

“Monetary Policy Risks in the Bond Markets and Macroeconomy”

Ivan Shaliastovich and Ram Yamarthy
The Wharton School, University of Pennsylvania

NYU Volatility Institute
April 24, 2015

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 (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 (eg. 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

Historical Works

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*
(Ang and Bekaert (2002), Bansal and Zhou (2003), Ang and Piazzesi (2003), Bansal and Yaron (2004), Hasseltoft (2011), Bansal and Shaliastovich (2013))
- *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))

Historical Works

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*
(Ang and Bekaert (2002), Bansal and Zhou (2003), Ang and Piazzesi (2003), Bansal and Yaron (2004), Hasseltoft (2011), Bansal and Shaliastovich (2013))
- *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 + π_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 + π_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
- 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:

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

- 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 Δc is log consumption growth, r_c is return on aggregate wealth portfolio, and π is inflation

Dynamic-CAPM SDF

- 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:

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

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

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

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

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

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:

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

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

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

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

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

- We exogenously specify consumption, inflation, and interest rate dynamics;
volatility news is solved endogenously

Economic Dynamics

- 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 π_{ij} .

Economic Dynamics

- 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 π_{ij} .
- The consumption / inflation processes are given by:

$$\begin{aligned}\Delta c_{t+1} &= \mu_c + x_{ct} + \sigma_c^* \epsilon_{c,t+1} \\ \pi_{t+1} &= \mu_\pi + x_{\pi t} + \sigma_\pi^* \epsilon_{\pi,t+1}\end{aligned}$$

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)

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

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

where Σ_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:

$$\tilde{\sigma}_{\pi t}^2 = \tilde{\sigma}_{\pi,0}^2 + \varphi_\pi \tilde{\sigma}_{\pi,t-1}^2 + \omega_\pi \eta_{\sigma\pi,t}$$

Economic Dynamics (II)

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

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

where Σ_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:

$$\tilde{\sigma}_{\pi t}^2 = \tilde{\sigma}_{\pi,0}^2 + \varphi_\pi \tilde{\sigma}_{\pi,t-1}^2 + \omega_\pi \eta_{\sigma\pi,t}$$

- Notice that the inflation variance is a linear combination of (1) a monetary policy portion and (2) a smooth variance component

Economic Dynamics (III)

- We have specified consumption and inflation dynamics; the last thing to specify is the rule for the short rate:

$$\begin{aligned}
 i_t &= i_0 + \alpha_c(s_t) \underbrace{(x_{ct} + \mu_c)}_{\text{Expected Growth}} + \alpha_\pi(s_t) \underbrace{(x_{\pi t} + \mu_\pi)}_{\text{Expected Inflation}} \\
 &= \alpha_0(s_t) + \alpha(s_t)' X_t
 \end{aligned}$$

Economic Dynamics (III)

- We have specified consumption and inflation dynamics; the last thing to specify is the rule for the short rate:

$$\begin{aligned}
 i_t &= i_0 + \alpha_c(s_t) \underbrace{(x_{ct} + \mu_c)}_{\text{Expected Growth}} + \alpha_\pi(s_t) \underbrace{(x_{\pi t} + \mu_\pi)}_{\text{Expected Inflation}} \\
 &= \alpha_0(s_t) + \alpha(s_t)' X_t
 \end{aligned}$$

- Regime, s_t , links movements in Taylor rule coefficients to those in inflation volatilities

Model Solution

- 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 [Details](#)

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:

$$\begin{aligned} 1 &= E_t [\exp(m_{t+1} + i_t)] \\ \implies \exp(V_t) &= E_t [\exp(m_{t+1} + i_t + V_t)] \\ &= E_t [\exp(-\gamma N_{CF,t+1} + N_{I,t+1} - N_{\pi,t+1} + N_{V,t+1})] \end{aligned}$$

