\right)}_{\text{propagation}} S_{t-1} + \underbrace{R\left(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b\right)}_{\text{amplification}} Q\varepsilon_t, \qquad \text{(State Eqn)}$$

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  1. **Level** $C(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b)$: moves with changes in CB's objectives and subj risk premium
  2. **Propagation** $T(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b)$: affect how today's state is related to tomorrow's
  3. **Amplification** $R(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b)$: **endogenous heteroskedasticity** of Gaussian shocks
- Investor **beliefs about future conduct of monetary policy** amplify and propagate shocks that are **entirely non-monetary** in nature.

Model Solution

- **Economic state**:

$$S_t = \left[S_t^M, m_t, pd_t, k_t, lp_t, \mathbb{E}_t^b\left(m_{t+1}\right), \mathbb{E}_t^b\left(pd_{t+1}\right)\right],$$

  where $S_t^M \equiv [\widetilde{y}_t, g_t, \pi_t, i_t, \overline{\pi}_t, f_t]$

- **Solution in form of MS-VAR**:

$$S_t = \underbrace{C\left(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b\right)}_{\text{level}} + \underbrace{T\left(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b\right)}_{\text{propagation}} S_{t-1} + \underbrace{R\left(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b\right)}_{\text{amplification}} Q\varepsilon_t, \qquad \text{(State Eqn)}$$

  where $\varepsilon_t = \left(\varepsilon_{f,t}, \varepsilon_{i,t}, \varepsilon_{g,t}, \varepsilon_{k,t}, \varepsilon_{lp,t}, \varepsilon_{\mu,t}\right)$ is the vector of Gaussian shocks.

- **Beliefs about future conduct of MP & ξ_t^P** affect equilibrium economy three ways:
  1. **Level** $C(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b)$: moves with changes in CB's objectives and subj risk premium
  2. **Propagation** $T(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b)$: affect how today's state is related to tomorrow's
  3. **Amplification** $R(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b)$: **endogenous heteroskedasticity** of Gaussian shocks

- **Endog heteroskedasticity** $\rightarrow$ *perceived quantity of risk & subj risk premia* vary only with ξ_t^P and expected **future conduct of monetary policy** via ξ_t^b .

Investor Decision Interval and Updating

- **Investor information set**: The time t information set $\mathbb{I}_t$ includes ξ_t^b, ξ_t^P and ξ_t^A, and additional data observable as of t.
- **Economic state S_t observed at end of t, but *during* t S_t is latent** $\rightarrow$ within the month investors filter information $\mathbb{I}_t$ to arrive at *nowcasts* of S_t.
- **Two ways agents use $\mathbb{I}_t$** :
  1. Given a monthly decision interval, update previous *nowcasts* of S_t and their subjective expectations on the basis of new information at the **end of every month**.
  2. Allocate attention to updating nowcasts and beliefs *within* a month when the **central bank releases information**.
     - Echoes real-world **"Fed watching"**
     - Mechanism by which **model accommodates swift market reactions** to Fed news
     - Updates **in the aftermath of Fed news** lead to *endogenous jumps* in **subjective expectations**, financial market **returns**, and **subjective risk premia**, which vary with ξ_t^b, ξ_t^P ..

Structural Estimation: Bayesian Methods Estimate Posterior

- **Mixed-frequency filtering**: Kim's (Kim (1994)) basic filter and approximation to the likelihood for **Markov-switching state space models** (combine State Eqn with Obs Eqn)
- **Mixed frequency structural estimation** **"zooms in"** on revisions in estimates of S_t and $\Pr(\xi_t^b|\boldsymbol{\theta}, X^{t-1+d_i/nd})$ *in tight windows* around FOMC announcements; **"zooms out"** at lower monthly frequencies when more data is available
- **Filter high frequency, forward-looking data** to infer, around Fed announcements:
  1. Jumps in beliefs ξ_t^b about prob of *exiting* current regime (Hamilton filter)
  2. Jumps in *nowcasts* of economic state S_t *(Fed information effect)* (Kalman filter)
     - **Granular detail**: decompose market responses into perceived sources of risk that drive jumps in forward-looking variables
  3. Endogenous jumps in *perceived risk* of stock market
- **Higher** *and* **lower frequency Macro data** informs the true policy regimes and structural relations over full sample, *including* the Alternative Rule Alternative Rule
- **Policy Rule Parameters** estimated under **flat priors**
- **Parameter uncertainty**: Random-walk metropolis Hastings MCMC algorithm

Data

Sample for structural estimation: 1961:M1-2020:M2. Data used for Obs Eqn Observation equation

- Fed news: 220 FOMC press releases spanning February 4, 1994 to February, 2020.
- Monthly: GDP growth, CPI inflation, fed funds rate (FFR), ratio of S&P 500 earnings to lagged GDP, the University of Michigan SOC 12- and 60-month ahead mean inflation forecast, Bluechip (BC), Survey of Professional Forecasters (SPF), and Livingston (LIV) survey's of mean 12-month and 120-month ahead CPI inflation forecast; SPF mean 12-month GDP deflator inflation forecast; BC and SPF mean 12-month ahead GDP growth forecasts. BC mean 12-month ahead FFR forecast. Moody's Baa 20-year bond return minus the 20-year U.S. Treasury bond ("Baa spread").
- Daily: mean of the Bloomberg (BBG) consensus 12-month ahead inflation and GDP growth forecasts.
- Minutely: ratio of S&P 500 market capitalization to lagged GDP, current contract and 6, 10, 20, and 35 month contracts of fed funds futures (FFF) prices.

PARAMETER AND LATENT STATE ESTIMATES

Policy Rule Parameter Estimates

- Large changes in policy rule across regimes

		Great Inflation Regime		Great Moderation Regime		Post-Millennial Regime	
		Realized	Alternative	Realized	Alternative	Realized	Alternative
Infl. target	π^T_ξ	12.53	11.85	1.91	0.82	2.49	0.06
Infl. activism	ψ_π	1.48	2.07	3.00	3.61	0.00	0.67
Growth activism	$\psi_{\Delta y}$	1.20	0.03	0.00	0.68	0.08	0.53
Rel. activism	$\psi_\pi / \psi_{\Delta y}$	1.24	59.41	6014	5.33	0.00	1.28
Autocorr. coef.	$\rho_{i,1} + \rho_{i,2}$	0.99	0.82	0.99	0.99	0.99	0.94

Notes: The table reports the posterior mode estimates of the parameters for the realized and perceived Alternative policy rules. **GI regime: 1961:Q1-1978:Q3**. **GM regime: 1978:Q4-2001:Q3**. **PM regime: 2001:Q4-2020:Q1**. The estimation sample spans 1961:Q1-2020:Q1.

Policy Rule Parameter Estimates

- GI vs GM regimes: GI has higher π target, lower activism on π

		Great Inflation Regime		Great Moderation Regime		Post-Millennial Regime	
		Realized	Alternative	Realized	Alternative	Realized	Alternative
Infl. target	π^T_ξ	12.53	11.85	1.91	0.82	2.49	0.06
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Policy Rule Parameter Estimates

- GM vs PM regimes: PM has higher π target, virtually *no* activism on π or Δy.

		Great Inflation Regime		Great Moderation Regime		Post-Millennial Regime	
		Realized	Alternative	Realized	Alternative	Realized	Alternative
Infl. target	π^T_ξ	12.53	11.85	1.91	0.82	2.49	0.06
Infl. activism	ψ_π	1.48	2.07	3.00	3.61	0.00	0.67
Growth activism	$\psi_{\Delta y}$	1.20	0.03	0.00	0.68	0.08	0.53
Rel. activism	$\psi_\pi / \psi_{\Delta y}$	1.24	59.41	6014	5.33	0.00	1.28
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Notes: The table reports the posterior mode estimates of the parameters for the realized and perceived Alternative policy rules. **GI regime: 1961:Q1-1978:Q3**. **GM regime: 1978:Q4-2001:Q3**. **PM regime: 2001:Q4-2020:Q1**. The estimation sample spans 1961:Q1-2020:Q1.

Policy Rule Parameter Estimates

- Alternative rule in PM: lower π target than realized PM rule, but investors expected much *more activism* to stabilize economy => PM Alt regime is *more hawkish and more active*

		Great Inflation Regime		Great Moderation Regime		Post-Millennial Regime	
		Realized	Alternative	Realized	Alternative	Realized	Alternative
Infl. target	π^T_ξ	12.53	11.85	1.91	0.82	2.49	0.06
Infl. activism	ψ_π	1.48	2.07	3.00	3.61	0.00	0.67
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Notes: The table reports the posterior mode estimates of the parameters for the realized and perceived Alternative policy rules. **GI regime: 1961:Q1-1978:Q3**. **GM regime: 1978:Q4-2001:Q3**. **PM regime: 2001:Q4-2020:Q1**. The estimation sample spans 1961:Q1-2020:Q1.

Other Parameter Estimates

- High degree of inertia in **household inflation expectations**

Parameter	Mode	Parameter	Mode	Parameter	Mode	Parameter	Mode
σ	0.05	γ^T	0.01	σ_f	17.25	σ_{lp}	0.62
β	0.75	σ_p	6.01	σ_i	0.03	σ_g	1.91
ϕ	0.74	β_p	0.99	σ_μ	0.13		
γ	1×10^{-4}	p_s	0.99	σ_k	6.13		

Notes: The table reports the posterior mode estimates of the parameters named in the row. The estimation sample spans 1961:Q1-2020:Q1.

Other Parameter Estimates

- Constant gain param γ controlling speed with which LT π expecations are updated is very low

Parameter	Mode	Parameter	Mode	Parameter	Mode	Parameter	Mode
σ	0.05	γ^T	0.01	σ_f	17.25	σ_{lp}	0.62
β	0.75	σ_p	6.01	σ_i	0.03	σ_g	1.91
ϕ	0.74	β_p	0.99	σ_μ	0.13		
γ	1×10^{-4}	p_s	0.99	σ_k	6.13		

Notes: The table reports the posterior mode estimates of the parameters named in the row. The estimation sample spans 1961:Q1-2020:Q1.

Other Parameter Estimates

- Inflation target signal param γ^T small $\rightarrow$ changes in $\pi^T_{\xi^P_t}$ had limited credibility to quickly change LR π^e of HHs $\rightarrow$ policy rule changes require large, persistent changes in real rates to substantially alter π_t and growth.

Parameter	Mode	Parameter	Mode	Parameter	Mode	Parameter	Mode
σ	0.05	γ^T	0.01	σ_f	17.25	σ_{lp}	0.62
β	0.75	σ_p	6.01	σ_i	0.03	σ_g	1.91
ϕ	0.74	β_p	0.99	σ_μ	0.13		
γ	1×10^{-4}	p_s	0.99	σ_k	6.13		

Notes: The table reports the posterior mode estimates of the parameters named in the row. The estimation sample spans 1961:Q1-2020:Q1.

Other Parameter Estimates

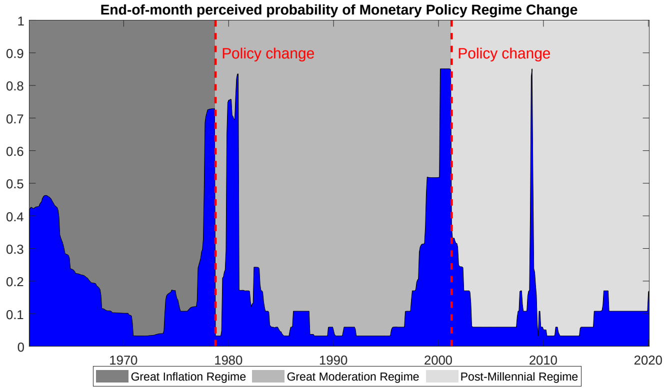
- Risk aversion moderate

Parameter	Mode	Parameter	Mode	Parameter	Mode	Parameter	Mode
σ	0.05	γ^T	0.01	σ_f	17.25	σ_{lp}	0.62
β	0.75	σ_p	6.01	σ_i	0.03	σ_g	1.91
ϕ	0.74	β_p	0.99	σ_μ	0.13		
γ	1×10^{-4}	p_s	0.99	σ_k	6.13		

Notes: The table reports the posterior mode estimates of the parameters named in the row. The estimation sample spans 1961:Q1-2020:Q1.

STRUCTURAL ESTIMATION RESULTS: MARKETS AND MONETARY POLICY

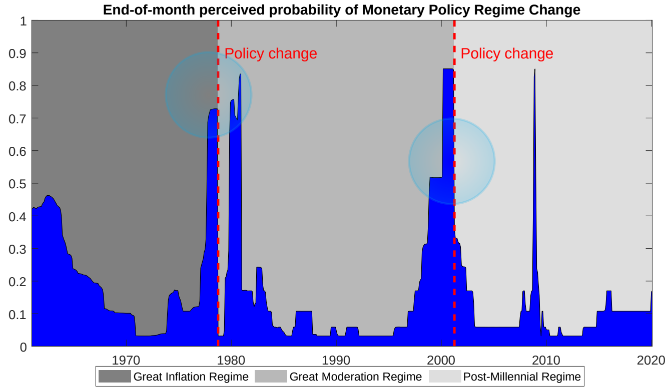
Perceived Probability of Monetary Policy Regime Change



Notes: The figure displays the estimated end-of-month perceived probability investors assign to exiting the current monetary policy rule within one year, computed as the estimated perceived transition probability of being in the Alternative rule at $t + 12$ under each $\xi_t^b = i$, weighted by the smoothed regime probabilities $\Pr(\xi_t^b = i | X_T; \boldsymbol{\theta})$. The sample spans 1961:M1-2020:M2.

