Monetary Policy Uncertainty and Economic Fluctuations

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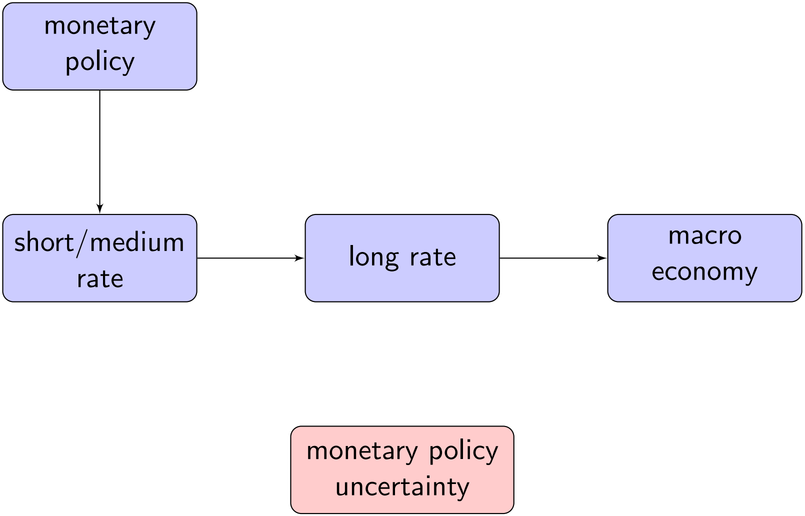
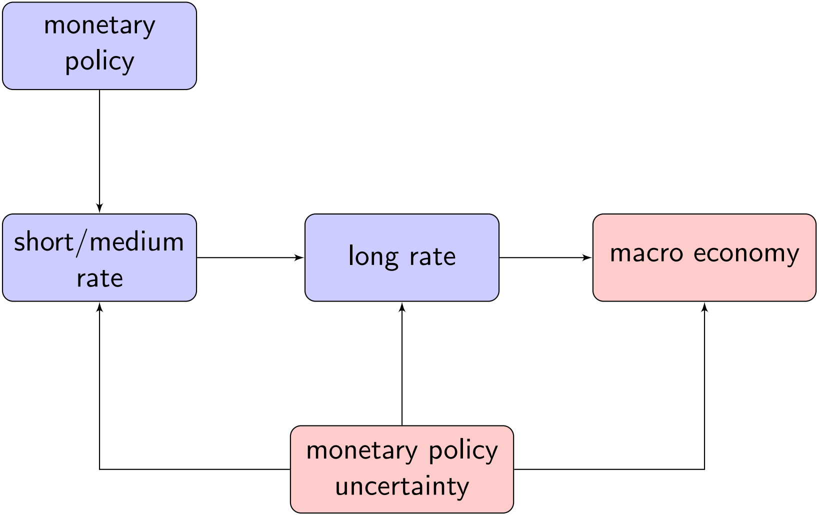
Monetary policy transmission



Question: monetary policy uncertainty $\rightarrow$ macroeconomy



Contribution: a new macro-finance model for uncertainty

Uncertainty

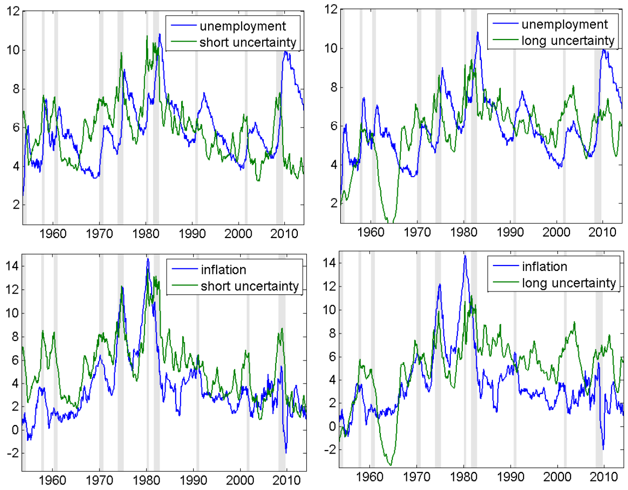
- first moment: conditional mean of macro variables
- second moment: volatility of interest rates

Term structure

- multiple volatility factors
- volatility factors and yield factors are distinct

Literature

Result highlight: two dimensions of uncertainty



Outline

Factors

- m_t : $M \times 1$ Macro factors
- g_t : $G \times 1$ Gaussian yield factors
- h_t : $H \times 1$ yield volatility factors

