“Monetary Policy Risks in the Bond Markets and Macroeconomy”

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Much work links the *levels of economic dynamics* with monetary policy
- Macro variables and the short term interest rate (New Keynesian models)
- Yield levels and monetary regimes (eg. Gallmeyer et al. (2009))

We explore the link between *economic uncertainty and monetary policy*
Economic Uncertainty and Monetary Policy

- Much work links the *levels of economic dynamics* with monetary policy
  - Macro variables and the short term interest rate (New Keynesian models)
  - Yield levels and monetary regimes (e.g. Gallmeyer et al. (2009))

- We explore the link between *economic uncertainty and monetary policy*

- We develop an economically-founded term structure model to infer the relationship of policy and macro-volatility

- Focus on the quantitative contribution of *monetary policy towards risk premia movements*, including the macro-uncertainty channel
Our Paper

- A novel asset pricing framework
  - Flexible dynamics of short rates and macroeconomy
  - Pricing restrictions of recursive-utility based models

- Macroeconomic dynamics
  - Persistent movements in expected growth and inflation
  - *Monetary policy affects inflation uncertainty*

- Time-varying monetary policy rule
  - Regime-dependent response of short rates to expected growth and expected inflation
This paper connects to many strands of literature...

- **Macro and MP Regime Shifts**
  (Hamilton (1988), Sims and Zha (2006), Among Many Others)

- **Time Variation in Asset Risk Premia**

- **Links b/w Term Structure and Monetary Policy**
  (Gallmeyer et al. (2009), Ang et al. (2011), Campbell et al. (2013), Chernov and Bikbov (2013), Song (2014), Backus et al. (2015))
Introduction

Historical Works

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- **Macro and MP Regime Shifts**
  (Hamilton (1988), Sims and Zha (2006), Among Many Others)

- **Time Variation in Asset Risk Premia**

- **Links b/w Term Structure and Monetary Policy**
  (Gallmeyer et al. (2009), Ang et al. (2011), **Campbell et al. (2013)**, Chernov and Bikbov (2013), Song (2014), Backus et al. (2015))

⇒ Our model accounts for links between macro volatility and policy
⇒ Monetary risks are accounted for in the joint solution of Euler equation, quantities, and financial prices
Model
Ingredients

- Representative Investor with Epstein and Zin (EZ) Preferences
- Novel SDF specification that allows for flexible modeling of consumption, inflation, and interest rate dynamics
- Regime-shifting Taylor Rule for one-period nominal interest rates
- Explore Financial Market implications with resulting Nonlinear Term Structure Model
Modeling Challenges

- We know from:
  
  Lucas (1978) : Preferences + $\pi_t$ Process $\implies y_t^1$
  
  Gallmeyer et al. (2009) : Preferences + Rule for $y_t^1 \implies \pi_t$ Process

- Ideally, we would like to have a more flexible form of the SDF that can allow us to have an exogenous expression of preferences, a short rate rule, and inflation, yet maintain tractability
Modeling Challenges

- We know from:
  - Lucas (1978): Preferences + $\pi_t$ Process $\Rightarrow y^1_t$
  - Gallmeyer et al. (2009): Preferences + Rule for $y^1_t \Rightarrow \pi_t$ Process

- Ideally, we would like to have a more flexible form of the SDF that can allow us to have an exogenous expression of preferences, a short rate rule, and inflation, yet maintain tractability.

- In this framework, we utilize an SDF that prices the risks of cash flow, real rate, and “volatility” news.
Nominal Economy

- The EZ agent maximizes lifetime utility ($U_t$) under endowment uncertainty:

$$U_t = \max \left[ (1 - \delta) C_t^{\frac{1-\gamma}{\theta}} + \delta \left( E_t \left[ U_{t+1}^{1-\gamma} \right] \right)^{\frac{1}{\theta}} \right]^{1-\gamma}$$