Perceived Probability of Monetary Policy Regime Change

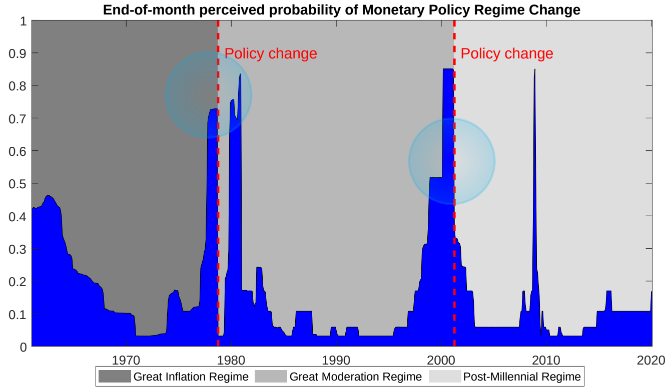
- Perceived prob of regime change fluctuates and increases before a realized rule change



Notes: The figure displays the estimated end-of-month perceived probability investors assign to exiting the current monetary policy rule within one year, computed as the estimated perceived transition probability of being in the Alternative rule at $t + 12$ under each $\xi_t^b = i$, weighted by the smoothed regime probabilities $\Pr(\xi_t^b = i | X_T; \boldsymbol{\theta})$. The sample spans 1961:M1-2020:M2.

Perceived Probability of Monetary Policy Regime Change

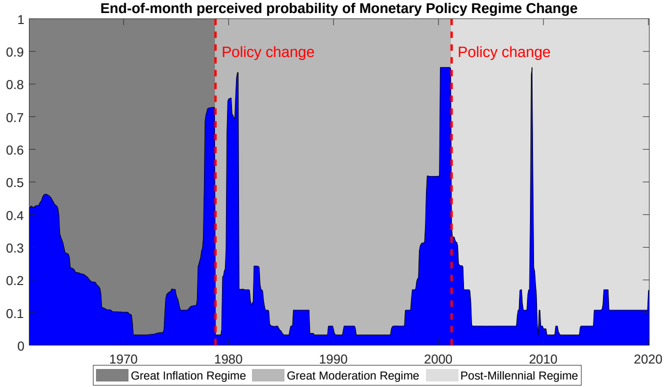
- Anticipation happens even though investors cannot perfectly predict new rule



Notes: The figure displays the estimated end-of-month perceived probability investors assign to exiting the current monetary policy rule within one year, computed as the estimated perceived transition probability of being in the Alternative rule at $t+12$ under each $\xi_t^b = i$, weighted by the smoothed regime probabilities $\Pr(\xi_t^b = i | X_T; \boldsymbol{\theta})$. The sample spans 1961:M1-2020:M2.

Perceived Probability of Monetary Policy Regime Change

- Beliefs about regime change continuously evolve *out*side of tight windows around FOMC



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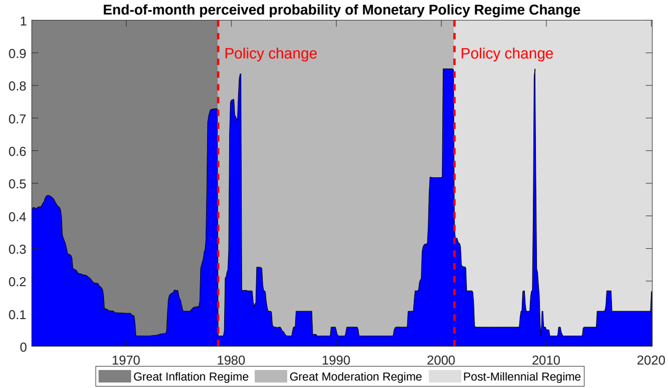
Perceived Probability of Monetary Policy Regime Change

- Announcements contain forward guidance on likely triggers of change in policy conduct



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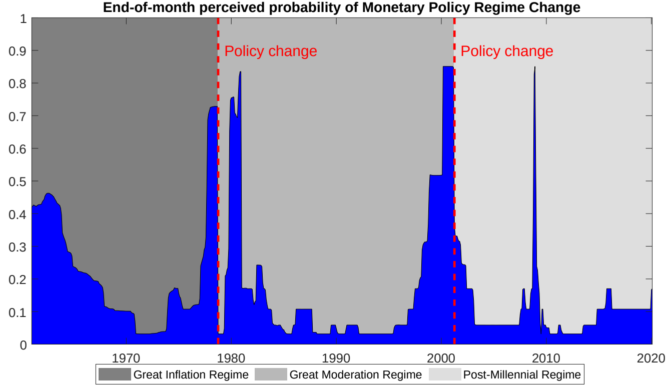
Perceived Probability of Monetary Policy Regime Change

- **Key result**: new data *in between* Fed communications cause revisions in beliefs about future monetary policy that have consequences for markets



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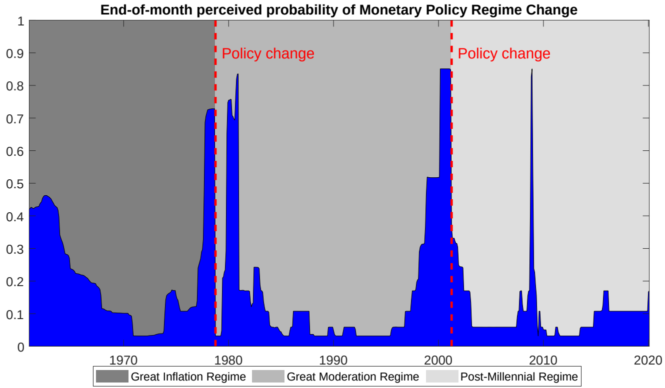
Perceived Probability of Monetary Policy Regime Change

- Event studies *under*estimate causal impact of Fed on markets



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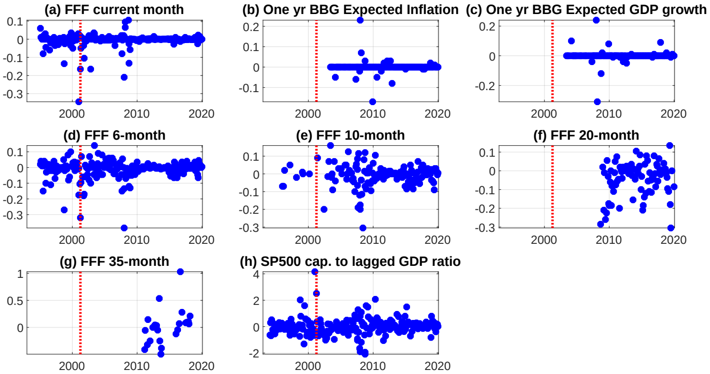
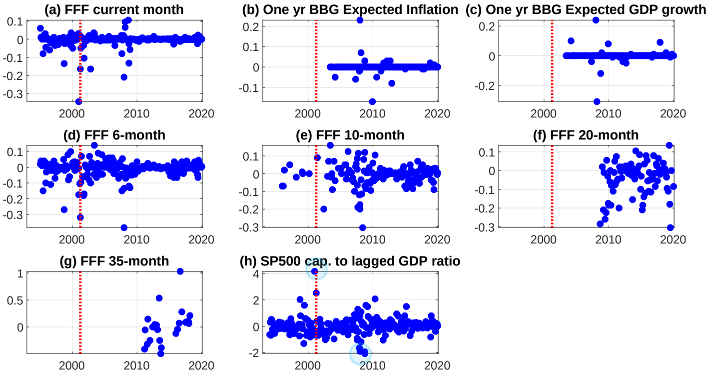
Jumps in Markets & Expectations at FOMC Announcements



Notes: For each FOMC meeting in our sample the figure shows the log change in the observed variables in a short time-window around FOMC meetings. For all but panels (b) and (c), this corresponds to a change measured from 10 minutes before to 20 minutes after an FOMC statement is released. For panels (b) and (c), this corresponds to one day before to one day after the FOMC statement is released. The full sample has 220 FOMC announcements spanning February 4th, 1994 to February 28th, 2020. The sample reported in the figure is 1993:M1-2020:M2.

Jumps in Markets & Expectations at FOMC Announcements

- Some announcements associated with **declines** within 30 min of an FOMC press release in stock market that **exceed 2% in absolute terms, or increases above 4%**.



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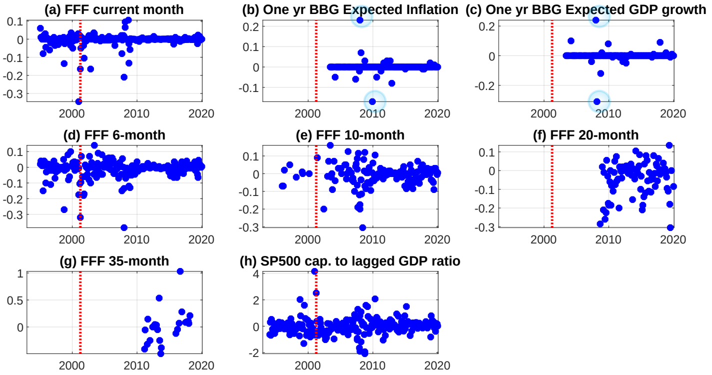
Jumps in Markets & Expectations at FOMC Announcements

- But also some big professional forecast revisions in one-year-ahead **inflation, GDP growth**.



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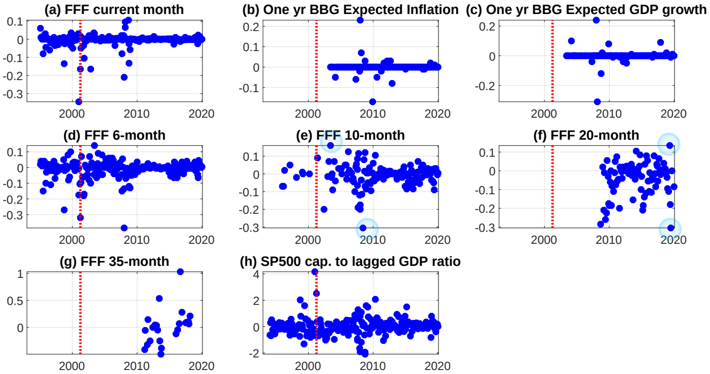
Jumps in Markets & Expectations at FOMC Announcements

- And some big jumps in futures markets.



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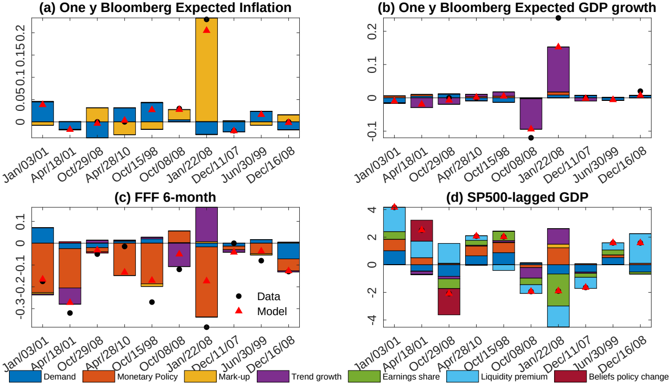
What do Markets Learn from Fed Announcements?

- Next results revisit debate in the literature. What do markets learn from monetary news?
  1. About monetary policy shocks?
  2. About the economic state? (What specifically about the state is learned?)
  3. About the likely conduct of future monetary policy?
- The above endogenously affect perceived risk in the stock market, i.e., subjective risk premia.
- Next: **our estimate** of contribution of **revisions in investors' perceived shocks and beliefs about future policy** to jumps in HF variables in **tight windows** around FOMC announcements.
- **Perceived shocks**: revisions in *nowcasts* of S_t $\rightarrow$ Our filtering allows us to **infer investor updating** not only of economic state S_t, but also *updating of shocks they perceive are hitting* the economy. Detail Granular detail on *why* beliefs about economic state are revised.
- Focus on **10 most quantitatively relevant announcements** for a particular variable (e.g., the stock market).

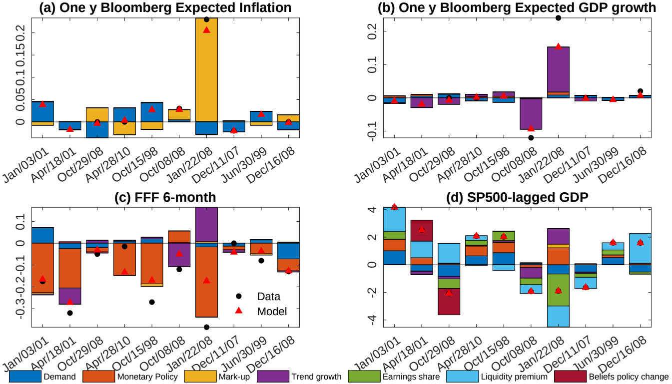
Top Ten FOMC Announcements for Jumps in the Stock Market



The figure reports the decomposition of movements in Bloomberg expected inflation, Bloomberg expected GDP growth, the 6-month FFF rates, and the stock market attributable to revisions in the perceived shocks hitting the economy and in the belief regimes for the 10 most relevant FOMC announcements based on changes in the SP500-lagged GDP ratio. Since there are no observation errors in the SP500 to lagged GDP observation equation, the black dot (data) and the red triangle (estimation) lie on top of each other in panel (d). The sample is 1961:M1-2020:M2.