- 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:

$$\begin{aligned} m_{t+1} &= S_0 + S'_{1,X} X_t + S_{1,\sigma\pi} \tilde{\sigma}_{\pi t}^2 \\ &+ \textcolor{red}{S}'_{2,\epsilon} \textcolor{blue}{\Sigma}_t \epsilon_{t+1} + \textcolor{red}{S}_{2,\eta\pi} \omega_{\pi} \eta_{\pi,t+1} \end{aligned}$$

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:

$$\begin{aligned} m_{t+1} &= S_0 + S'_{1,X} X_t + S_{1,\sigma\pi} \tilde{\sigma}_{\pi t}^2 \\ &+ \textcolor{red}{S}'_{2,\epsilon} \textcolor{blue}{\Sigma}_t \epsilon_{t+1} + \textcolor{red}{S}_{2,\eta\pi} \omega_\pi \eta_{\pi,t+1} \end{aligned}$$

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

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

$$y_t^n(s_t) = -\frac{1}{n} p_t^n = \mathcal{A}^n(s_t) + \mathcal{B}_X^{n'}(s_t) X_t + \mathcal{B}_{\sigma\pi}^n(s_t) \tilde{\sigma}_{\pi t}^2$$

Nominal Term Structure

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

$$\begin{aligned} m_{t+1} &= S_0 + S'_{1,X} X_t + S_{1,\sigma\pi} \tilde{\sigma}_{\pi t}^2 \\ &+ \textcolor{red}{S}'_{2,\epsilon} \textcolor{blue}{\Sigma}_t \epsilon_{t+1} + \textcolor{red}{S}_{2,\eta\pi} \omega_\pi \eta_{\pi,t+1} \end{aligned}$$

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

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

$$y_t^n(s_t) = -\frac{1}{n} p_t^n = \mathcal{A}^n(s_t) + \mathcal{B}_X^{n'}(s_t) X_t + \mathcal{B}_{\sigma\pi}^n(s_t) \tilde{\sigma}_{\pi t}^2$$

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

$$rp_t^n = E_t \left[\frac{P_{t+1}^{n-1}}{P_t^n} \right] - y_t^1 = r_0(s_t) + r_{\sigma\pi}(s_t) \tilde{\sigma}_{\pi t}^2$$

Estimation

Empirical Implementation

- 2 monetary regimes
- Filtered Time Series: $\{x_{ct}, x_{\pi t}, \tilde{\sigma}_{\pi t}^2, s_t\}$ 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

State Space

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

$$\begin{aligned}
 \text{(Measurement)} \quad & y_{t+1}^{1:N} = \mathcal{A}^{1:N}(s_{t+1}) + \mathcal{B}_X^{1:N}(s_{t+1})X_{t+1} + \mathcal{B}_{\sigma\pi}^{1:N}(s_{t+1})\tilde{\sigma}_{\pi,t+1}^2 + \textcolor{red}{u}_{t+1,y} \\
 & \Delta c_{t+1} = \mu_c + e_1' X_t + \sigma_c^* \epsilon_{c,t+1} \\
 & \pi_{t+1} = \mu_\pi + e_2' X_t + \sigma_\pi^* \epsilon_{\pi,t+1} \\
 & X_{SPF,t+1} = X_{t+1} + \textcolor{red}{u}_{t+1,X} \\
 \\
 & \iff Y_{t+1}^{DATA} = f_Y(\mathbb{Z}_t, \mathbb{Z}_{t+1}) + \textcolor{red}{\Sigma}_{u,Y} u_{t+1,Y}
 \end{aligned}$$