Dynamics

$$\begin{aligned} m_{t+1} &= \mu_m + \Phi_m m_t + \Phi_{mg} g_t + \Phi_{mh} h_t + \Sigma_m \varepsilon_{m,t+1}. \\ g_{t+1} &= \mu_g + \Phi_{gm} m_t + \Phi_g g_t + \Phi_{gh} h_t + \Sigma_{gm} \varepsilon_{m,t+1} + \Sigma_g D_t \varepsilon_{g,t+1}, \\ h_{t+1} &= \mu_h + \Phi_h h_t + \Sigma_{hm} \varepsilon_{m,t+1} + \Sigma_{hg} D_t \varepsilon_{g,t+1} + \Sigma_h \varepsilon_{h,t+1}. \end{aligned}$$

where the diagonal time-varying volatility is a function of h_t

$$D_t = \text{diag}\left(\exp\left(\frac{\Gamma_0 + \Gamma_1 h_t}{2}\right)\right).$$

h_t enters the model through

- conditional mean: h_t
- conditional variance: D_t

Impulse responses

Bond prices

Short rate

$$r_t = \delta_0 + \delta_1' g_t.$$

Pricing equation

$$P_t^n = \mathbb{E}_t^{\mathbb{Q}} \left[\exp\left(-r_t\right) P_{t+1}^{n-1} \right]$$

under risk neutral dynamics

$$g_{t+1} = \mu_g^{\mathbb{Q}} + \Phi_g^{\mathbb{Q}} g_t + \Sigma_g^{\mathbb{Q}} \varepsilon_{g,t+1}^{\mathbb{Q}}$$

Bond prices

Bond prices are exponentially affine

$$P_t^n = \exp\left(\bar{a}_n + \bar{b}_n' g_t\right)$$

where

$$\bar{a}_n = -\delta_0 + \bar{a}_{n-1} + \mu_g^{\mathbb{Q}\prime} \bar{b}_{n-1} + \frac{1}{2} \bar{b}_{n-1}' \Sigma_g^{\mathbb{Q}} \Sigma_g^{\mathbb{Q}\prime} \bar{b}_{n-1},$$
$$\bar{b}_n = -\delta_1 + \Phi_g^{\mathbb{Q}\prime} \bar{b}_{n-1}.$$

Yields $y_t^n \equiv -\frac{1}{n} \log P_t^n$ are linear

$$y_t^n = a_n + b_n' g_t$$

with $a_n = -\frac{1}{n}\bar{a}_n$, $b_n = -\frac{1}{n}\bar{b}_n$. ▸ SDF

Novel approach

- bond prices identical to Gaussian ATSMs

Bayesian estimation

Model

- non-Gaussian non-linear state space form
- likelihood not known in closed form

MCMC

- In each step, conditionally linear Gaussian state space model
- Kalman filter: draw parameters not conditioning on the state variables
- forward filtering and backward sampling: draw state variables jointly

particle filter: compute likelihood

Observed yields

Stack

$$y_t^n = a_n + b_n' g_t$$

for different maturities $n_1, n_2, ..., n_N$ to

$$Y_t = A + B g_t + \eta_t$$

where $A = (a_{n_1}, \ldots, a_{n_N})'$, $B = (b_{n_1}', ..., b_{n_N}')'$.

State space form I conditional on $h_{0:T}$

Transition equation

$$g_{t+1} = \mu_g + \Phi_{gm} m_t + \Phi_g g_t + \Phi_{gh} h_t + \Sigma_{gm} \varepsilon_{m,t+1} + \Sigma_g D_t \varepsilon_{g,t+1}$$

Observation equations

$$\begin{aligned} m_{t+1} &= \mu_m + \Phi_m m_t + \Phi_{mg} g_t + \Phi_{mh} h_t + \Sigma_m \varepsilon_{m,t+1} \\ h_{t+1} &= \mu_h + \Phi_h h_t + \Sigma_{hm} \varepsilon_{m,t+1} + \Sigma_{hg} D_t \varepsilon_{g,t+1} + \Sigma_h \varepsilon_{h,t+1} \\ Y_{t+1} &= A + B g_{t+1} + \eta_{t+1} \end{aligned}$$

State space form II conditional on $g_{1:T}$

Transition equation

$$h_{t+1} = \mu_h + \Phi_h h_t + \Sigma_{hm}\varepsilon_{m,t+1} + \Sigma_{hg} D_t \varepsilon_{g,t+1} + \Sigma_h \varepsilon_{h,t+1}$$

Observation equation I

$$m_{t+1} = \mu_m + \Phi_m m_t + \Phi_{mg} g_t + \Phi_{mh} h_t + \Sigma_m \varepsilon_{m,t+1}$$

Observation equation II: Define $\tilde{g}_t = D_{t-1}^{\frac{1}{2}} \varepsilon_{gt}$, $\hat{g}_t = \log(\tilde{g}_t \odot \tilde{g}_t)$ is linear in h_t

$$\hat{g}_{t+1} = \Gamma_0 + \Gamma_1 h_t + \hat{\varepsilon}_{t+1}$$

Approximate the error with mixture of normals using Omori, Chib, Shephard, and Nakajima(2007).