Top Ten FOMC Announcements for Jumps in the Stock Market

- Most events → *downward* revision in 6-mo FFF rate, implying policy more accommodative than anticipated–see Cieslack '18, Schmeling et. al., '20; Bauer & Swanson '21



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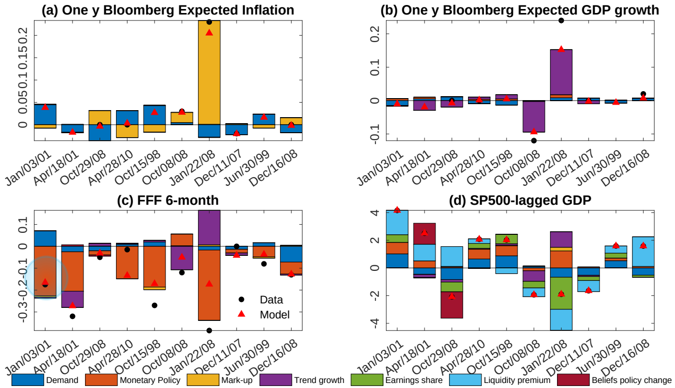
Top Ten FOMC Announcements for Jumps in the Stock Market

- Biggest jump: FOMC of Jan 3, 2001 when FFR lowered by unusually large 50 basis points



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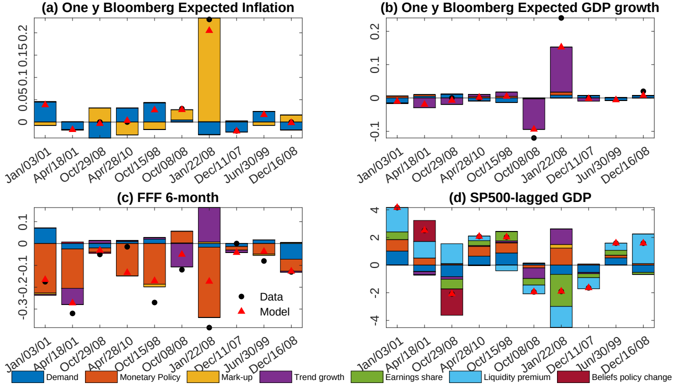
Top Ten FOMC Announcements for Jumps in the Stock Market

- Surprise movements not solely the result of perceived monetary policy shock.



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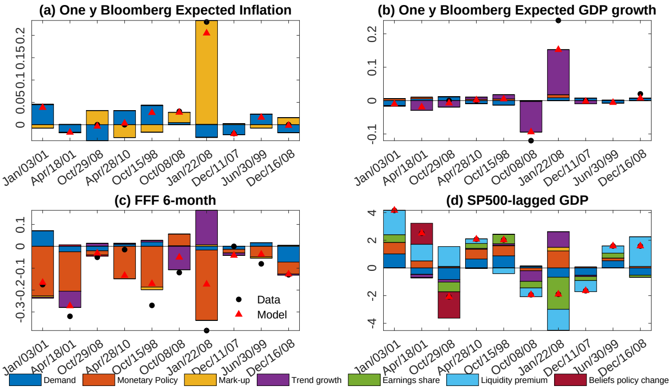
Top Ten FOMC Announcements for Jumps in the Stock Market

- Jan 3, 2001: *down*ward revision in nowcast for liquidity premium *up*ward revision in nowcasts for agg demand & earnings share,



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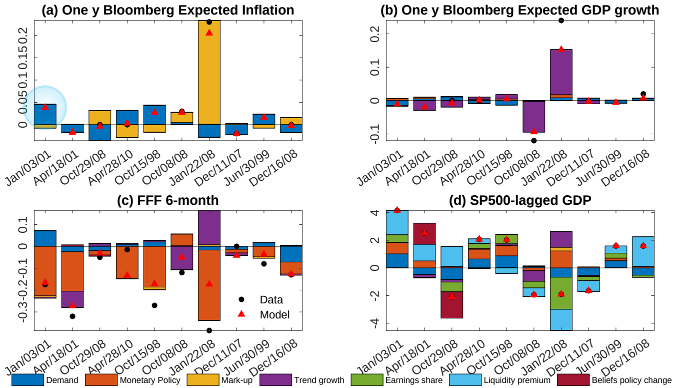
Top Ten FOMC Announcements for Jumps in the Stock Market

- Inflation expectations revised up (higher perceived demand).



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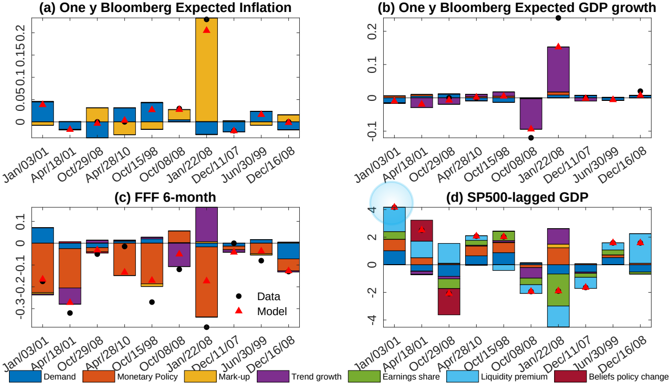
Top Ten FOMC Announcements for Jumps in the Stock Market

- Market up 4.2% in the 30 minutes around Jan 03, 2001 FOMC: higher nowcasts for demand, earnings share & lower lp_t as well as accommodative MP shock



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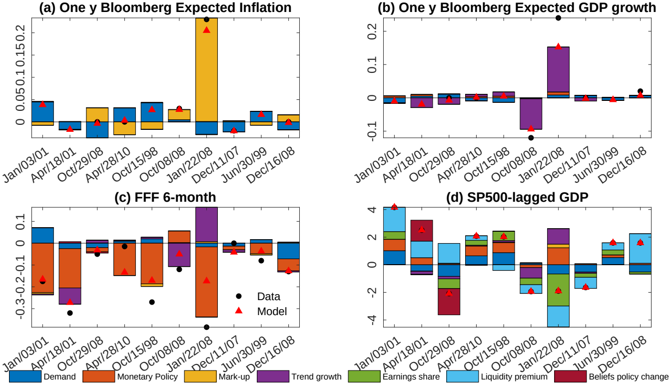
Top Ten FOMC Announcements for Jumps in the Stock Market

- Shows "information effects"(Romer & Romer '00; Campbell et. al., '12; Nakamura & Steinsson '18); adds granular detail on *why* expectations were revised



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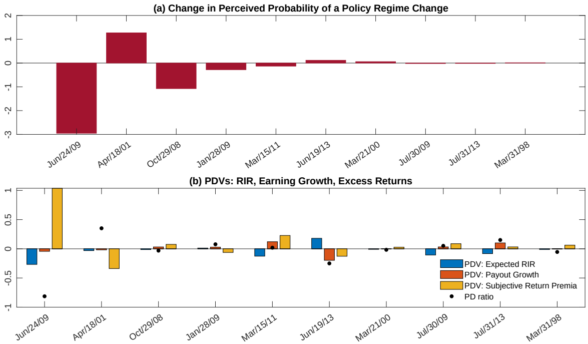
Jumps in Stock Market Valuations When Beliefs Change

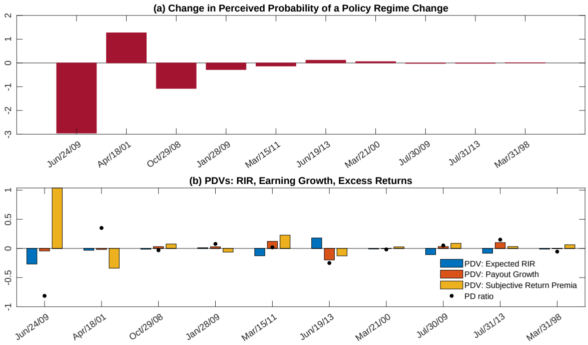
- **Panel (a)**: Top ten FOMC for jumps in beliefs about **monetary policy regime change**



Notes: Panel (a) shows the pre-/post-FOMC announcement change (10 minutes before/20 minutes after) in the perceived probability that financial markets assign to a switch in the monetary policy rule occurring within one year, for the 10 most quantitatively important FOMC announcements based on changes in investor beliefs about the future conduct of monetary policy. Panel (b) shows a decomposition of the model's fluctuations in the log price-payout ratio $pd = pdv_t(\Delta d) - pdv_t(r^{ex}) - pdv_t(rir)$ in 30 minute windows around these 10 announcements that are driven by subjective equity risk premium variation, as measured by $pdv_t(r^{ex})$ (yellow bar), subjective expected future real interest rate fluctuations, as measured by $pdv_t(RIR)$ (blue bar), and subjective expected earnings growth, as measured by $pdv_t(\Delta d)$ (red bar). PD ratio is $pdv_t(\Delta d) - pdv_t(r^{ex}) - pdv_t(rir)$. The sample is 1961:M1-2020:M2

Jumps in Stock Market Valuations When Beliefs Change

- Panel (b): decomposes price-payout fluctuations around FOMC into $pd = pdv_t(\Delta d) - pdv_t(r^{ex}) - pdv_t(rir)$, where $pdv_t(x) \equiv \sum_{h=0}^{\infty} \beta_p^h \mathbb{E}_t^b [x_{t+1+h}]$



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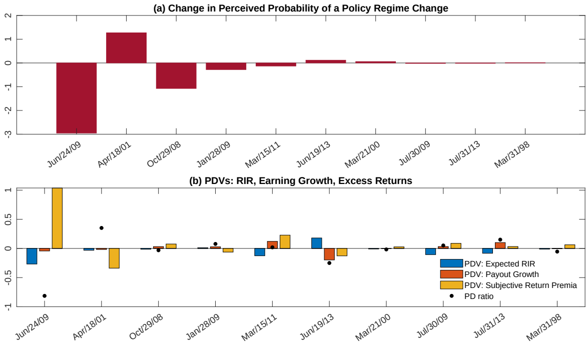
Jumps in Stock Market Valuations When Beliefs Change

- June 24, '09 Fed announced: maintain FFR 0-0.25%, continued expansion of balance sheet, rates kept "low for long"



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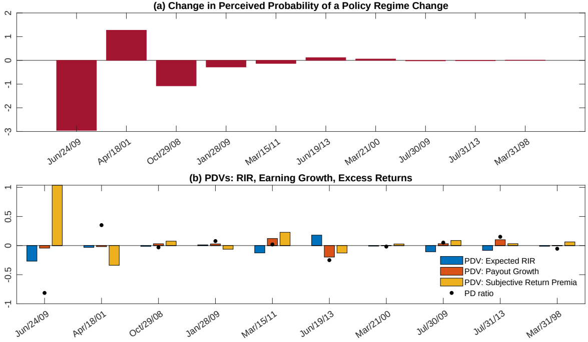
Jumps in Stock Market Valuations When Beliefs Change

- PM period: ↘ **in perceived prob of exiting policy rule–panel (a)** contributes to ↘ market due to ↗ subjective perception of SM *risk*–panel (b). Why?



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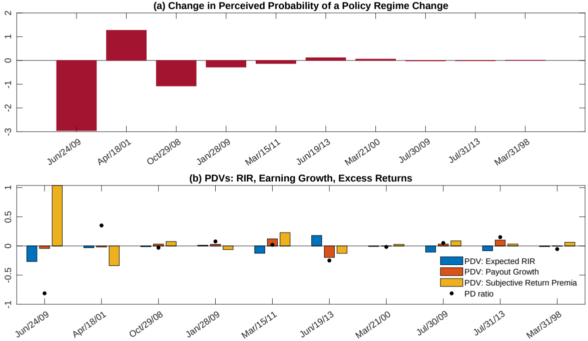
Jumps in Stock Market Valuations When Beliefs Change

- Lower perceived prob of moving to PM Alternative rule w/ *more active* Fed engaged in **stabilizing the economy** ⇒ higher volatility and perceived risk in market



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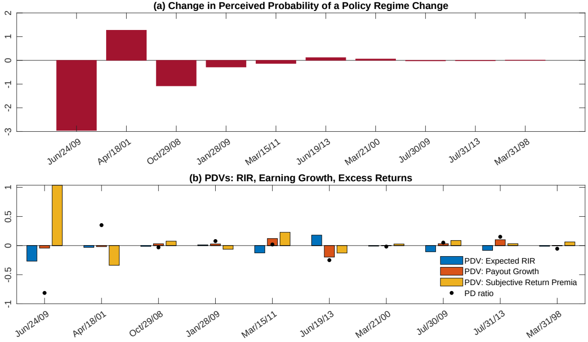
Jumps in Stock Market Valuations When Beliefs Change

- Dovish tone of announcement on June 24, 2009, supported the market through lower expected real interest rates, but *not enough to offset* increase in subj risk premia



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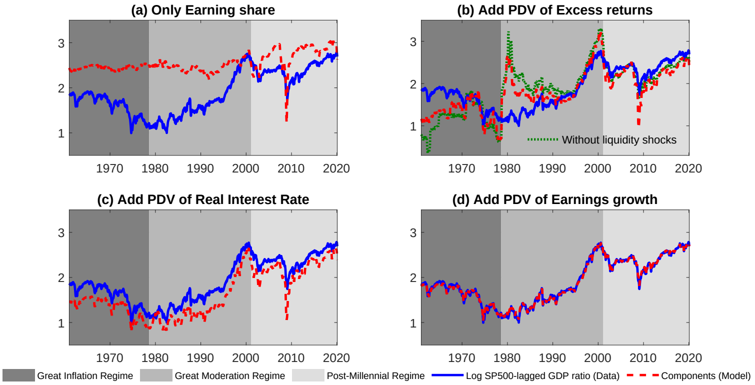
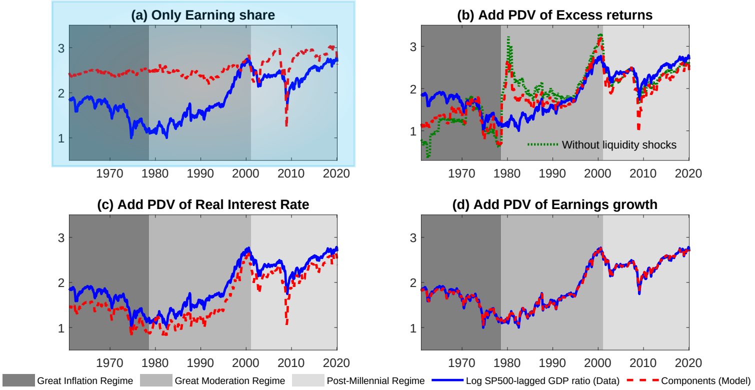
Fluctuations in the Stock Price-Output Ratio Over the Sample



Notes: The blue (solid) line shows the data for the SP500-to-lagged GDP ratio. The dashed (red) lines represent a component in the model. The log ratio in the model may be decomposed as $pgdp_t = ey_t + pdv_t(\Delta d) - pdv_t(r^{ex}) - pdv_t(rir)$, where $pdv_t(x) \equiv \sum_{h=0}^{\infty} \beta_p^h \mathbb{E}_t^b \left[x_{t+1+h}\right]$ and ey_t is the earnings-lagged output ratio plus linearization constant. **Panel (a)** plots $pgdp_t$ along with ey_t. **Panel (b)** plots $pgdp_t$ with $ey_t - pdv_t(r^{ex})$. **Panel (c)** plots $pgdp_t$ with $ey_t - pdv_t(r^{ex}) - pdv_t(rir)$. **Panel (d)** plots $pgdp_t$ along with $ey_t + pdv_t(\Delta d) - pdv_t(r^{ex}) - pdv_t(rir)$. The sample spans 1961:M1 - 2020:M2.