State Space

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

(Measurement)

$$\begin{aligned}
 y_{t+1}^{1:N} &= \mathcal{A}^{1:N}(s_{t+1}) + \mathcal{B}_X^{1:N}(s_{t+1})X_{t+1} + \mathcal{B}_{\sigma\pi}^{1:N}(s_{t+1})\tilde{\sigma}_{\pi,t+1}^2 + \textcolor{red}{u}_{t+1,y} \\
 \Delta c_{t+1} &= \mu_c + e_1' X_t + \sigma_c^* \epsilon_{c,t+1} \\
 \pi_{t+1} &= \mu_\pi + e_2' X_t + \sigma_\pi^* \epsilon_{\pi,t+1} \\
 X_{SPF,t+1} &= X_{t+1} + \textcolor{red}{u}_{t+1,X}
 \end{aligned}$$

$$\Longleftrightarrow Y_{t+1}^{DATA} = f_Y(\mathbb{Z}_t, \mathbb{Z}_{t+1}) + \textcolor{red}{\Sigma}_{u,Y} \textcolor{red}{u}_{t+1,Y}$$

(Transition)

$$\begin{aligned}
 X_{t+1} &= \Pi X_t + \Sigma_t(\tilde{\sigma}_{\pi t}^2, s_t) \epsilon_{t+1} \\
 \tilde{\sigma}_{\pi t}^2 &= \tilde{\sigma}_{\pi,0}^2 + \varphi_\pi \tilde{\sigma}_{\pi,t-1}^2 + \omega_\pi \eta_{\sigma\pi,t} \\
 s_t &\sim \text{Discrete Markov Process with } T(\mathbb{P}_s)
 \end{aligned}$$

State Space

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

$$\begin{aligned}
 \text{(Measurement)} \quad & y_{t+1}^{1:N} = \mathcal{A}^{1:N}(s_{t+1}) + \mathcal{B}_X^{1:N}(s_{t+1})X_{t+1} + \mathcal{B}_{\sigma\pi}^{1:N}(s_{t+1})\tilde{\sigma}_{\pi,t+1}^2 + \textcolor{red}{u}_{t+1,y} \\
 & \Delta c_{t+1} = \mu_c + e_1' X_t + \sigma_c^* \epsilon_{c,t+1} \\
 & \pi_{t+1} = \mu_\pi + e_2' X_t + \sigma_\pi^* \epsilon_{\pi,t+1} \\
 & X_{SPF,t+1} = X_{t+1} + \textcolor{red}{u}_{t+1,X}
 \end{aligned}$$

$$\Longleftrightarrow Y_{t+1}^{DATA} = f_Y(\mathbb{Z}_t, \mathbb{Z}_{t+1}) + \textcolor{red}{\Sigma}_{u,Y} \textcolor{red}{u}_{t+1,Y}$$

$$\begin{aligned}
 \text{(Transition)} \quad & X_{t+1} = \Pi X_t + \Sigma_t(\tilde{\sigma}_{\pi t}^2, s_t) \epsilon_{t+1} \\
 & \tilde{\sigma}_{\pi t}^2 = \tilde{\sigma}_{\pi,0}^2 + \varphi_\pi \tilde{\sigma}_{\pi,t-1}^2 + \omega_\pi \eta_{\sigma\pi,t} \\
 & s_t \sim \text{Discrete Markov Process with } T(\mathbb{P}_s)
 \end{aligned}$$

- The set of parameters (θ) is given by:

$$\{\Pi, \delta^{\alpha\pi}, \tilde{\sigma}_{c0}^2, \tilde{\sigma}_{\pi0}^2, \varphi_\pi, \omega_\pi, \sigma_c^*, \sigma_\pi^*, i_0, \kappa_1, \gamma, \mu_c, \mu_\pi, \alpha_c^{1:2}, \alpha_\pi^{1:2}, \mathbb{P}_s\}$$