- Equilibrium solution to log nominal SDF can be written as:

$$m_{t+1} = \theta \log \delta - \frac{\theta}{\psi} \Delta c_{t+1} + (\theta - 1) r_{c,t+1} - \pi_{t+1}$$

where $\Delta c$ is log consumption growth, $r_c$ is return on aggregate wealth portfolio, and $\pi$ is inflation.
The Euler restriction gives us that:

$$E_t [m_{t+1} + i_{t+1}] = 1$$

and the log-linearized wealth constraint:

$$r_{c,t+1} = \log \frac{W_{t+1}}{W_t - C_t} \approx \kappa_0 + wc_{t+1} - \frac{1}{\kappa_1} wc_t + \Delta c_{t+1}$$

Using forward recursions of these two equations and the EZ pricing kernel we can derive the SDF as a function of innovations to future news.
Dynamic-CAPM SDF (II)

Following Bansal et al. (2013) and Campbell et al. (2013), we formulate the SDF as a function of cash flow, real interest rate, and vol news:

\[
m_{t+1} = -i_t - V_t - \gamma N_{CF,t+1} + N_{R,t+1} + N_{V,t+1}
\]

\[
V_t = \log E_t (\exp (m_{t+1} - E_t(m_{t+1})))
\]

\[
N_{CF,t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\kappa_1} \Delta c_{t+j+1}
\]

\[
N_{R,t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\kappa_1} (i_{t+j} - \pi_{t+j+1})
\]

\[
N_{V,t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\kappa_1} V_{t+j}
\]

We exogenously specify consumption, inflation, and interest rate dynamics; volatility news is solved endogenously.
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We exogenously specify consumption, inflation, and interest rate dynamics; volatility news is solved endogenously.
Denote the regime of monetary policy as $s_t$, which is governed by an $N$-state Markov switching process. Transition from state $j$ to state $i$ will be given by probability $\pi_{ij}$. The consumption / inflation processes are given by:

$$\triangle c_{t+1} = \mu c_t + x_{ct} + \sigma c \epsilon_{ct+1}$$

$$\pi_{t+1} = \mu \pi_t + x_{\pi t} + \sigma \pi \epsilon_{\pi t+1}$$

where we model the expected components of endowments with stochastic volatility.
Economic Dynamics

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- The consumption / inflation processes are given by:

\[
\begin{align*}
\Delta c_{t+1} &= \mu_c + x_c t + \sigma_c^* \epsilon_{c,t+1} \\
\pi_{t+1} &= \mu_\pi + x_\pi t + \sigma_\pi^* \epsilon_{\pi,t+1}
\end{align*}
\]

where we model the expected components of endowments with stochastic volatility.
Economic Dynamics (II)

- The joint, demeaned VAR process $X_t = [x_{ct}, x_{\pi t}]'$ will be given by:

$$X_{t+1} = \Pi X_t + \Sigma_t \epsilon_{t+1}$$
Economic Dynamics (II)

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$$X_{t+1} = \Pi X_t + \Sigma_t \epsilon_{t+1}$$

where $\Sigma_t$ is given by:

$$\Sigma_t = \begin{pmatrix} \sigma_{c0} & 0 \\ 0 & \sigma_{\pi,t} \end{pmatrix} = \begin{pmatrix} \sigma_{c0} & 0 \\ 0 & \sqrt{\delta_{\pi}(s_t) + \tilde{\sigma}_{\pi,t}^2} \end{pmatrix}$$

and the transient, continuous portions of volatility are given by:

$$\tilde{\sigma}_{\pi t}^2 = \tilde{\sigma}_{\pi,0}^2 + \varphi_{\pi} \tilde{\sigma}_{\pi,t-1}^2 + \omega_{\pi} \eta_{\sigma_{\pi},t}$$
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- Notice that the inflation variance is a linear combination of (1) a monetary policy portion and (2) a smooth variance component.
We have specified consumption and inflation dynamics; the last thing to specify is the rule for the short rate:

\[ i_t = i_0 + \alpha_c(s_t) (x_{ct} + \mu_c) + \alpha_\pi(s_t) (x_{\pi t} + \mu_\pi) \]

\[ = \alpha_0(s_t) + \alpha(s_t)' X_t \]
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i_t = i_0 + \alpha_c(s_t) \left( x_{ct} + \mu_c \right) + \alpha_\pi(s_t) \left( x_{\pi t} + \mu_\pi \right) \\
= \alpha_0(s_t) + \alpha(s_t)' X_t
\]