Fluctuations in the Stock Price-Output Ratio Over the Sample

- Earnings share ey_t plays little role up to 2000, contributes to **sharp drop in GFC, and boosts market after** (similar to Greenwald, Lettau, Ludvigson '19).



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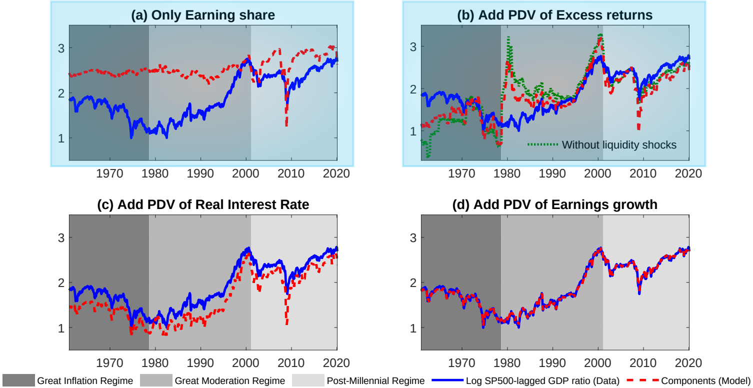
Fluctuations in the Stock Price-Output Ratio Over the Sample

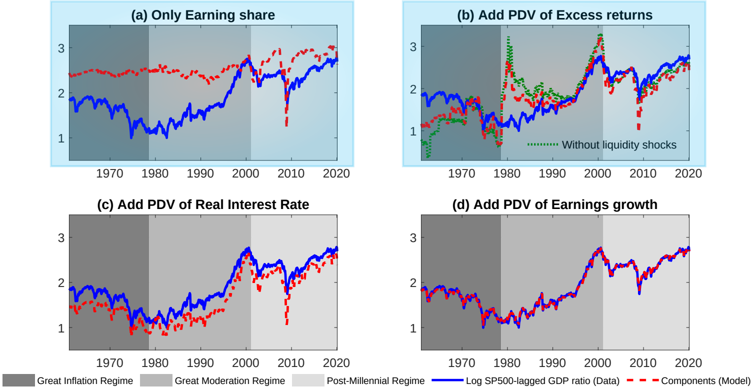
- Difference between (a) and (b) show role of equity return premia, which play **large role in SM especially in PM period**.



Notes: The blue (solid) line shows the data for the SP500-to-lagged GDP ratio. The dashed (red) lines represent a component in the model. The log ratio in the model may be decomposed as $pgdp_t = ey_t + pdv_t(\Delta d) - pdv_t(r^{ex}) - pdv_t(rir)$, where $pdv_t(x) \equiv \sum_{h=0}^{\infty} \beta_p^h \mathbb{E}_t^b \left[x_{t+1+h}\right]$ and ey_t is the earnings-lagged output ratio plus linearization constant. **Panel (a)** plots $pgdp_t$ along with ey_t. **Panel (b)** plots $pgdp_t$ with $ey_t - pdv_t(r^{ex})$. **Panel (c)** plots $pgdp_t$ with $ey_t - pdv_t(r^{ex}) - pdv_t(rir)$. **Panel (d)** plots $pgdp_t$ along with $ey_t + pdv_t(\Delta d) - pdv_t(r^{ex}) - pdv_t(rir)$. The sample spans 1961:M1 - 2020:M2.

Fluctuations in the Stock Price-Output Ratio Over the Sample

- Equity return premia, depend only on: ξ_t^P, **beliefs ξ_t^b about future policy regimes, and** lp_t; lp_t plays small role, underscoring role of **monetary policy in subj risk premia**.



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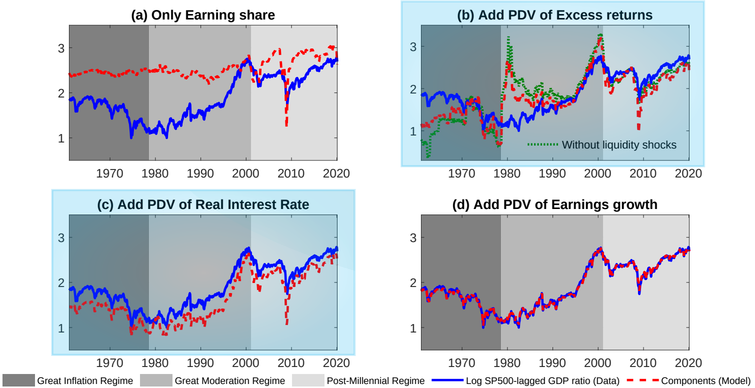
Fluctuations in the Stock Price-Output Ratio Over the Sample

- Diff btw (b) and (c) show role of subjective expected real short-rates, which **supported the market in GI** regime, but **dragged it down during Volcker in GM** regime.



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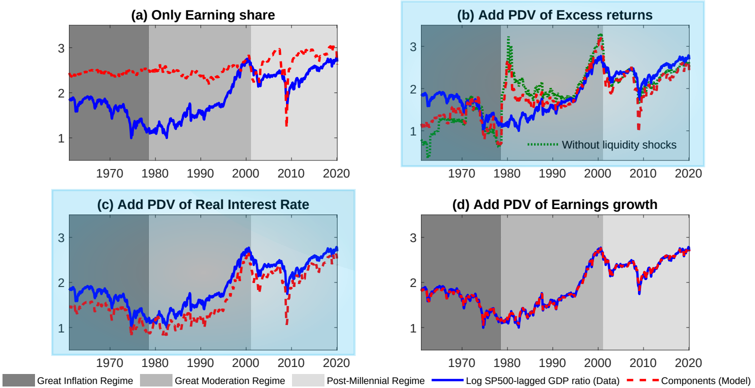
Fluctuations in the Stock Price-Output Ratio Over the Sample

- **Volcker disinflation & GM** set stage for high valuations in 1990s by reducing volatility and lowering premia, but *initially* it tanked the market due to **high real rates**



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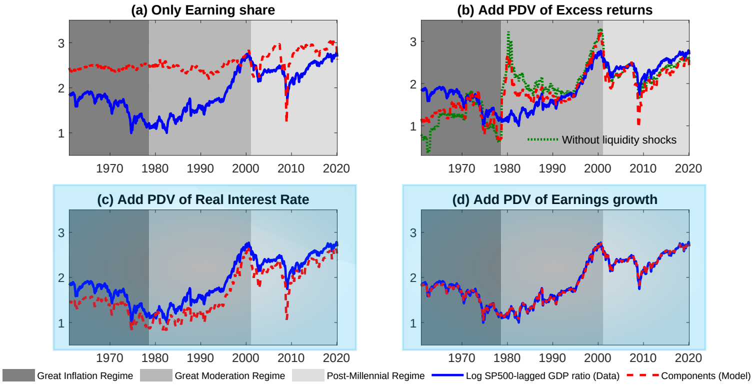
Fluctuations in the Stock Price-Output Ratio Over the Sample

- Diff btw (c) and (d) show role of expected cash-flow growth, which **plays a small role in SM fluctuations** over time.



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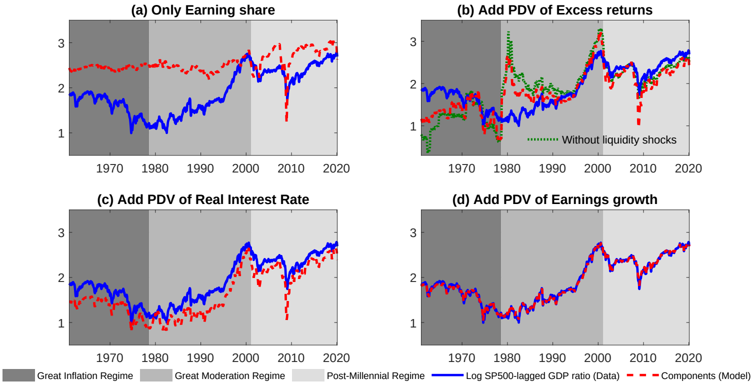
Fluctuations in the Stock Price-Output Ratio Over the Sample

- Results underscore importance of investor expectations about **future short rates** and **return premia driven by ξ_t^P & beliefs about future policy** in SM variation.



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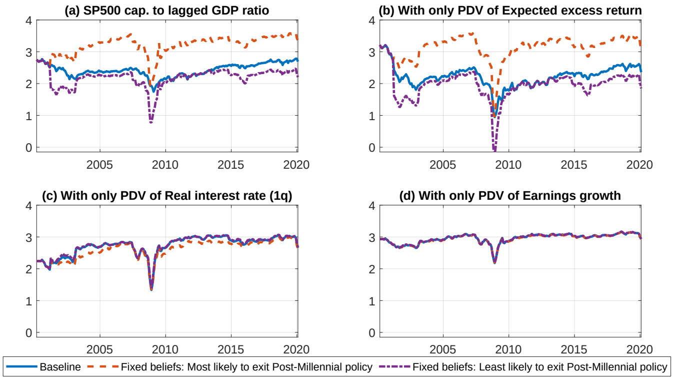
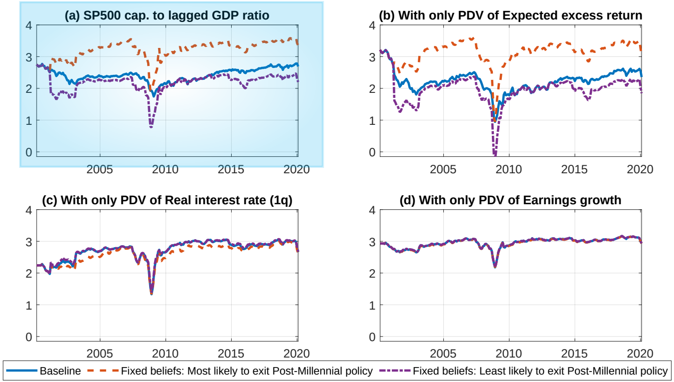
Do Beliefs Matter? Counterfactual Simulation for PM Period



Notes: The red (dashed) line corresponds to a counterfactual simulation in which the $(B+1)$-dimensional belief regime probability vector $\pi_{t|T}$ is replaced by a counterfactual vector equal to $(1,...,0,0)\prime$ at each t. The purple (dashed-dotted) line corresponds to a counterfactual simulation in which $\pi_{t|T}$ is replaced by a counterfactual vector equal to $(0,...,1,0)\prime$ at each t. **Panel (a)** plots the price-lagged output ratio $pgdp_t = ey_t + pdv_t(\Delta d) - pdv_t(r^{ex}) - pdv_t(rir)$, where $pdv_t(x) \equiv \sum_{h=0}^{\infty} \beta_p^h \mathbb{E}_t^b \left[x_{t+1+h}\right]$. **Panel (b)** plots $ey_t - pdv_t(r^{ex})$. **Panel (c)** plots $ey_t - pdv_t(rir)$. **Panel (d)** plots $ey_t - pdv_t(\Delta d)$. The sample spans 2000:M3 to 2020:M2.

Do Beliefs Matter? Counterfactual Simulation for PM Period

- **Big gap between red and purple** lines shows investor beliefs about future conduct of policy play large role in SM fluctuations.



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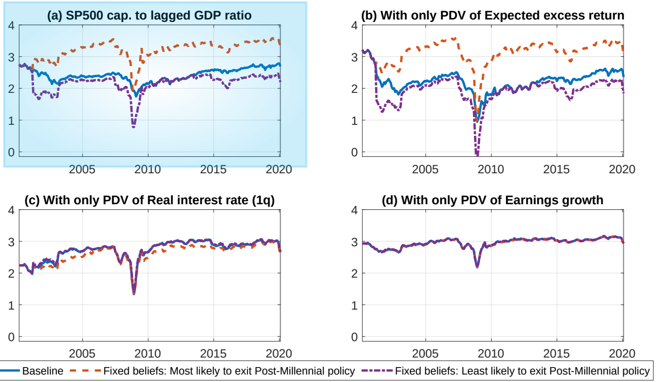
Do Beliefs Matter? Counterfactual Simulation for PM Period

- Had investors counterfactually maintained the belief CB was **very likely to exit the PM policy rule**, the SM would have been *much higher than it was over most of the period*.