Sketch of MCMC algorithm

- Conditional on $h_{0:T}$, use state space form I
  - Draw θ_g using Kalman filter without depending on $g_{1:T}$
  - Draw $g_{1:T}$ using forward filtering and backward sampling
- Conditional on $g_{1:T}$, use state space form II
  - Draw θ_h using Kalman filter without depending on $h_{0:T}$
  - Draw $h_{0:T-1}$ using forward filtering and backward sampling
- Draw the remaining parameters

Particle filter

- Calculate the likelihood of the model: $p\left(Y_{1:T};\theta\right)$
- Calculate filtered estimates
- We use the mixture Kalman filter, see Chen and Liu (2000)

Data

Monthly from June 1953 to December 2013

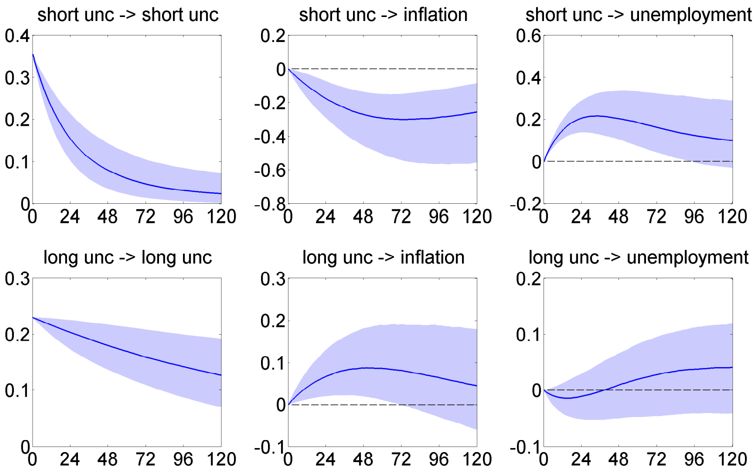
Yields

- Fama-Bliss zero-coupon yields from CRSP
- maturities: 1m, 3m, 1y, 2y, 3y, 4y, 5y
- g_t is 3m, 5y and 1y with errors
- h_t captures volatility of 3m and 5y

Macro

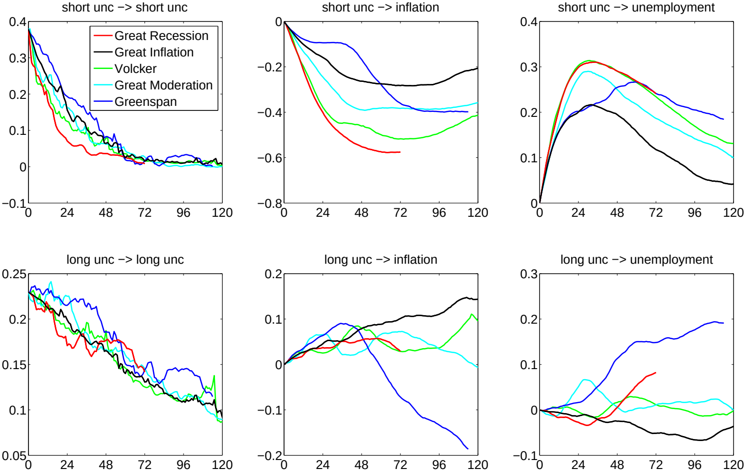
- FRED
- CPI inflation
- unemployment rate