Regime, \( s_t \), links movements in Taylor rule coefficients to those in inflation volatilities.
Recall that the log-SDF is given by:

\[ m_{t+1} = -i_t - V_t - \gamma N_{CF,t+1} + (N_{I,t+1} - N_{\pi,t+1}) + N_{V,t+1} \]

We take into account the risks associated with monetary regime switches and continuous state movements when computing each type of news.
Model Solution (II)

- To receive $V_t$ we guess and verify by conjecturing a nonlinear form:

$$V_t(s_t) = V_0(s_t) + V_1(s_t)'X_t + V_2\pi(s_t)\tilde{\sigma}_{\pi,t}^2$$

- Solve using 1 period Euler relation:

$$1 = E_t [\exp(m_{t+1} + i_t)]$$

$$\implies \exp(V_t) = E_t [\exp(m_{t+1} + i_t + V_t)]$$

$$= E_t [\exp(-\gamma N_{CF,t+1} + N_{I,t+1} - N_{\pi,t+1} + N_{V,t+1})]$$

- For every set of parameters, we can solve for a $V_t$ process that satisfies no-arbitrage restriction
Nominal Term Structure

With solution to $V_t$ we can re-express the SDF as:

$$m_{t+1} = S_0 + S_{1,X} X_t + S_{1,\sigma} \tilde{\sigma}_{\pi t}$$
$$+ S_{1,\epsilon} \sum_t \epsilon_{t+1} + S_{2,\eta} \omega_{\pi t} \eta_{\pi t}$$

where we have regime-dependent loadings and time-varying quantities of risks.
Nominal Term Structure

- With solution to $V_t$ we can re-express the SDF as:

$$m_{t+1} = S_0 + S'_1, X_t + S_{1,\sigma\pi} \tilde{\sigma}_{\pi t}^2$$

$$+ S'_{2,\epsilon} \Sigma_t \epsilon_{t+1} + S_{2,\eta\pi} \omega_{\pi,t+1}$$

where we have regime-dependent loadings and time-varying quantities of risks.

- We can now show that log bond prices and hence yields, $y^n_t$, take a nonlinear structure in states

$$y^n_t(s_t) = -\frac{1}{n} p^n_t = A^n(s_t) + B^n_X(s_t) X_t + B^n_{\sigma\pi}(s_t) \tilde{\sigma}_{\pi t}^2$$
Nominal Term Structure

- With solution to $V_t$ we can re-express the SDF as:

$$m_{t+1} = S_0 + S'_{1,X}X_t + S_{1,\sigma\pi}\tilde{\sigma}^2_{\pi t} + S'_{2,\epsilon}\sum \epsilon_{t+1} + S_{2,\eta\pi}\omega_{\pi}\eta_{\pi,t+1}$$

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- Risk premia in this economy will take a similar form as well:

$$rp^n_t = E_t \left[ \frac{P^{n-1}_{t+1}}{P^n_t} \right] - y^1_t = r_0(s_t) + r_{\sigma\pi}(s_t)\tilde{\sigma}^2_{\pi t}$$
Estimation
Empirical Implementation

- 2 monetary regimes
- Filtered Time Series: \( \{x_{ct}, x_{\pi t}, \tilde{\sigma}^2_{\pi t}, s_t\} \) using Bayesian MCMC methods
- Estimation is from 1969 onwards at a quarterly basis using bond yields \{3M, 1Y - 5Y\} from Fed & CRSP
- Nondurables and Services Consumption and GDP Deflator Inflation from the BEA
- Expectations data from Survey of Professional Forecasters
Our state space for estimation is given by (indicates measurement error):

\[
\begin{align*}
\Delta c_{t+1} &= \mu_c + e_1' X_t + \sigma_c^* \epsilon_c, t+1 \\
\pi_{t+1} &= \mu_\pi + e_2' X_t + \sigma_\pi^* \epsilon_\pi, t+1 \\
X_{SPF,t+1} &= X_{t+1} + u_{t+1}, X \\
Y_{t+1}^{DATA} &= f_Y (Z_t, Z_{t+1}) + \Sigma u, Y u_{t+1}, Y
\end{align*}
\]
Our state space for estimation is given by (indicates measurement error):