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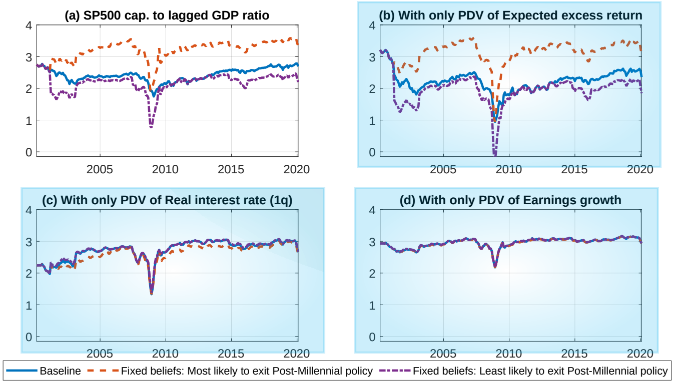
Do Beliefs Matter? Counterfactual Simulation for PM Period

- **Panels (b)-(d) show** beliefs matter b/c of affect on subjective return premia, *rather than* on expected short-rates or payout growth.



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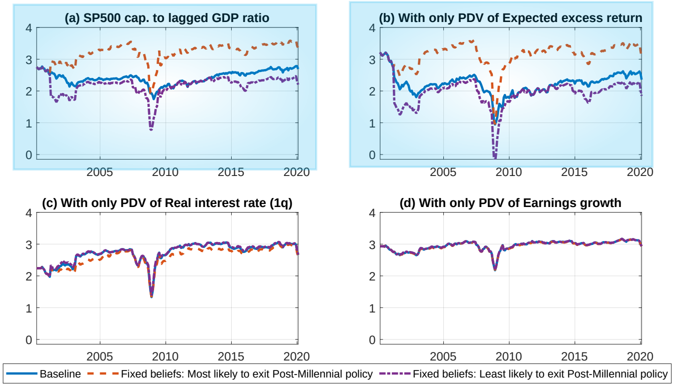
Do Beliefs Matter? Counterfactual Simulation for PM Period

- Subj return premia lower & SM higher had investors **counterfactually believed Fed** was very likely to shift to a rule w/ *greater activism* in stabilizing the economy.



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Conclusion

- **We integrate a high-frequency monetary event study** into a mixed-frequency macro-finance model and **structural estimation**.
- Model **more plausible** *nonrecurrent* **regime changes** & use forward-looking data to infer what agents expect from the *next* policy regime.
- Methodology provides **rich, granular detail** on why markets react to news & can be used in **other settings** to assess responses to **monetary or non-monetary news**.

Conclusion

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- Model **more plausible** *nonrecurrent* **regime changes** & use forward-looking data to infer what agents expect from the *next* policy regime.
- Methodology provides **rich, granular detail** on why markets react to news & can be used in **other settings** to assess responses to **monetary or non-monetary news**.
- **Why do financial markets react strongly** to central bank communications?
  1. B/C **beliefs about future policy ultimately react**, which in turn affects **perceived quantity of stock market risk**
  2. Realized shifts in policy rule have a **persistent influence on short rates** & determine how active the Fed is in stabilizing the economy, affecting valuations.
  3. Occasional big revisions *around announcements* in **beliefs about the economic state** ("information effects") as with FOMC of January 3, 2001 when the market surged 4.2%.
- **Much causal impact occurs outside of tight windows** around Fed communications as beliefs continuously evolve $\rightarrow$ **event studies understate the impact of policy** on markets.

APPENDIX

Why Markets React: Granular Detail

- **High frequency data** $X_{t-1+d_i/nd}$ yield estimates $S^j_{t|t-1+d_i/nd}$ and $\Pr(\xi^b = j | X_{t-1+d_i/nd}, X^{t-1})$ in the minutes, days surrounding an FOMC press release.
- **Estimates** for *perceived* shocks:

$$S^j_{t|t-1+d_i/nd} = C\left(\theta_{\xi^P_t}, \xi^b_t = j, \mathbf{H}^b\right) + T(\theta_{\xi^P_t}, \xi^b_t = j, \mathbf{H}^b) S_{t-1} + R(\theta_{\xi^P_t}, \xi^b_t = j, \mathbf{H}^b) Q \varepsilon^j_{t|t-1+d_i/nd},$$

- **Decompose** *jumps* in variables at FOMC into
  1. Contribution of one particular perceived shock by setting all other shocks to zero and integrating out the belief regimes.
  2. Contribution of changing beliefs is the remaining part, with all shocks set to zero
- **Announcement-related revisions** are difference between $d_i = d_{post}$ and $d_i = d_{pre}$ estimates of $S^j_{t|t-1+d_i/nd}$ and $\Pr(\xi^b = j | X_{t-1+d_i/nd}, X^{t-1})$ in tight windows around FOMC

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Using Forward-Looking Data to Infer the Alternative Policy Rule

- **Forward-looking data** used to infer agent's **perceived Alternative future policy rule**.
- **BBG, BC, SPF, and LIV survey forecasts** discipline investor expectations of inflation, growth
- **FFF data and mean of BC survey** of FFR discipline investor expectations of FFR
- **Stock market data** disciplines estimates of subjective risk premia, cash-flow expectations.
- **Example 1**: data may indicate investors expect lower values for inflation and growth in the output gap but a higher future FFR in a manner would be **inconsistent with the current rule**.
- **Example 2**: stock market data may indicate **subjective risk premia** are **lower than justified by the current rule**, indicating investors expect a future rule with more *active stabilization*.
- **Combination of 1 and 2** then contribute to an **estimated perceived Alternative rule** characterized by a **lower inflation target and more activism** against inflation and growth.

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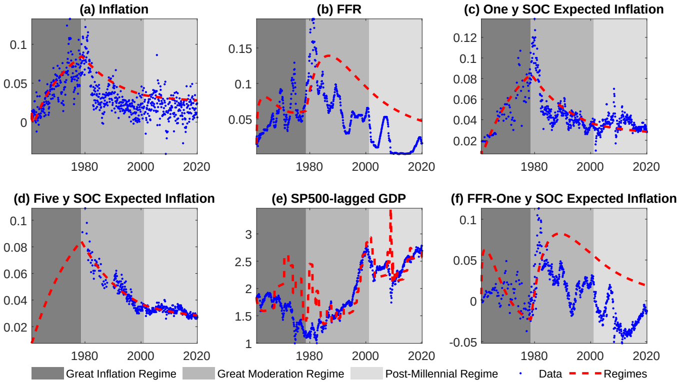
Monetary Policy and Beliefs About Policy Over the Sample

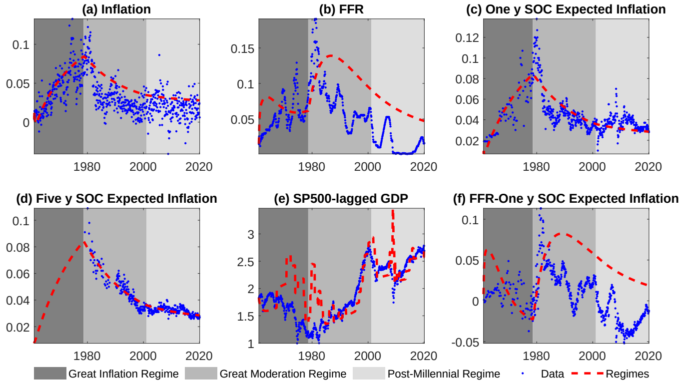
- **Simulation**: observables and estimated S_t are taken as at beginning of our sample with all Gaussian shocks shut down.



Notes: The red dashed line shows the component of the series fluctuations attributable solely to realized regime changes in the policy rule and investor beliefs about shifts in the rule. The observed series are in blue, dashed lines. The sample spans 1961:M1 - 2020:M2.

Monetary Policy and Beliefs About Policy Over the Sample

- The red lines show marginal contribution of changes in policy rule and fluctuating investor beliefs about the probability of exiting the current rule.



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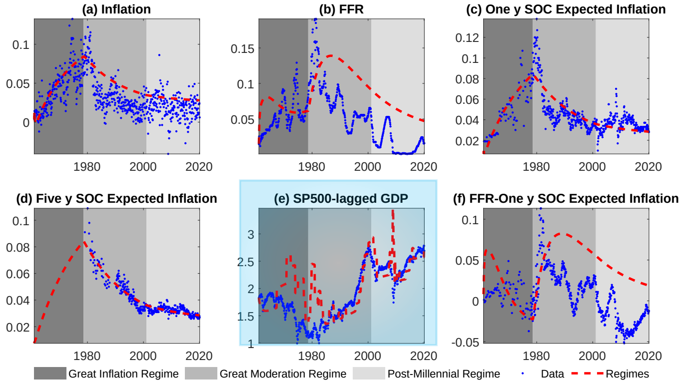
Monetary Policy and Beliefs About Policy Over the Sample

- MP regimes and beliefs about future MP conduct cause large fluctuations in the stock market



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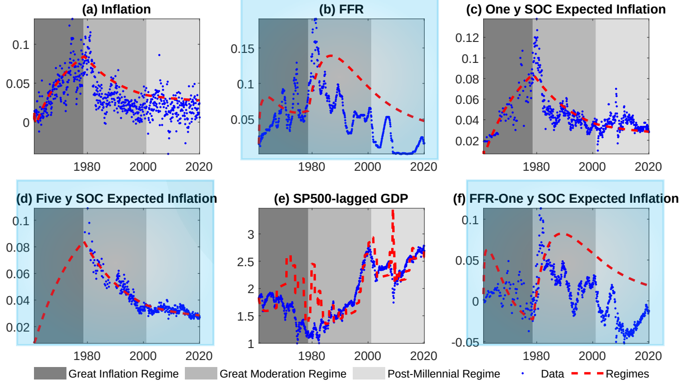
Monetary Policy and Beliefs About Policy Over the Sample

- Large fraction of secular decline in FFR, expected inflation, and RIR since about 1980 due to regime changes in conduct of MP (similar to BLL)



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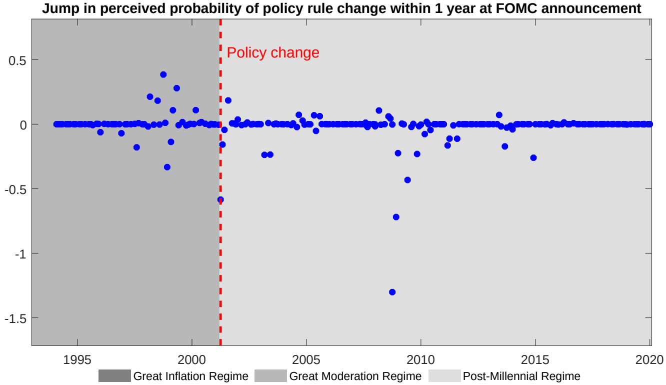
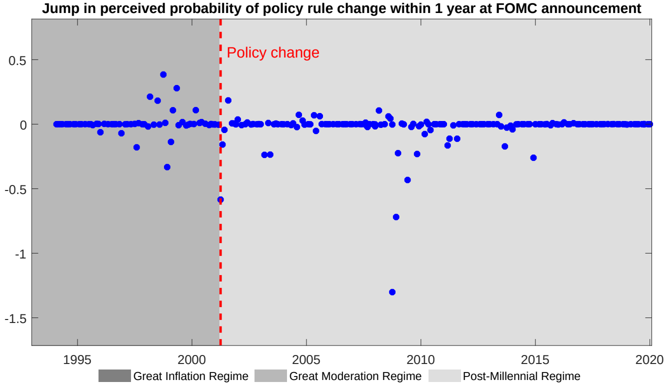
Jumps in Beliefs at FOMC Press Releases



Notes: The figure displays, for each FOMC announcement in our sample, the pre-/post- FOMC announcement change (10 minutes before/20 minutes after) in the probability that financial markets assign to a switch in the monetary policy rule occurring within one year. The full sample has 220 announcements spanning February 4th, 1994 to February 28th, 2020. The sample reported in the figure is 1993:M1-2020:M2.

Jumps in Beliefs at FOMC Press Releases

- Most FOMC announcements result in little change in beliefs about policy change



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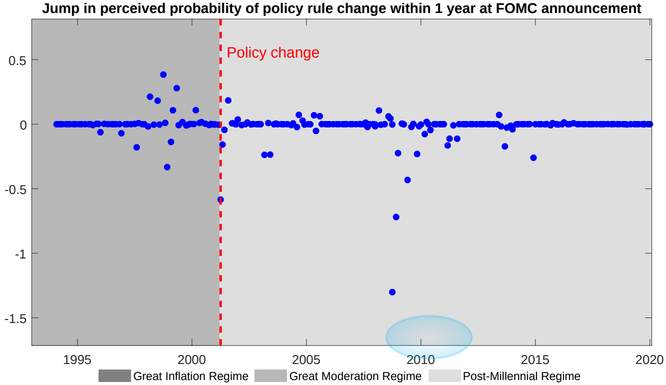
Jumps in Beliefs at FOMC Press Releases

- Big jumps down post-GFC on April 29 & June 24, 2009, March 15, 2011.