State Space

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

$$\begin{aligned}
 \text{(Measurement)} \quad & y_{t+1}^{1:N} = \mathcal{A}^{1:N}(s_{t+1}) + \mathcal{B}_X^{1:N}(s_{t+1})X_{t+1} + \mathcal{B}_{\sigma\pi}^{1:N}(s_{t+1})\tilde{\sigma}_{\pi,t+1}^2 + \textcolor{red}{u}_{t+1,y} \\
 & \Delta c_{t+1} = \mu_c + e_1' X_t + \sigma_c^* \epsilon_{c,t+1} \\
 & \pi_{t+1} = \mu_\pi + e_2' X_t + \sigma_\pi^* \epsilon_{\pi,t+1} \\
 & X_{SPF,t+1} = X_{t+1} + \textcolor{red}{u}_{t+1,X}
 \end{aligned}$$

$$\Longleftrightarrow Y_{t+1}^{DATA} = f_Y(\mathbb{Z}_t, \mathbb{Z}_{t+1}) + \textcolor{red}{\Sigma}_{u,Y} u_{t+1,Y}$$

$$\begin{aligned}
 \text{(Transition)} \quad & X_{t+1} = \Pi X_t + \Sigma_t(\tilde{\sigma}_{\pi t}^2, s_t) \epsilon_{t+1} \\
 & \tilde{\sigma}_{\pi t}^2 = \tilde{\sigma}_{\pi,0}^2 + \varphi_\pi \tilde{\sigma}_{\pi,t-1}^2 + \omega_\pi \eta_{\sigma\pi,t} \\
 & s_t \sim \text{Discrete Markov Process with } T(\mathbb{P}_s)
 \end{aligned}$$

- The set of parameters (θ) is given by:

$$\{\Pi, \delta^{\alpha\pi}, \tilde{\sigma}_{c0}^2, \tilde{\sigma}_{\pi0}^2, \varphi_\pi, \omega_\pi, \sigma_c^*, \sigma_\pi^*, i_0, \kappa_1, \gamma, \mu_c, \mu_\pi, \alpha_c^{1:2}, \alpha_\pi^{1:2}, \mathbb{P}_s\}$$

- Keep in mind, each $\theta \longrightarrow \{\mathcal{A}, \mathcal{B}_X, \mathcal{B}_{\sigma\pi}\}$, so state space coefficients are all model-based

Estimation Technique

- We draw parameters using a Bayesian MCMC algorithm, using **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, θ , satisfies

$$\underbrace{P(\theta|Y^{DATA})}_{\text{Posterior}} \propto \underbrace{P(Y^{DATA}|\theta)}_{\text{Likelihood}} \times \underbrace{P(\theta)}_{\text{Prior}}$$

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, θ , satisfies

$$\underbrace{P(\theta|Y^{DATA})}_{\text{Posterior}} \propto \underbrace{P(Y^{DATA}|\theta)}_{\text{Likelihood}} \times \underbrace{P(\theta)}_{\text{Prior}}$$

- 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:

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

States^j can be drawn individually, for given θ , 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:

$$\theta^* = \theta^{j-1} + \Sigma_{draw} \varepsilon$$

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

- After getting sufficient number of draws, remove burn-in and report results across draws of θ

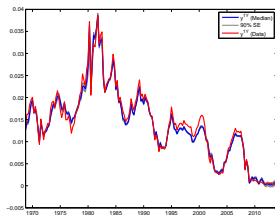
Results

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

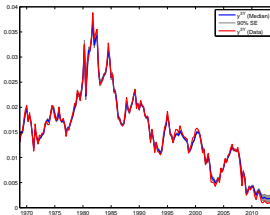
Model Fit (In-Sample Yields)