(Measurement) \[ y_{t+1}^{1:N} = A^{1:N}(s_{t+1}) + B_{X}^{1:N}(s_{t+1})X_{t+1} + B_{\sigma_\pi}^{1:N}(s_{t+1})\tilde{\sigma}_\pi^2,t+1 + u_{t+1,y} \]
\[ \Delta c_{t+1} = \mu_c + e'_1 X_t + \sigma^*_c \epsilon_{c,t+1} \]
\[ \pi_{t+1} = \mu_\pi + e'_2 X_t + \sigma^*_{\pi} \epsilon_{\pi,t+1} \]
\[ X_{SPF,t+1} = X_{t+1} + u_{t+1,X} \]

\[ \iff \]
\[ Y_{t+1}^{DATA} = f_Y(\mathbb{Z}_t, \mathbb{Z}_{t+1}) + \sum_{u,Y} u_{t+1,Y} \]

(Transition) \[ X_{t+1} = \Pi X_t + \Sigma_t(\tilde{\sigma}_\pi^2, s_t)\epsilon_{t+1} \]
\[ \tilde{\sigma}_\pi^2 = \tilde{\sigma}_{\pi,0}^2 + \varphi_\pi \tilde{\sigma}_{\pi,t-1}^2 + \omega_\pi \eta_{\sigma_\pi,t} \]
\[ s_t \sim \text{Discrete Markov Process with } T(\mathbb{P}_s) \]
State Space

Our state space for estimation is given by (indicates measurement error):

(Measurement)\[ y_{t+1}^{1:N} = A^{1:N}(s_{t+1}) + B^{1:N}_X(s_{t+1})X_{t+1} + B^{1:N}_{\sigma\pi}(s_{t+1})\tilde{\sigma}_{\pi,t+1}^2 + u_{t+1,y} \]
\[ \Delta c_{t+1} = \mu_c + e'_1 X_t + \sigma^*_c \epsilon_{c,t+1} \]
\[ \pi_{t+1} = \mu_\pi + e'_2 X_t + \sigma^*_\pi \epsilon_{\pi,t+1} \]
\[ X_{SPF,t+1} = X_{t+1} + u_{t+1,x} \]

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The set of parameters (\( \theta \)) is given by:

\[ \{ \Pi, \delta^\alpha, \tilde{\sigma}_{\pi 0}^2, \tilde{\sigma}_{c 0}^2, \varphi_{\pi}, \omega_{\pi}, \sigma^*_c, \sigma^*_\pi, i_0, \kappa_1, \gamma, \mu_c, \mu_\pi, \alpha^{1:2}_c, \alpha^{1:2}_\pi, \mathbb{P}_s \} \]
Our state space for estimation is given by (indicates measurement error):

(Measurement)
\[
y_{t+1}^{1:N} = A^{1:N}(s_{t+1}) + B_X^{1:N}(s_{t+1})X_{t+1} + B_{\sigma \pi}^{1:N}(s_{t+1})\tilde{\sigma}_{\pi,t+1}^2 + u_{t+1,y}
\]
\[
\Delta c_{t+1} = \mu_c + e_1'X_t + \sigma_c^*\epsilon_c,t+1
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\pi_{t+1} = \mu_\pi + e_2'X_t + \sigma_\pi^*\epsilon_\pi,t+1
\]
\[
X_{SPF,t+1} = X_{t+1} + u_{t+1,X}
\]

\[\Longleftrightarrow\]
\[
Y_{t+1}^{DATA} = f_Y(Z_t, Z_{t+1}) + \Sigma_{u,Y}u_{t+1,Y}
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(Transition)
\[
X_{t+1} = \Pi X_t + \Sigma_t(\tilde{\sigma}_{\pi,t}^2, s_t)\epsilon_{t+1}
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\tilde{\sigma}_{\pi t}^2 = \tilde{\sigma}_{\pi,0}^2 + \varphi_{\pi} \tilde{\sigma}_{\pi,t-1}^2 + \omega_{\pi} \eta_{\sigma \pi, t}
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s_t \sim \text{Discrete Markov Process with } T(\mathbb{P}_s)
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The set of parameters (\(\theta\)) is given by:

\[
\{\Pi, \delta^{\alpha \pi}, \tilde{\sigma}_{c0}^2, \tilde{\sigma}_{\pi 0}^2, \varphi_{\pi}, \omega_{\pi}, \sigma_c^*, \sigma_\pi^*, i_0, \kappa_1, \gamma, \mu_c, \mu_\pi, \alpha_{c}^{1:2}, \alpha_{\pi}^{1:2}, \mathbb{P}_s\}
\]

Keep in mind, each \(\theta \rightarrow \{A, B_X, B_{\sigma \pi}\}\), so state space coefficients are all model-based.
Estimation Technique

- We draw parameters using a Bayesian MCMC algorithm, using \textit{Particle-Filter} evaluation of the likelihood function.
Estimation Technique

- We draw parameters using a Bayesian MCMC algorithm, using Particle-Filter evaluation of the likelihood function.
- The posterior distribution of the parameter vector, $\theta$, satisfies

$$P(\theta|Y_{DATA}) \propto P(Y_{DATA}|\theta) \times P(\theta)$$

$P(Y_{DATA}|\theta)$ can be evaluated using a particle filter approach. For $J$ "particles" of the exogenous states, we have:

$$P(Y_{DATA}|\theta) \approx 1/J \sum_{j=1}^{J} P(Y_{DATA}|States_j, \theta)$$

States $j$ can be drawn individually for given $\theta$, and we evaluate each set's probabilities using particle weights.
Estimation Technique

- We draw parameters using a Bayesian MCMC algorithm, using **Particle-Filter** evaluation of the likelihood function.
- The posterior distribution of the parameter vector, \( \theta \), satisfies

\[
P(\theta | Y^{DATA}) \propto P(Y^{DATA} | \theta) \times P(\theta)
\]

- To evaluate the likelihood, we need to take into account state uncertainty. We use a particle filter approach. That is to say for \( J \) “particles” of the exogenous states we use:

\[
P(Y^{DATA} | \theta) \approx \frac{1}{J} \sum_{j=1}^{J} P(Y^{DATA} | States^j, \theta)
\]

\( States^j \) can be drawn individually, for given \( \theta \), and we evaluate each set’s probabilities using particle weights.
Estimation Technique (II)

- To draw parameters we can use Random-Walk Metropolis-Hastings algorithm where we draw:
  \[ \theta^* = \theta_{j-1} + \sum_{draw} \varepsilon \]

\[ \text{Accept w/Prob} \quad \alpha = \frac{P(\theta^* | Y^{DATA})}{P(\theta_{j-1} | Y^{DATA})} \]

- After getting sufficient number of draws, remove burn-in and report results across draws of \( \theta \)
Results

- Model Fit
- Parameter Estimates
- Counterfactuals, among which:
  - Within-Regime Characteristics
  - Risk Premia Movements
  - Role of MP Shifts
Model Fit (In-Sample Yields)

Data, Posterior Median (Solid), 90% Credible Sets (shaded)

(i) In-Sample $y^1_t$

(ii) In-Sample $y^3_t$

(iii) In-Sample $y^5_t$

→ We fit bond yields with low measurement error
Latent States (Filtered Expectations)

Data, Posterior Median (Solid), 90% Credible Sets (shaded)

(i) Filtered $x_{ct}$

(ii) Filtered $x_{\pi t}$

→ Model measures of macroeconomic expectations are close to the data

Shaliastovich and Yamarthy
MP Risks in Bond Markets & Macroeconomy
April 24, 2015
Results

Latent States (Filtered Expectations)

Data, Posterior Median (Solid), 90% Credible Sets (shaded)

(i) Filtered $\tilde{\sigma}^2_{\pi t}$

(ii) Filtered $s_t$

$\Rightarrow$ Non-policy related inflation volatility jumps in levels in the 1980’s and declines to very low value recently

$\Rightarrow$ Regimes are consistent with anecdotal evidence and other literature