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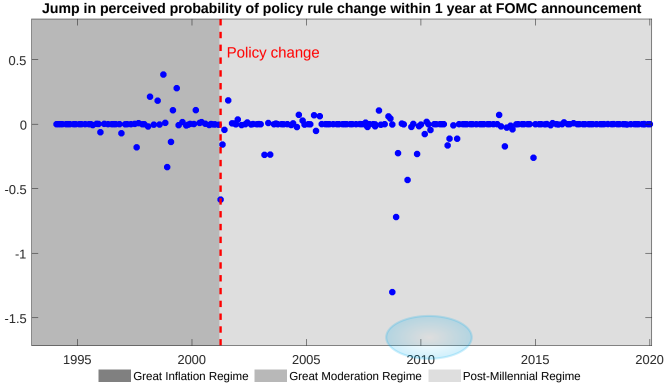
Jumps in Beliefs at FOMC Press Releases

- These statements repeated the "low-for-long" mantra



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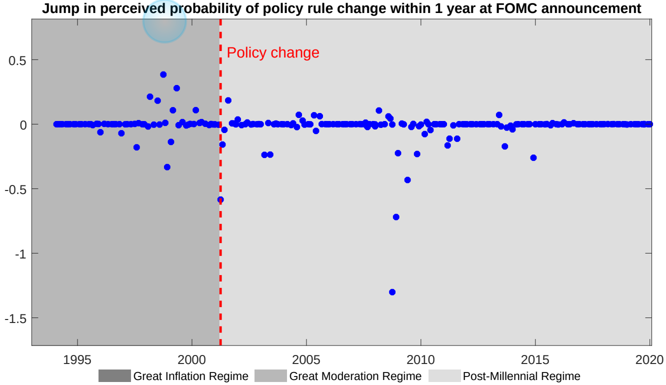
Jumps in Beliefs at FOMC Press Releases

- Big jump on Oct 15, 1998 after collapse of LTCM and Russian Financial Crisis, when the perceived probability of policy change sharply increased



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Monetary Policy Spread (mps) and Nonrecurrent Regimes

- True data generating process for ξ_t^P $\rightarrow$ infrequent, **nonrecurrent** regime changes in r_{ξ_t}

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Monetary Policy Spread (mps) and Nonrecurrent Regimes

- True data generating process for $\xi_t^P \to$ infrequent, **nonrecurrent** regime changes in r_{ξ_t}
- r_{ξ_t} follows Markov-switching process modeled with transition matrix over N_P nonrecurrent regimes ($N_P - 1$ *structural breaks*).

$$\mathbf{H} = \begin{bmatrix} p_{11} & 0 & \cdots & \cdots & \cdots & \cdots & 0 \\ 1-p_{11} & p_{22} & 0 & \cdots & \cdots & \cdots & 0 \\ 0 & 1-p_{22} & p_{33} & 0 & \cdots & \cdots & \vdots \\ \vdots & 0 & 1-p_{33} & \ddots & & & \\ \vdots & \vdots & 0 & \vdots & \ddots & & \vdots \\ \vdots & \vdots & \vdots & \vdots & \ddots & p_{N_P,N_P} & 0 \\ 0 & \cdots & \cdots & \cdots & 0 & 1-p_{N_P,N_P} & 1 \end{bmatrix}, \tag{1}$$

where $\mathbf{H}_{ij} \equiv p\left(\xi_t^P = i | \xi_{t-1}^P = j\right)$

Back

Nonrecurrent Regime Changes: Motivating Example

- **Example:** If only one structural break ($N_P = 2$),

$$\mathbf{H} = \begin{bmatrix} p_{11} & 0 \\ 1 - p_{11} & 1 \end{bmatrix}$$

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- Econometrician observes historical sequence ξ_t^P of realized dovish or hawkish regimes for the mps_t. Use Bayesian model comparison in structural model to decide number of structural breaks, N_P.

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Investor beliefs key to how shifts in stance of MP affect asset valuations, return premia

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- **FOMC, Aug 9, 2011:** "economic conditions are likely to warrant exceptionally low levels for the federal funds rate *at least* [emphasis added] through mid-2013."
- **FOMC, Sept 16, 2020:** "the committee will aim to achieve inflation moderately above 2 percent for *some time* [emphasis added] . . . ." and expects to maintain "an accommodative stance" until "inflation expectations remain *well anchored* [emphasis added] at 2 percent."

Structural Estimation: Overview

State Equation: $S_t = \left[S_t^M, m_t, pd_t, k_t, z_t, lp_t, \mathbb{E}_t^b\left(m_{t+1}\right), \mathbb{E}_t^b\left(pd_{t+1}\right)\right]$

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Back to plot Back to data

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Back to plot Back to data

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Data: Fed Funds Futures and Eurodollar Futures

Fed funds futures

- CME group, January 3, 1995 to June 2, 2020
- Priced at $100 - f_t^{(n)}$, where $f_t^{(n)}$ is avg. effective FFR in month n of contract expiry.
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For both types of contracts, the implied contract rate is recovered by subtracting 100 from the price and multiplying by -1.

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- Calculate surprise component of FFFs, following **?** in unwinding avg. rate into a surprise measure

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Implied rate from FFFs in inner window around current FOMC:

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Current FOMC surprise as scaled change in current Fed funds implied rates:

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Longer horizon surprises around jth meeting, after current meeting, as:

$$e^j_{t+\Delta t} \equiv \frac{m^j}{m^j - d^j} \left[\left(f^j_{t+\Delta t} - f^j_{t-\Delta t} \right) - \frac{d^j}{m^j} e^{j-1}_t \right].$$

Data: Bloomberg Survey Data

Daily quarter-over-quarter real GDP growth median and mean forecasts from Bloomberg Terminal, starting in 2003:Q1. Construct annual GDP growth forecasts as follows:

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   - Question A12 asks (emphasis in original): *During the next 12 months, do you think that prices in general will go up, or go down, or stay where they are now?*
   - A12b asks (emphasis in original): *By about what percent do you expect prices to go (up/down) on the average, during the <u>next</u> 12 months?*

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   - Question A13 asks (emphasis in original): *What about the outlook for prices over the next 5 to 10 years? Do you think prices will be higher, about the same, or lower, 5 to 10 years from now?*
   - A13b asks (emphasis in original): *By about what percent per year do you expect prices to go (up/down) on the average, during the next 5 to 10 years*?

Data: Bluechip Data (BC)

Quarterly and annual PGDP inflation (1986:Q1 - present) and CPI inflation (1984:Q3 - present): quarter-over-quarter percentage change in the respective price index. Quarterly and annual inflation forecasts constructed as follows. Let $\mathbb{F}_t^{(i)}\left[gP_{t+h}^{(Q/Q)}\right]$ be forecaster i's prediction of Q/Q % change in PGDP or CPI h quarters ahead. Annualized inflation forecasts for forecaster i in the next quarter:

$$\mathbb{F}_t^{(i)}\left[\pi_{t+1,t}\right] = 400 \times \ln\left(1 + \frac{\mathbb{F}_t^{(i)}\left[gP_{t+1}^{(Q/Q)}\right]}{100}\right)^{\frac{1}{4}}$$

Annual Inflation forecasts:

$$\mathbb{F}_t^{(i)}\left[\pi_{t+4,t}\right] = 100 \times \ln\left(\prod_{h=1}^{4}\left(1 + \frac{\mathbb{F}_t^{(i)}\left[gP_{t+h}^{(Q/Q)}\right]}{100}\right)^{\frac{1}{4}}\right)$$

Quarterly nowcasts of inflation:

$$\mathbb{N}_t^{(i)}\left[\pi_{t,t-1}\right] = 400 \times \ln\left(1 + \frac{\mathbb{N}_t^{(i)}\left[gP_{t}^{(Q/Q)}\right]}{100}\right)^{\frac{1}{4}}$$

where $\mathbb{N}_t^{(i)}\left[gP_{t}^{(Q/Q)}\right]$ is forecaster i's nowcast of Q/Q % change in PGDP or CPI for the current quarter. Annual nowcasts of inflation for forecaster i:

$$\mathbb{N}_t^{(i)}\left[\pi_{t,t-4}\right] = 100 \times \ln\left(\frac{\mathbb{N}_t^{(i)}\left[P_t\right]}{P_{t-4}}\right),$$

Computing Expectations with Regime Switching and Alternative Policy Rules

Data on expectations provide info about perceived prob. of moving across belief regimes as well as parameters of alternative regime.

For GDP growth, interested in avg. growth over certain horizon. State vector contains $\widetilde{y}_t$.

$$\begin{aligned}\mathbb{E}_t^b\left[\left(gdp_{t+h}-gdp_t\right)h^{-1}|\xi_t=j\right] &= \mathbb{E}_t^b\left[\left(\widetilde{y}_{t+h}-\widetilde{y}_t+h\mu\right)h^{-1}|\xi_t=j\right]\\ &= h^{-1}\mathbb{E}_t^b\left[\widetilde{y}_{t+h}|\xi_t=j\right]-h^{-1}\widetilde{y}_t+\mu\end{aligned}$$

where μ is avg. growth rate in the economy and $\widetilde{y}_t$ is GDP in deviations from trend. With deterministic growth, $gdp_{t+h}-gdp_t-h\mu\equiv\widetilde{y}_{t+h}-\widetilde{y}_t$. We then have

$$\begin{aligned}\mathbb{E}_t^b\left[\left(gdp_{t+h}-gdp_t\right)h^{-1}|\xi_t=j\right] &= h^{-1}\mathbb{E}_t^b\left[\widetilde{y}_{t+h}|\xi_t=j\right]-h^{-1}\widetilde{y}_t+\mu\\ &= h^{-1}\left[\underbrace{e_{\widetilde{y}}w\widetilde{\Omega}^s_{\{1,nm\},\{n(j-1)+1,nj\}}}_{Z_{\xi_t,\widetilde{y}_{t+s}}}\underbrace{S_t}_{(n\times1)}+\underbrace{e_{\widetilde{y}}w\widetilde{\Omega}^s_{\{1,nm\},nm+j}}_{D_{\xi_t,\widetilde{y}_{t+s}}}-e_{\widetilde{y}}S_t\right]+\mu\\ &= \underbrace{h^{-1}\left[e_{\widetilde{y}}w\widetilde{\Omega}^s_{\{1,nm\},\{n(j-1)+1,nj\}}-e_{\widetilde{y}}\right]}_{Z_{\xi_t,\widetilde{y}_{t+s}-\widetilde{y}_t}}\underbrace{S_t}_{(n\times1)}+h^{-1}\underbrace{e_{\widetilde{y}}w\widetilde{\Omega}^s_{\{1,nm\},nm+j}}_{D_{\xi_t,\widetilde{y}_{t+s}}}+\mu\end{aligned}$$

Estimation

The model solution in state space form is:

$$
\begin{aligned}
X_t &= D_{\xi_t^b,t} + Z_{\xi_t^b,t}\left[S_t', \widetilde{y}_{t-1}\right]' + U_t v_t \\
S_t &= C\left(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b\right) + T(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b)S_{t-1} + R(\theta_{\xi_t^P}, \xi_t^b, \mathbf{H}^b)Q\varepsilon_t \\
Q &= diag\left(\sigma_{\varepsilon_1}, ..., \sigma_{\varepsilon_G}\right), \; \varepsilon_t \sim N\left(0, I\right) \\
U &= diag\left(\sigma_1, ..., \sigma_X\right), \; v_t \sim N\left(0, I\right) \\
\xi_t^P &= 1...N_P, \; \xi_t^b = 1, ...B+1, H_{i,j} = p\left(\xi_t^b = i | \xi_{t-1}^b = j\right).
\end{aligned}
$$

where X_t is a $N_X \times 1$ vector of data, v_t are observation errors, U_t is a diagonal matrix with standard devs. of observation errors on main diagonal, and $D_{\xi_t^b,t}$, and $Z_{\xi_t^b,t}$ are parameters mapping model counterparts of X_t into latent discrete- and continuous-valued state variables ξ_t^b and S_t, respectively, where $S_t = \left[S_t^M, m_t, pd_t, k_t, z_t, lp_t, \mathbb{E}_t^b\left(m_{t+1}\right), \mathbb{E}_t^b\left(pd_{t+1}\right)\right]$.
Perceived transition probabilities:

$$
\mathbf{H}^b = \begin{bmatrix}
p_{11} & \cdots & p_{1B} & 0 \\
\vdots & \ddots & \vdots & \vdots \\
p_{B1} & \cdots & p_{BB} & 0 \\
1 - \sum_{i=1}^B p_{i1} & \cdots & 1 - \sum_{i=1}^B p_{iB} & p_{B+1,B+1} = 1
\end{bmatrix},
$$

where $\mathbf{H}_{ij}^b \equiv p\left(\xi_t^b = i | \xi_{t-1}^b = j\right)$.

$$
C_{\xi^P,j} = C\left(\theta_{\xi^P}, \xi_t^b = j\right), \; T_{\xi^P,j} = T\left(\theta_{\xi^P}, \xi_t^b = j\right), \; R_{\xi^P,j} = R\left(\theta_{\xi^P}, \xi_t^b = j\right).
$$

Kim's Approximation to the Likelihood

For $t = 1$ to T_1 and $\theta_{\xi_t^P}$ relevant when $\xi_t^P = 1$:

1. Suppose we have information up through $t-1$. Conditional on $\xi_{t-1}^b = i$ and $\xi_t^b = j$ run the Kalman filter given below for $i, j = 1, 2, ..., B$

$$
\begin{aligned}
S_{t|t-1}^{(i,j)} &= C_{\xi_t^P,j} + T_{\xi_t^P,j} S_{t-1|t-1}^{i} \\
P_{t|t-1}^{(i,j)} &= T_{\xi_t^P,j} P_{t-1|t-1}^{i} T'_{\xi_t^P,j} + R_{\xi_t^P,j} Q^2 R'_{\xi_t^P,j} \text{ with } Q^2 = QQ' \\
e_{t-1+d_i/nd|t-1}^{(i,j)} &= X_{t-1+d_i/nd} - D_{j,t-1+d_i/nd} - Z_{j,t-1+d_i/nd} \left[\widetilde{S}_{t|t-1}^{(i,j)\prime}, \widetilde{y}_{t-1} \right] \\
f_{t|t-1}^{(i,j)} &= Z_{j,t-1+d_1/nd} P_{t|t-1}^{(i,j)} Z'_{j,t-1+d_1/nd} + U_{t-1+d_1/nd}^2 \\
S_{t|t-1+d_i/nd}^{(i,j)} &= S_{t|t-1}^{(i,j)} + P_{t|t-1}^{(i,j)} Z'_{j,t-1+d_i/nd} \left(f_{t|t-1}^{(i,j)} \right)^{-1} e_{t-1+d_i/nd|t-1}^{(i,j)} \\
P_{t|t-1+d_i/nd}^{(i,j)} &= P_{t|t-1}^{(i,j)} - P_{t|t-1}^{(i,j)} Z'_{j,t-1+d_i/nd} \left(f_{t|t-1}^{(i,j)} \right)^{-1} Z_{j,t-1+d_i/nd} P_{t|t-1}^{(i,j)}
\end{aligned}
$$