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

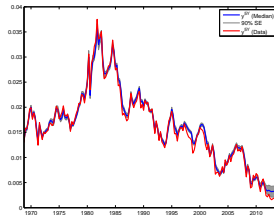
(i) In-Sample y_t^{1Y}



(ii) In-Sample y_t^{3Y}



(iii) In-Sample y_t^{5Y}

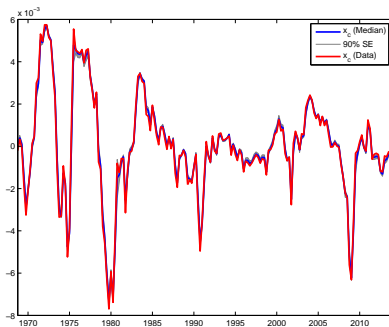


⇒ We fit bond yields with low measurement error

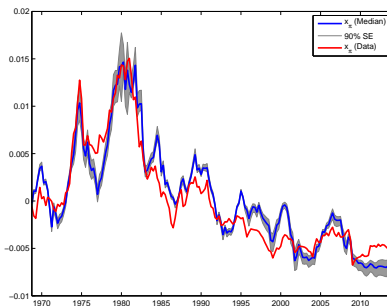
Latent States (Filtered Expectations)

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

(i) Filtered x_{ct}



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

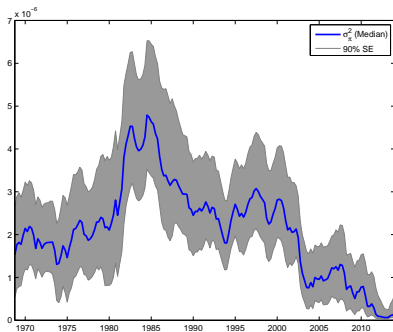


⇒ Model measures of macroeconomic expectations are close to the data

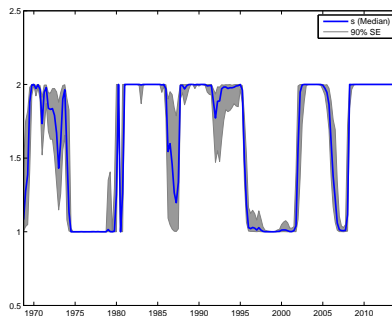
Latent States (Filtered Expectations)

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

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



(ii) Filtered s_t



⇒ Non-policy related inflation volatility jumps in levels in the 1980's and declines to very low value recently

⇒ Regimes are consistent with anecdotal evidence and other literature

[Details](#)

Parameter Values

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

	II	II	
x_{ct}	.991 (.972, .998)	-.011 (-.032, -.004)	
$x_{\pi t}$	0.00	.955 (.920, .978)	
	$\frac{\tilde{\sigma}_{i,0}^2}{1-\varphi_i} \times 10^5$	φ_i	$\omega_i \times 10^6$
$\tilde{\sigma}_{ct}^2$.025 (.013, .068)	—	—
$\tilde{\sigma}_{\pi t}^2$.021 (.009, .043)	.976 (.962, .992)	.190 (.186, .194)

Parameter Values

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

	Π	Π	
x_{ct}	.991 (.972, .998)	-.011 (-.032, -.004)	
$x_{\pi t}$	0.00	.955 (.920, .978)	
	$\frac{\tilde{\sigma}_{i,0}^2}{1-\varphi_i} \times 10^5$	φ_i	$\omega_i \times 10^6$
$\tilde{\sigma}_{ct}^2$.025 (.013, .068)	–	–
$\tilde{\sigma}_{\pi t}^2$.021 (.009, .043)	.976 (.962, .992)	.190 (.186, .194)

⇒ The **inflation non-neutrality** is key to receive upward sloping yield levels and risk premia levels!

Parameter Values (II)

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

	$\delta_{\pi}(i) \times 10^5$	$\alpha_c(i)$	$\alpha_{\pi}(i)$	π_{ii}		
Regime $i = 1$	0.00	.091 (.023, .274)	.791 (.622, 1.01)	.975 (.945, .994)		
Regime $i = 2$.0083 (.0063, .0099)	.315 (.174, .524)	1.90 (1.66, 1.99)	.929 (.893, .971)		
	γ	i_0	μ_c	μ_{π}	σ_c^*	σ_{π}^*
Other Pars	24.38 (22.81, 26.09)	.013	.0045	.0091	.0038 (.0029, .0050)	.0039 (.0029, .0050)

Parameter Values (II)