Details

Shaliastovich and Yamarthy
MP Risks in Bond Markets & Macroeconomy
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Parameter Values

Posterior medians are provided. Values in parentheses are (10%, 90%) credible sets.

\[
\begin{array}{c|c|c}
\hline
 & \Pi & \Pi \\
\hline
x_{ct} & .991 & -.011 \\
 & (.972, .998) & (-.032, -.004) \\
x_{\pi t} & 0.00 & .955 \\
 & & (.920, .978) \\
\hline
\end{array}
\]

\[
\begin{array}{c|c|c|c}
\hline
\bar{\sigma}^2_i & 1 - \varphi_i & \varphi_i & \omega_i \times 10^6 \\
\hline
\bar{\sigma}^2_{ct} & .025 & - & - \\
 & (.013, .068) & & \\
\bar{\sigma}^2_{\pi t} & .021 & .976 & .190 \\
 & (.009, .043) & (.962, .992) & (.186, .194) \\
\hline
\end{array}
\]

The inflation non-neutrality is key to receive upward sloping yield levels and risk premia levels!
## Parameter Values

Posterior medians are provided. Values in parentheses are (10%, 90%) credible sets.

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<thead>
<tr>
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<th>II</th>
<th>III</th>
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<th>$\tilde{\sigma}^2_{i,0} \times 10^5$</th>
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Parameter Values (II)

Posterior medians are provided. Values in parentheses are (10%, 90%) credible sets.

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<th>$\delta_{\pi}(i) \times 10^5$</th>
<th>$\alpha_c(i)$</th>
<th>$\alpha_{\pi}(i)$</th>
<th>$\pi_{ii}$</th>
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<td>$i = 1$</td>
<td>0.00</td>
<td>0.91</td>
<td>0.791</td>
<td>0.975</td>
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<tr>
<td></td>
<td>($0.023$, $0.274$)</td>
<td>($0.622$, $1.01$)</td>
<td>($0.945$, $0.994$)</td>
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<tr>
<td>$i = 2$</td>
<td>0.0083</td>
<td>0.315</td>
<td>1.90</td>
<td>0.929</td>
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<tr>
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<td>($0.0063$, $0.0099$)</td>
<td>($0.174$, $0.524$)</td>
<td>($1.66$, $1.99$)</td>
<td>($0.893$, $0.971$)</td>
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Other Pars

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<th>$\gamma$</th>
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We can interpret regime 1 as an "Aggressive Policy" state while regime 2 exhibits a "Passive Policy." Aggressive regimes generate more macroeconomic volatility (about one quarter of total inflation vol in levels!)
Parameter Values (II)

Posterior medians are provided. Values in parentheses are (10%, 90%) credible sets.

\[
\begin{array}{ccccc}
\delta_{\pi}(i) \times 10^5 & \alpha_c(i) & \alpha_{\pi}(i) & \pi_{ii} \\
\hline
\text{Regime } i = 1 & 0.00 & 0.091 & 0.791 & 0.975 \\
 & & (.023, .274) & (.622, 1.01) & (.945, .994) \\
\text{Regime } i = 2 & .0083 & .315 & 1.90 & .929 \\
 & & (.0063, .0099) & (.174, .524) & (1.66, 1.99) & (.893, .971) \\
\hline
\end{array}
\]

\[
\begin{array}{cccccc}
\gamma & i_0 & \mu_c & \mu_{\pi} & \sigma_c^* & \sigma_{\pi}^* \\
\hline
\text{Other Pars} & 24.38 & .013 & .0045 & .0091 & .0038 & .0039 \\
 & & (22.81, 26.09) & & & (.0029, .0050) & (.0029, .0050) \\
\hline
\end{array}
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⇒ We can interpret regime 1 as an “Aggressive Policy” state while regime 2 exhibits a “Passive Policy.”
Parameter Values (II)

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$\implies$ We can interpret regime 1 as an “Aggressive Policy” state while regime 2 exhibits a “Passive Policy.”

$\implies$ Aggressive regimes generate more macroeconomic volatility (about one quarter of total inflation vol in levels!)
Within-Regime Characteristics

We take median parameters and fix policy variables at each regime’s values.