Kim's Approximation to the Likelihood

2. Run the Hamilton filter to calculate $\Pr\left(\xi_t^b, \xi_{t-1}^b | X^t\right)$ and $\Pr\left(\xi_t^b | X^t\right)$, for $i, j = 1, 2, ..., B$

$$
\begin{aligned}
\Pr\left(\xi_t^b, \xi_{t-1}^b | X^{t-1}\right) &= \Pr\left(\xi_t^b | \xi_{t-1}^b\right) \Pr\left(\xi_{t-1}^b | X^{t-1}\right) \\
\ell\left(X_{t-1+d_i/nd} | X^{t-1}\right) &= \textstyle\sum_{j=1}^{B} \sum_{i=1}^{B} f\left(X_{t-1+d_i/nd} | \xi_{t-1}^b = i, \xi_t^b = j, X^{t-1}\right) \Pr\left[\xi_{t-1}^b = i, \xi_t^b = j | X^{t-1}\right] \\
f\left(X_{t-1+d_i/nd} | \xi_{t-1}^b = i, \xi_t^b = j, X^{t-1}\right) &= (2\pi)^{-N_X/2} |f_{t+1|t}^{(i,j)}|^{-1/2} \exp\left\{-\frac{1}{2} e_{t-1+d_i/nd|t-1}^{(i,j)\prime} f_{t|t-1}^{(i,j)} e_{t-1+d_i/nd|t-1}^{(i,j)}\right\} \\
\mathcal{L}(\theta) &= \mathcal{L}(\theta) + \ln\left(\ell\left(X_{t-1+d_i/nd} | X^{t-1}\right)\right) \\
\Pr\left(\xi_t^b, \xi_{t-1}^b | X_{t-1+d_i/nd}, X^{t-1}\right) &= \frac{\ell\left(X_{t-1+d_i/nd}, \xi_t^b, \xi_{t-1}^b | X^{t-1}\right)}{\ell\left(X_{t-1+d_i/nd} | X^{t-1}\right)} = \frac{\ell\left(X_{t-1+d_i/nd}, \xi_t^b, \xi_{t-1}^b, X^{t-1}\right) \Pr\left(\xi_t^b, \xi_{t-1}^b | X^{t-1}\right)}{\ell\left(X_{t-1+d_i/nd} | X^{t-1}\right)} \\
\Pr\left(\xi_t^b | X_{t-1+d_i/nd}, X^{t-1}\right) &= \sum_{i=1}^{B+1} \Pr\left(\xi_t^b, \xi_{t-1}^b = i | X_{t-1+d_i/nd}, X^t\right)
\end{aligned}
$$

Kim's Approximation to the Likelihood

3. Using $\Pr\left(\xi_t^b, \xi_{t-1}^b | X_{t-1+d_i/nd}, X^{t-1}\right)$ and $\Pr\left(\xi_t^b | X_{t-1+d_i/nd}, X^{t-1}\right)$, collapse the $B \times B$ values of $S_{t|t-1+d_i/nd}^{(i,j)}$ and $P_{t|t-1+d_i/nd}^{(i,j)}$ into B values represented by $S_{t|t-1+d_i/nd}^{j}$ and $P_{t|t-1+d_i/nd}^{j}$:

$$S_{t|t-1+d_i/nd}^{j} = \frac{\sum_{i=1}^{B} \Pr\left[\xi_{t-1}^b = i, \xi_t^b = j | X_{t-1+d_i/nd}, X^{t-1}\right] S_{t|t-1+d_i/nd}^{(i,j)}}{\Pr\left[\xi_t^b = j | X_{t-1+d_i/nd}, X^{t-1}\right]}$$

$$P_{t|t-1+d_i/nd}^{j} = \frac{\sum_{i=1}^{B} \Pr\left[\xi_{t-1}^b = i, \xi_t^b = j | X_{t-1+d_i/nd}, X^{t-1}\right] \left(P_{t|t-1+d_i/nd}^{(i,j)} + \left(\tilde{S}_{t|t-1+d_i/nd}^{j} - \tilde{S}_{t|t-1+d_i/nd}^{(i,j)}\right)\left(\tilde{S}_{t|t-1+d_i/nd}^{j} - \tilde{S}_{t|t-1+d_i/nd}^{(i,j)}\right)'\right)}{\Pr\left[\xi_t^b = j | X_{t-1+d_i/nd}, X^{t-1}\right]}$$

Kim's Approximation to the Likelihood

3. Using $\Pr\left(\xi_t^b, \xi_{t-1}^b | X_{t-1+d_i/nd}, X^{t-1}\right)$ and $\Pr\left(\xi_t^b | X_{t-1+d_i/nd}, X^{t-1}\right)$, collapse the $B \times B$ values of $S_{t|t-1+d_i/nd}^{(i,j)}$ and $P_{t|t-1+d_i/nd}^{(i,j)}$ into B values represented by $S_{t|t-1+d_i/nd}^{j}$ and $P_{t|t-1+d_i/nd}^{j}$:

$$S_{t|t-1+d_i/nd}^{j} = \frac{\sum_{i=1}^{B} \Pr\left[\xi_{t-1}^b = i, \xi_t^b = j | X_{t-1+d_i/nd}, X^{t-1}\right] S_{t|t-1+d_i/nd}^{(i,j)}}{\Pr\left[\xi_t^b = j | X_{t-1+d_i/nd}, X^{t-1}\right]}$$

$$P_{t|t-1+d_i/nd}^{j} = \frac{\sum_{i=1}^{B} \Pr\left[\xi_{t-1}^b = i, \xi_t^b = j | X_{t-1+d_i/nd}, X^{t-1}\right] \left(P_{t|t-1+d_i/nd}^{(i,j)} + \left(\tilde{S}_{t|t-1+d_i/nd}^{j} - \tilde{S}_{t|t-1+d_i/nd}^{(i,j)}\right)\left(\tilde{S}_{t|t-1+d_i/nd}^{j} - \tilde{S}_{t|t-1+d_i/nd}^{(i,j)}\right)'\right)}{\Pr\left[\xi_t^b = j | X_{t-1+d_i/nd}, X^{t-1}\right]}$$

4. If $t - 1 + d_i/nd = t$, move to the next period by setting $t - 1 = t$ and returning to step 1

Kim's Approximation to the Likelihood

3. Using $\Pr\left(\xi_t^b, \xi_{t-1}^b | X_{t-1+d_i/nd}, X^{t-1}\right)$ and $\Pr\left(\xi_t^b | X_{t-1+d_i/nd}, X^{t-1}\right)$, collapse the $B \times B$ values of $S_{t|t-1+d_i/nd}^{(i,j)}$ and $P_{t|t-1+d_i/nd}^{(i,j)}$ into B values represented by $S_{t|t-1+d_i/nd}^{j}$ and $P_{t|t-1+d_i/nd}^{j}$:

$$S_{t|t-1+d_i/nd}^{j} = \frac{\sum_{i=1}^{B} \Pr\left[\xi_{t-1}^b = i, \xi_t^b = j | X_{t-1+d_i/nd}, X^{t-1}\right] S_{t|t-1+d_i/nd}^{(i,j)}}{\Pr\left[\xi_t^b = j | X_{t-1+d_i/nd}, X^{t-1}\right]}$$

$$P_{t|t-1+d_i/nd}^{j} = \frac{\sum_{i=1}^{B} \Pr\left[\xi_{t-1}^b = i, \xi_t^b = j | X_{t-1+d_i/nd}, X^{t-1}\right] \left(P_{t|t-1+d_i/nd}^{(i,j)} + \left(\tilde{S}_{t|t-1+d_i/nd}^{j} - \tilde{S}_{t|t-1+d_i/nd}^{(i,j)}\right)\left(\tilde{S}_{t|t-1+d_i/nd}^{j} - \tilde{S}_{t|t-1+d_i/nd}^{(i,j)}\right)'\right)}{\Pr\left[\xi_t^b = j | X_{t-1+d_i/nd}, X^{t-1}\right]}$$

4. If $t - 1 + d_i/nd = t$, move to the next period by setting $t - 1 = t$ and returning to step 1
5. Else, store the updated $S_{t|t-1+d_i/nd}^{j}$, $P_{t|t-1+d_i/nd}^{j}$, $\Pr\left(\xi_t^b, \xi_{t-1}^b | X_{t-1+d_i/nd}, X^{t-1}\right)$, and $\Pr\left(\xi_t^b | X_{t-1+d_i/nd}, X^{t-1}\right)$, and repeat steps 1-5 keeping $t - 1$ fixed.

Kim's Approximation to the Likelihood

- At $t = T_1 + 1$ use $\theta_{\xi_t^P}$ relevant when $\xi_t^P = 2$, set $t - 1 = t$, and repeat steps 1-5
- At $t = T_2 + 1$ use $\theta_{\xi_t^P}$ relevant when $\xi_t^P = 3$, set $t - 1 = t$, and repeat steps 1-5
- $\vdots$
- At $t = T_{N_P - 1} + 1$ use $\theta_{\xi_t^P}$ relevant when $\xi_t^P = N_P$, set $t - 1 = t$ and repeat steps 1-5
- At $t = T_N = T$ stop. Obtain $\mathcal{L}(\theta) = \sum_{t=1}^{T} \ln\left(\ell\left(X_t | X^{t-1}\right)\right)$.

The algorithm above is described in general terms; in principle the intermonth loop could be repeated at every instant within a month for which we have new data. In application, we repeat steps 1-5 only at certain minutes or days pre- and post-FOMC meeting.

Observation Equation

Observation Equation: $X_t = D_{\varsigma_t^b, t} + Z_{\varsigma_t^b, t} \left[S_t', \widetilde{y}_{t-1}\right]' + U_t v_t$

- $\widehat{g}_t = g_t - g$, and $\widehat{lp}_t = lp_t - lp$.
- $\widetilde{y}_t = \ln\left(Y_t / A_t\right), \Delta \ln\left(A_t\right) \equiv g_t = g + \rho_g \left(g_t - g\right) + \sigma_g \varepsilon_{g,t} \Rightarrow \widetilde{y}_t - \widetilde{y}_{t-1} = \Delta \ln\left(Y_t\right) - g_t \Rightarrow \Delta \ln\left(Y_t\right) = \widetilde{y}_t - \widetilde{y}_{t-1} + g_t = \widetilde{y}_t - \widetilde{y}_{t-1} + \widehat{g}_t + g$.
- Annualizing the monthly growth rates to get annualized GDP growth $=> \Delta \ln\left(GDP_t\right) \equiv 12 \Delta \ln\left(Y_t\right) = 12g + 12\left(\widetilde{y}_t + \widehat{g}_t - \widetilde{y}_t\right)$.

Observation Equation

Observation Equation: $X_t = D_{\xi_t^b,t} + Z_{\xi_t^b,t}\left[S_t', \widetilde{y}_{t-1}\right]' + U_t v_t$

- $\widehat{g}_t = g_t - g$, and $\widehat{lp}_t = lp_t - lp$.
- $\widetilde{y}_t = \ln\left(Y_t/A_t\right), \Delta\ln\left(A_t\right) \equiv g_t = g + \rho_g\left(g_t - g\right) + \sigma_g \varepsilon_{g,t} \Rightarrow \widetilde{y}_t - \widetilde{y}_{t-1} = \Delta\ln\left(Y_t\right) - g_t \Rightarrow \Delta\ln\left(Y_t\right) = \widetilde{y}_t - \widetilde{y}_{t-1} + g_t = \widetilde{y}_t - \widetilde{y}_{t-1} + \widehat{g}_t + g$.
- Annualizing the monthly growth rates to get annualized GDP growth $=> \Delta\ln\left(GDP_t\right) \equiv 12\Delta\ln\left(Y_t\right) = 12g + 12\left(\widetilde{y}_t + \widehat{g}_t - \widetilde{y}_t\right).$

Note that:

$$\begin{aligned}
\mathbb{E}_t^m\left[\pi_{t,t+h}\right] &= \left[h + (h-1)\phi + (h-2)\phi^2 + ... + \phi^{h-1}\right]\alpha_t^m + \left[\phi + \phi^2 + ... + \phi^h\right]\pi_t \\
&= \left[h + (h-1)\phi + (h-2)\phi^2 + ... + \phi^{h-1}\right](1-\phi)\overline{\pi}_t + \left[\phi + \phi^2 + ... + \phi^h\right]\pi_t
\end{aligned}$$