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

	$\delta_{\pi}(i) \times 10^5$	$\alpha_c(i)$	$\alpha_{\pi}(i)$	π_{ii}		
Regime $i = 1$	0.00	.091 (.023, .274)	.791 (.622, 1.01)	.975 (.945, .994)		
Regime $i = 2$.0083 (.0063, .0099)	.315 (.174, .524)	1.90 (1.66, 1.99)	.929 (.893, .971)		
	γ	i_0	μ_c	μ_{π}	σ_c^*	σ_{π}^*
Other Pars	24.38 (22.81, 26.09)	.013	.0045	.0091	.0038 (.0029, .0050)	.0039 (.0029, .0050)

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

Parameter Values (II)

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

	$\delta_{\pi}(i) \times 10^5$	$\alpha_c(i)$	$\alpha_{\pi}(i)$	π_{ii}		
Regime $i = 1$	0.00	.091 (.023, .274)	.791 (.622, 1.01)	.975 (.945, .994)		
Regime $i = 2$.0083 (.0063, .0099)	.315 (.174, .524)	1.90 (1.66, 1.99)	.929 (.893, .971)		
	γ	i_0	μ_c	μ_{π}	σ_c^*	σ_{π}^*
Other Pars	24.38 (22.81, 26.09)	.013	.0045	.0091	.0038 (.0029, .0050)	.0039 (.0029, .0050)

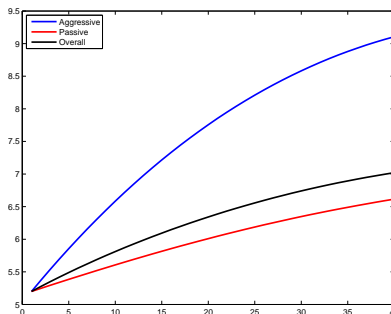
⇒ We can interpret regime 1 as an “Aggressive Policy” state while regime 2 exhibits a “Passive Policy.”

⇒ Aggressive regimes generate **more macroeconomic volatility** (about one quarter of total inflation vol in levels!)

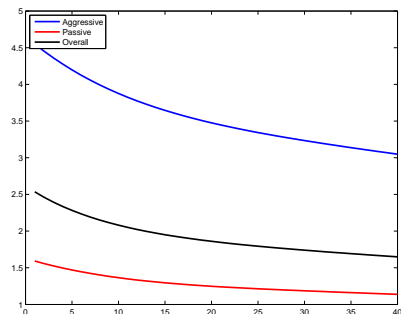
Within-Regime Characteristics

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

(i) Yield Levels



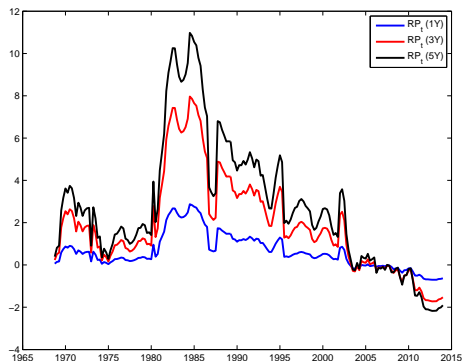
(ii) Volatilities



⇒ Aggressive regimes are associated with higher levels and volatilities.

Risk Premia Movements

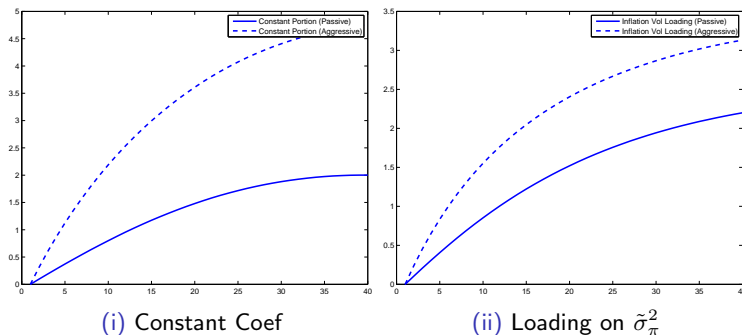
Figure: Model-Implied, In-Sample Risk Premia