Impulse responses

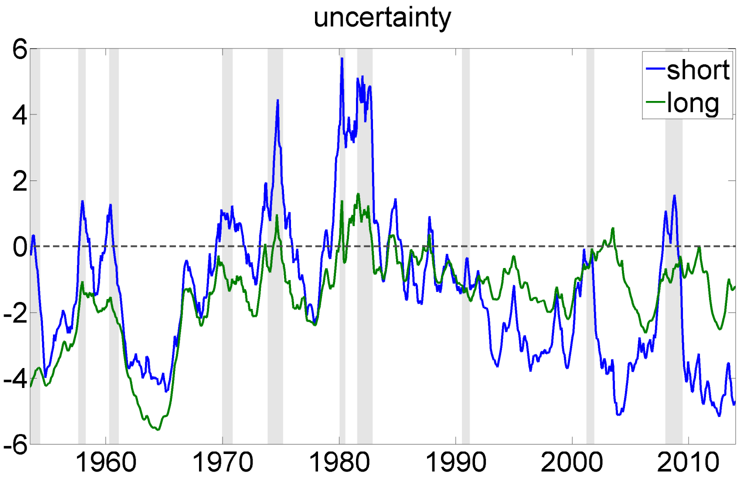


▸ model

Time-varying impulse responses



Magnitude of uncertainty



Uncertainty and recession

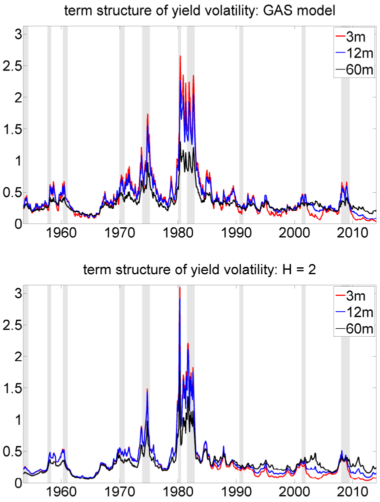
$$h_{jt} = \alpha + \beta \mathbb{1}_{recession,t} + u_{jt}$$

- Coeff: 2.3 for short term; 0.6 for long term
- p-values: 0 for both

Model specification

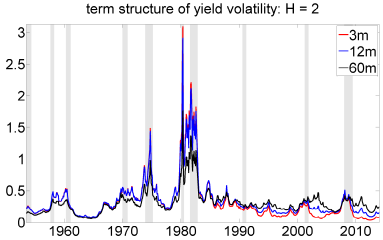
- $M = 0, 2$
- $G = 3$
- $H = 0, 1, 2, 3$

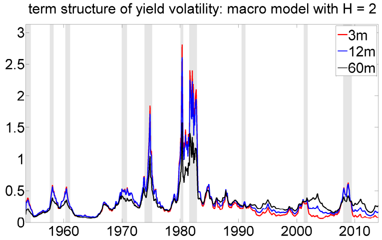
Yield volatilities: how many factors?



BIC chooses $H = 2$ as well.

Yield volatilities: adding macro variables





Cross section of yields

Table : measurement errors (bp)

	$\mathbb{H}_0$	$\mathbb{H}_1$	$\mathbb{H}_2$	$\mathbb{H}_3$	macro
1m	0.2524	0.9917	1.0170	1.0539	1.0059
3m	0.1283	0.7155	0.6539	0.6196	0.7007
12m	0.1262	0.7726	0.7599	0.7583	0.7995
24m	0.0941	1.0499	0.9904	0.9586	0.9894
36m	0.0781	0.9577	0.8912	0.8489	0.8822
48m	0.1070	0.9103	0.8748	0.8598	0.8804
60m	0.0841	0.9382	0.8644	0.8728	0.9298

Conclusion

We propose a new model

- study the effect of monetary policy uncertainty on macro variables
- uncertainty enters both the first and second moments
- the model has multiple volatility factors
- volatility factors evolve separately from yield factors

We find

- 2 volatility factors capture the cross section of yield volatility
- increases in either of them lead higher unemployment rates
- but they interact with inflation in opposite directions.

Literature: topic

Uncertainty

- first moment
  - Uncertainty: *Baker, Bloom, and Davis(2013), Jurado, Ludvigson, and Ng(2013), Bekaert, Hoerova, and Lo Duca(2013)*
- second moment
  - SV in VAR: *Cogley and Sargent (2001, 2005), and Primiceri(2005)*

Term structure models

- Spanned model: *Dai and Singleton(2000) and Duffee(2002)*
  - does not fit yield volatility
- Unspanned model: *Collin-Dufresne and Goldstein(2002), Collin-Dufresne, Goldstein and Jones(2009)*
  - restrict yield fitting
  - only 1 volatility factor

Literature: method

Volatility in mean with different applications

- GARCH : *Engle, Lilien, and Robins(1987) and Elder(2004)*
- SV: *Jo (2013)*

Bayesian

- *Chib and Ergashev(2009) and Bauer(2014)*

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Stochastic discount factor

Pricing equation I

$$P_t^n = \mathbb{E}_t^{\mathbb{Q}} \left[\exp\left(-r_t\right) P_{t+1}^{n-1} \right]$$

Pricing equation II

$$P_t^n = \mathbb{E}_t \left[\mathcal{M}_{t+1} P_{t+1}^{n-1} \right].$$

Pricing kernel

$$\mathcal{M}_{t+1} = \frac{\exp\left(-r_t\right) p^{\mathbb{Q}}\left(g_{t+1} | \mathcal{I}_t; \theta\right)}{p\left(g_{t+1} | \mathcal{I}_t; \theta\right)}$$

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