Observation Equation

X_t is defined as:

$$
\begin{bmatrix}
\Delta\ln(GDP_t) \\ Inflation \\ FFR \\ SOC(Inflation)_{12m} \\ SOC(Inflation)_{60m} \\ f_t^{(0)} \\ BC(Inflation)_{12m} \\ SPF(Inflation)_{12m} \\ Liv(Inflation)_{12m} \\ SPF(GDPDInfl)_{12m} \\ BBG(Inflation)_{12m} \\ Liv(Inflation)_{120m} \\ SPF(Inflation)_{120m} \\ BC(FFR)_{12m} \\ BC(\Delta GDP)_{12m} \\ BBG(\Delta GDP)_{12m} \\ SPF(\Delta GDP)_{12m} \\ f_t^{(n)} \\ Baa_t \\ pgdp_t \\ egdp_t
\end{bmatrix}
=
\begin{bmatrix}
12g \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ D_{\pi_{t,t+12},\xi_t^b} \\ D_{\pi_{t,t+12},\xi_t^b} \\ D_{\pi_{t,t+12},\xi_t^b} \\ D_{\pi_{t,t+12},\xi_t^b} \\ D_{\pi_{t,t+12},\xi_t^b} \\ D_{\pi_{t,t+120},\xi_t^b} \\ D_{\pi_{t,t+120},\xi_t^b} \\ D_{i_{t,t+12},\xi_t^b} \\ D_{y_{t+s},\xi_t^b} \\ D_{y_{t+s},\xi_t^b} \\ D_{y_{t+s},\xi_t^b} \\ D_{i_{t+X},\xi_t} \\ C_{Baa} \\ \ln(K)+g \\ C_{egdp}
\end{bmatrix}
+
\begin{bmatrix}
12\left(\widetilde{y}_t+\widehat{g}_t-\widetilde{y}_t\right) \\ 12\pi_t \\ 12i_t \\ \left[h+(h-1)\phi+(h-2)\phi^2+...+\phi^{11}\right](1-\phi)\overline{\pi}_t+\left[\phi+\phi^2+...+\phi^{12}\right]\pi_t \\ \left[h+(h-1)\phi+(h-2)\phi^2+...+\phi^{59}\right](1-\phi)\overline{\pi}_t+\left[\phi+\phi^2+...+\phi^{60}\right]\pi_t \\ 12i_t \\ Z_{\pi_{t,t+12},\xi_t^b}S_t \\ Z_{\pi_{t,t+12},\xi_t^b}S_t \\ Z_{\pi_{t,t+12},\xi_t^b}S_t \\ Z_{\pi_{t,t+12},\xi_t^b}S_t \\ Z_{\pi_{t,t+12},\xi_t^b}S_t \\ Z_{\pi_{t,t+120},\xi_t^b}S_t \\ Z_{\pi_{t,t+120},\xi_t^b}S_t \\ Z_{i_{t,t+12},\xi_t^b}S_t \\ Z_{\xi_t^b,y_{t+s}-y_t}S_t \\ Z_{\xi_t^b,y_{t+s}-y_t}S_t \\ Z_{\xi_t^b,y_{t+s}-y_t}S_t \\ Z_{i_{t+X},\xi_t^b}S_t \\ B\widehat{l}p_t \\ \widetilde{k}_t+pd_t+\widehat{g}_t+\widetilde{y}_t-\widetilde{y}_{t-1} \\ K\widetilde{k}_t
\end{bmatrix}
+U_t v_t
$$

Computing the Posterior

Likelihood from Kim's approximation combined with prior distribution for parameters to obtain posterior. Block algorithm used to find posterior mode, with draws from posterior using standard Metropolis-Hastings algorithm initialized around posterior mode.

Computing the Posterior

Likelihood from Kim's approximation combined with prior distribution for parameters to obtain posterior. Block algorithm used to find posterior mode, with draws from posterior using standard Metropolis-Hastings algorithm initialized around posterior mode.

- Step 1: Draw a new set of parameters from the proposal distribution: $\vartheta \sim N\left(\theta_{n-1}, c\overline{\Sigma}\right)$

Computing the Posterior

Likelihood from Kim's approximation combined with prior distribution for parameters to obtain posterior. Block algorithm used to find posterior mode, with draws from posterior using standard Metropolis-Hastings algorithm initialized around posterior mode.

- Step 1: Draw a new set of parameters from the proposal distribution: $\vartheta \sim N\left(\theta_{n-1}, c\overline{\Sigma}\right)$
- Step 2: Compute $\alpha\left(\theta^{m};\vartheta\right) = \min\left\{p\left(\vartheta\right)/p\left(\theta^{m-1}\right), 1\right\}$ where $p\left(\theta\right)$ is the posterior evaluated at θ.

Computing the Posterior

Likelihood from Kim's approximation combined with prior distribution for parameters to obtain posterior. Block algorithm used to find posterior mode, with draws from posterior using standard Metropolis-Hastings algorithm initialized around posterior mode.

- Step 1: Draw a new set of parameters from the proposal distribution: $\vartheta \sim N\left(\theta_{n-1}, c\overline{\Sigma}\right)$
- Step 2: Compute $\alpha\left(\theta^m; \vartheta\right) = \min\left\{p\left(\vartheta\right) / p\left(\theta^{m-1}\right), 1\right\}$ where $p\left(\theta\right)$ is the posterior evaluated at θ.
- Step 3: Accept the new parameter and set $\theta^m = \vartheta$ if $u < \alpha\left(\theta^m; \vartheta\right)$ where $u \sim U\left([0,1]\right)$, otherwise set $\theta^m = \theta^{m-1}$

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The matrix $\overline{\Sigma}$ corresponds to the inverse of the Hessian computed at the posterior mode $\overline{\theta}$. The parameter c is set to obtain an acceptance rate of around 30%. We use four chains of $540,000$ draws each (1 of every 200 draws is saved) and are used to form an estimate of the posterior distribution from which we make draws. Convergence checked using Brooks-Gelman-Rubin potential reduction scale factor.

Risk Adjustment with Lognormal Approximation

Extend the approach in Bansal and Zhou (2002) of approximating a model with Markov-switching random variables using a risk-adjustment while maintaining conditional log-normality. Consider the forward looking log price-payout ratio, where applying the approximation implied by conditional log-normality:

$$
\begin{aligned}
pd_t &= \kappa_0 + \mathbb{E}_t^b \left[m_{t+1} + \Delta d_{t+1} + \kappa_{pd,1} pd_{t+1} \right] + \\
&\quad + .5 \mathbb{V}_t^b \left[m_{t+1} + \Delta d_{t+1} + \kappa_{pd,1} pd_{t+1} \right]
\end{aligned}
$$

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\end{aligned}
$$

We follow Bansal and Zhou (2002) and approximate conditional variance as weighted avg. of objective variance across regimes, conditional on ξ_t.

$$
S_t = C_{\xi_t} + T_{\xi_t} S_{t-1} + R_{\xi_t} Q \varepsilon_t,
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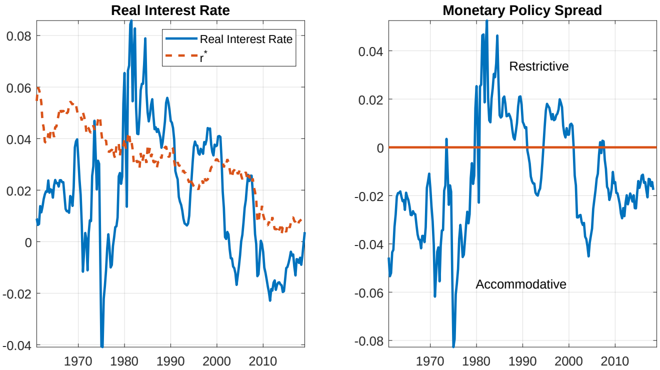
The approximation takes the form:

$$\mathbb{V}_t^b \left[x_{t+1} \right] \approx e_x \mathbb{E}_t^b \left[R_{\xi_{t+1}} Q Q' R'_{\xi_{t+1}} \right] e_x$$

where e_x extracts desired linear combo of variables in S_t.

Real Interest Rate

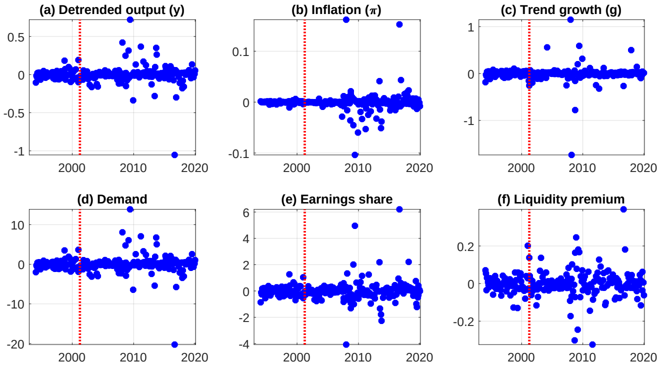
- Bullets here Figure 1



Notes: The real interest rate is measured as the federal funds rate minus a four quarter moving average of inflation. The left panel plots this observed series along with an estimate of r^* from Laubach and Williams (2003). The right panel plots the monetary policy spread, i.e., the spread between the real funds rate and the Laubach and Williams (2003) natural rate of interest. The sample spans 1961:Q1-2020:Q1.

HF Changes in State Variables

- Bullets here Figure 7



Notes: The figure displays, for each FOMC announcement in our sample, the change in the perceived state of the economy from 10 minutes before to 20 minutes after an FOMC statement is released. The full sample has 220 FOMC announcements spanning February 4th, 1994 to February 28th, 2020. The sample reported in the figure is 1993:M1-2020:M2.

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APPENDIX

Table A.1: **Other Parameters**

Parameter	Mode	Parameter	Mode	Parameter	Mode	Parameter	Mode
σ	0.0650	ϕ	0.7436	ρ_k	0.9980	scale BAA	0.3998
δ	0.5372	r^*	0.0000	λ_k	26.9629	σ_d	23.4733
β	0.7161	γ_3	0.0051	ρ_{lp}	0.8407	σ_i	0.0331
κ_1	0.0036	K	0.0507	δ_1	0.2338	σmup	0.1379
γ	0.0001	σ^{AP}	5.8542	δ_2	0.1887	σ_k	6.2614
$\rho\mu$	0.0914	β^{AP}	0.9936	$\lambda_{k,2}$	10.7499	σ_{lp}	0.5699
κ_0	0.0026	lp	-0.0130	b (persistence beliefs)	0.9876	σ_μ	1.7200
βa	0.3905	$\lambda_{\pi,1}$	0.4244		0.9286		
$\gamma\pi$	0.0000	$\lambda_{\pi,2}$	0.3139		0.1090		
ρ_d	0.5010	γ_2	0.0383	int BAA	0.0140		

Note: This table reports the key parameters of the model.

Top Ten FOMC: 6-month FFF rate

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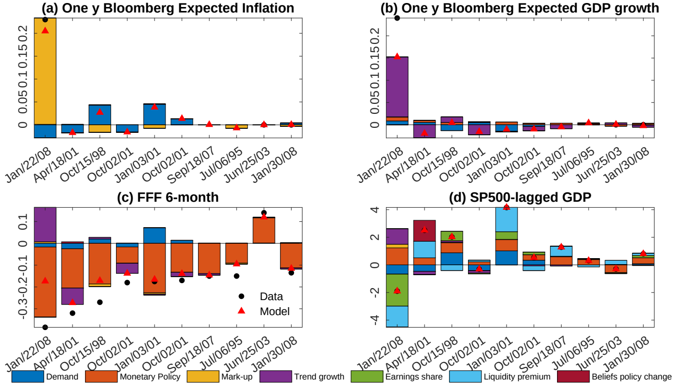

Note: The figure displays the decomposition of movements in Bloomberg expected inflation, Bloomberg expected GDP growth, the 6-month FFF rates, and the stock market in revisions about the underlying shocks affecting the macroeconomy for the 10 most relevant FOMC announcements based on changes in the 6-month FFF rate. Because we do not have measurement error in the equations for the S&P500 to lagged GDP ratio, the black dot (data) and the red triangles (estimation) lie on top of each other, so the black dot is obscured.

back

Top Ten FOMC: Bloomberg Expected Inflation

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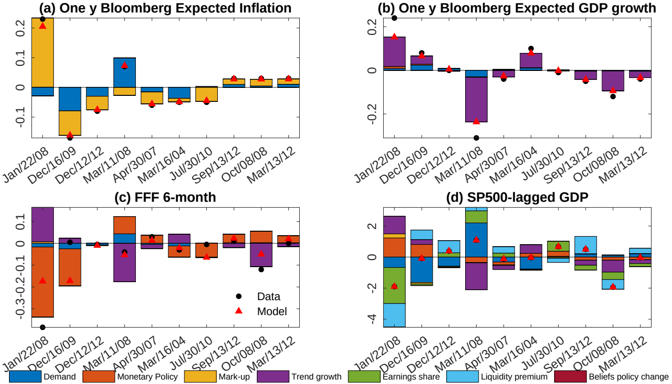

Note: The figure displays the decomposition of movements in Bloomberg expected inflation, Bloomberg expected GDP growth, the 6-month FFF rates, and the stock market in revisions about the underlying shocks affecting the macroeconomy for the 10 most relevant FOMC announcements based on changes in the Bloomberg one-year inflation expectations. Because we do not have measurement error in the equations for the S&P500 to lagged GDP ratio, the black dot (data) and the red triangles (estimation) lie on top of each other, so the black dot is obscured.

back

Top Ten FOMC: Bloomberg Expected GDP growth

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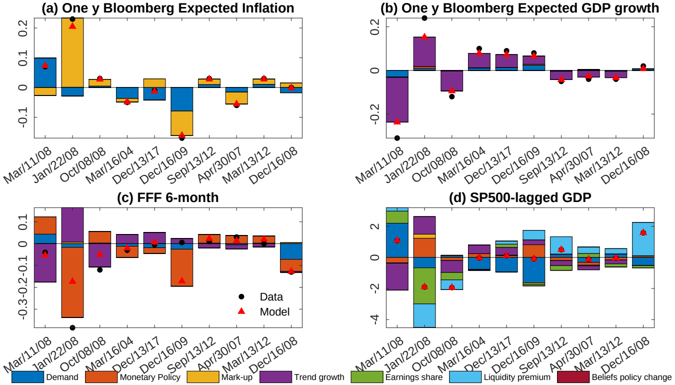

Note: The figure displays the decomposition of movements in Bloomberg expected inflation, Bloomberg expected GDP growth, the 6-month FFF rates, and the stock market in revisions about the underlying shocks affecting the macroeconomy for the 10 most relevant FOMC announcements based on changes in Bloomberg Expected GDP growth. Because we do not have measurement error in the equations for the S&P500 to lagged GDP ratio, the black dot (data) and the red triangles (estimation) lie on top of each other, so the black dot is obscured.

back