- ⇒ Upward sloping RP term structure, model breaks Expectation Hypothesis
- ⇒ Estimates also capture recent negative risk premia period

Risk Premia Movements (II)

Figure: Risk Premia Loadings



⇒ Aggressive regimes identify with higher risk premia levels and volatilities

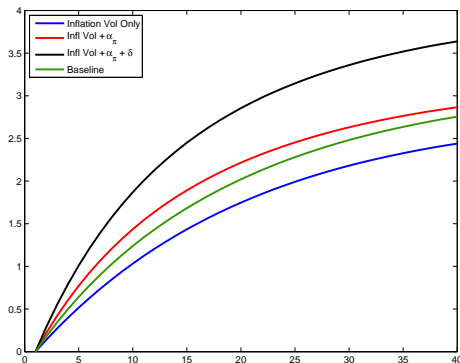
⇒ Recent negative risk-premia period, identified through low $\tilde{\sigma}_{\pi t}^2$

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 + α_π)
 - (c) Allow variation in $\delta^\pi(s_t)$ (Infl vol + $\alpha_\pi + \delta$)
 - (d) Allow all variations (Baseline)

Experiments (II)

Figure: Risk Premia Volatilities (II)



- ⇒ Vol effects are sizeable. $\{\alpha_\pi, \delta^\pi\}$ both raise overall RP Vol by $\sim 20\%$ each.
- ⇒ Variation in growth sensitivity, α_c decreases it

Differing Signs of Volatility Movements

- We can rewrite the risk premia as:

$$rp_t^n = Cons(s_t) + \underbrace{r_{\sigma c}(s_t)}_{<0} \tilde{\sigma}_{c0}^2 + \underbrace{r_{\sigma \pi}(s_t)}_{>0} \tilde{\sigma}_{\pi t}^2$$

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

- Variation in α_c largely affects $r_{\sigma c}$ while α_π 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

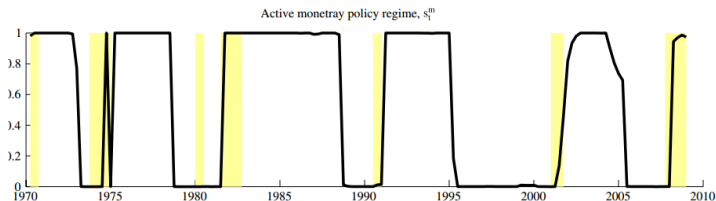
We can show that Cash Flow (N_{CF}), Inflation News (N_{π}), and Interest Rate News (N_I) are given by:

$$\begin{aligned}
 N_{CF,t+1}(s_t, s_{t+1}) &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \kappa_1^j \Delta c_{t+j+1} \\
 &= F_{CF,0}(s_t, s_{t+1}) + F_{CF,\epsilon}(\dots)' \Sigma_t \epsilon_{t+1} + \sigma_c^* \epsilon_{c,t+1} \\
 N_{\pi,t+1}(s_t, s_{t+1}) &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \kappa_1^j \pi_{t+j+1} \\
 &= F_{\pi,0}(s_t, s_{t+1}) + F_{\pi,\epsilon}(\dots)' \Sigma_t \epsilon_{t+1} + \sigma_{\pi}^* \epsilon_{\pi,t+1} \\
 N_{I,t+1}(s_t, s_{t+1}) &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \kappa_1^j i_{t+j} \\
 &= F_{I,0}(s_t, s_{t+1}) + F_{I,X}(\dots)' X_t + F_{I,\epsilon}(\dots)' \Sigma_t \epsilon_{t+1}
 \end{aligned}$$

where F_{\dots} are functions of model primitives (parameters of state governance, regime transition matrix, etc.)

Use of Output Gap

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. [▶ Back](#)