(i) Yield Levels

(ii) Volatilities

⇒ Aggressive regimes are associated with higher levels and volatilities.
Risk Premia Movements

Figure: Model-Implied, In-Sample Risk Premia

⇒ Upward sloping RP term structure, model breaks Expectation Hypothesis
⇒ Estimates also capture recent negative risk premia period
Aggressive regimes identify with higher risk premia levels and volatilities

Recent negative risk-premia period, identified through low \( \tilde{\sigma}^2_{\pi t} \)
Experiments

- What is the marginal contribution of non-policy volatility? Of policy volatility? Of time-varying coefficients?

- We test this by examining risk premia moments with four specifications:
  
  (a) Keep constant all regime shifting constants (Infl Vol Only)
  (b) Allow variation in $\alpha_\pi(s_t)$ (Infl vol + $\alpha_\pi$)
  (c) Allow variation in $\delta_\pi(s_t)$ (Infl vol + $\alpha_\pi + \delta$)
  (d) Allow all variations (Baseline)
Vol effects are sizeable. \( \{\alpha_\pi, \delta_\pi\} \) both raise overall RP Vol by \( \sim 20\% \) each.

Variation in growth sensitivity, \( \alpha_c \) decreases it.
Differing Signs of Volatility Movements

We can rewrite the risk premia as:

\[ \text{r}_{p_t^n} = Cons(s_t) + r_{\sigma_c}(s_t) \tilde{\sigma}_c^2 + r_{\sigma_\pi}(s_t) \tilde{\sigma}_\pi^2 \]

where the second portion denotes the piece from growth-related volatility

- Variation in \( \alpha_c \) largely affects \( r_{\sigma_c} \) while \( \alpha_\pi \) variation affects \( r_{\sigma_\pi} \)
- Growth sensitivity variation decreases risk premia volatility
- Signs of risk premia loadings are consistent with empirical results
Conclusion

- We propose a theory-based, flexible asset pricing model that disentangles slow-moving components of stochastic volatility from monetary policy aggressiveness.
- Through an estimation of a two-regime monetary setup, we show the importance of the monetary channel in stochastic volatility and asset risk premia.
  - Aggressive monetary policies increase macro-volatility.
  - Aggressive regimes are associated with higher yield levels, more volatility, and greater risk premia variability.
  - The policy portion of fundamental inflation vol increases risk premia volatility in conjunction with movements in the inflation sensitivity of the Taylor rule.

⇒ Thank you for attending! Comments and questions are very much welcome.
Appendix
Details on Model Solution

We can show that Cash Flow \((N_{CF})\), Inflation News \((N_{\pi})\), and Interest Rate News \((N_{I})\) are given by:

\[
N_{CF,t+1}(s_t, s_{t+1}) = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \kappa_1^j \Delta c_{t+j+1} \\
= F_{CF,0}(s_t, s_{t+1}) + F_{CF,\epsilon}(\ldots)'\Sigma_t \epsilon_{t+1} + \sigma_c^* \epsilon_{c,t+1}
\]

\[
N_{\pi,t+1}(s_t, s_{t+1}) = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \kappa_1^j \pi_{t+j+1} \\
= F_{\pi,0}(s_t, s_{t+1}) + F_{\pi,\epsilon}(\ldots)'\Sigma_t \epsilon_{t+1} + \sigma_\pi^* \epsilon_{\pi,t+1}
\]

\[
N_{I,t+1}(s_t, s_{t+1}) = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \kappa_1^j i_{t+j} \\
= F_{I,0}(s_t, s_{t+1}) + F_{I,\epsilon}(\ldots)'\Sigma_t \epsilon_{t+1} + F_{I,X}(\ldots)'X_t + F_{I,\epsilon}(\ldots)'\Sigma_t \epsilon_{t+1}
\]

where \(F_{\ldots}\) are functions of model primitives (parameters of state governance, regime transition matrix, etc.)
Chernov and Bikbov (2013) uses output gap in a New Keynesian setting to identify regimes.

Estimation of active regime in their work is very similar. Picks up in 1980’s, and mid 2000’s. Also increases in ZLB period.