Monetary Policy, Real Activity, and Credit Spreads: Evidence from Bayesian Proxy SVARs

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Federal Reserve Board

September 2017

- SVARs have been extensively used to study the macroeconomic effects of monetary policy shocks.

  Bernanke & Blinder (1992); Christiano et. al (1996); Romer & Romer (2004); Boivin, Kiley, and Mishkin (2010); Gertler & Karadi (2015); Arias et al (2016)

- Effects of MP muted during Great Moderation and have no role in business cycle fluctuations.

  Ramey (2016)

- This paper provides new evidence on the importance of monetary policy for business cycle fluctuations for the 1994–2007 period.

INTRODUCTION

Methodology and Preview of Results

- We develop a Bayesian framework to estimate SVARs augmented with proxies for the structural shocks.

  Stock & Watson (2012); Mertens & Ravn (2013a,b)

- Excellent proxies of surprise changes in monetary policy

  Gürkaynak, Swanson & Sack (2005); Gilchrist, Lopez-Salido & Zakrajsek (2014)

- Main findings:
  - MP shocks are recessionary and key drivers of the cycle.
  - Systematic component of monetary policy reacts to corporate credit spreads.
  - Failure to account for this systematic reaction induces attenuation in the response of *all* variables to MP shock.

- We uncover the same relationship between monetary policy and corporate spreads in the narrative identification of Romer and Romer (2004).

SVAR Model

- Consider the Structural VAR:

$$\begin{aligned} y_t' A_0 &= \sum_{\ell=1}^{p} y_{t-\ell}' A_\ell + c + e_t' \quad \text{for } 1 \le t \le T, \\ &= x_t' A_+ + e_t' \end{aligned}$$

  - y_t: $n \times 1$ vector of endogenous variables
  - $e_t' \sim \mathcal{N}(0, I_n)$: $n \times 1$ vector of structural shocks
  - A_ℓ: $n \times n$ matrix of parameters for $0 \le \ell \le p$

- Reduced-form representation:

$$y_t' = x_t' \Phi + u_t'$$

where $\Phi = A_+ A_0^{-1}$ and $u_t' \sim \mathcal{N}(0, \Sigma)$ with $\Sigma = (A_0 A_0')^{-1}$.

The Monetary Policy Equation

- Assume policy rate r_t is ordered first in y_t.
- First equation of the SVAR is the monetary policy equation:

$$y_t' A_{0,1} = x_t' A_{+,1} + e_{MP,t}$$

- We can rewrite the monetary policy equation as:

$$r_t = \sum_{j=2}^{n} y_{j,t}' \psi_{0,j} + \sum_{l=1}^{p} y_{t-l}' \psi_l + \sigma_{MP} e_{MP,t}$$

- Identification of $e_{MP,t}$ requires identification of the systematic component of monetary policy.

Bayesian Proxy SVAR

- Assume m_t is a noisy measure of $e_{MP,t}$:

$$m_t = \beta e_{MP,t} + \sigma_\nu \nu_t, \quad \nu_t \sim \mathcal{N}(0,1) \text{ and } \nu_t \perp e_t.$$

- Assumptions on proxy m_t:
  - $E[m_t e_{MP,t}] = \beta$
  - $E[m_t e'_{/MP,t}] = 0.$

- **Joint likelihood:**

$$p(Y_{1:T}, M_{1:T}|A_0, A_+, \beta, \sigma_\nu) = \underbrace{p(Y_{1:T}|\Phi, \Sigma)}_{OLD} \times \underbrace{p(M_{1:T}|Y_{1:T}, A_0, A_+, \beta, \sigma_\nu)}_{NEW}$$

- What does the conditional density look like?

Conditional Likelihood

$m_t|y_t, \ldots \sim N(\mu_{m|y}, V_{m|y})$ with

$$\mu_{M|Y} = \beta e_{MP,1:T} \equiv \beta \left[Y_{1:T} A_{0,1} - X_{1:T} A_{+,1} \right] \quad \text{and} \quad V_{M|Y} = \sigma_\nu^2 I_T,$$

- Proxy informs identification of the systematic component.
- How much information? Relevance indicator $\rho = \frac{\beta^2}{\beta^2 + \sigma_\nu^2}$
  - $\rho = 0 \rightarrow$ model not identified.
  - ρ large $\rightarrow$ model well identified.
  - ρ small $\rightarrow$ model weakly identified.
- Bayesian inference: Weak identification not a conceptual problem, irregularly shaped posterior density.

Prior Distributions

- Measurement equation:

$$
\begin{aligned}
p(\beta) &: \mathcal{N}(0,1) \\
p(\sigma_\nu) &: \mathcal{IG}(2, 0.02) \text{ (Baseline Prior)} \\
p(\sigma_\nu) &: \sigma_\nu = 0.5 \times std(M_{1:T}) \text{ (High Relevance Prior)}
\end{aligned}
$$

- Prior distributions for (A_0, A_+) specified in terms of reduced form parameters:

$$
\begin{aligned}
p(\Phi, \Sigma) &: \text{Minn. Prior, gives closed form } p(\Phi, \Sigma | Y_{1:T}). \\
p(\Omega | \Phi, \Sigma) &: \text{Uniform Prior (Haar measure)}
\end{aligned}
$$

Rubio-Ramirez & al (2009)

Posterior Sampler

THE PROXY

High Frequency Identification of Policy Surprises

- $\mathbf{m_t}$: surprise component of changes in asset prices around monetary policy announcements.

  Kuttner (2001); Gürkaynak & Swanson & Sack (2005); Gilchrist & Lopez-Salido & Zakrajsek (2014)

- We use:
  - Changes in current-month federal funds futures.
  - 30-minute window (10-min before; 20-min after).

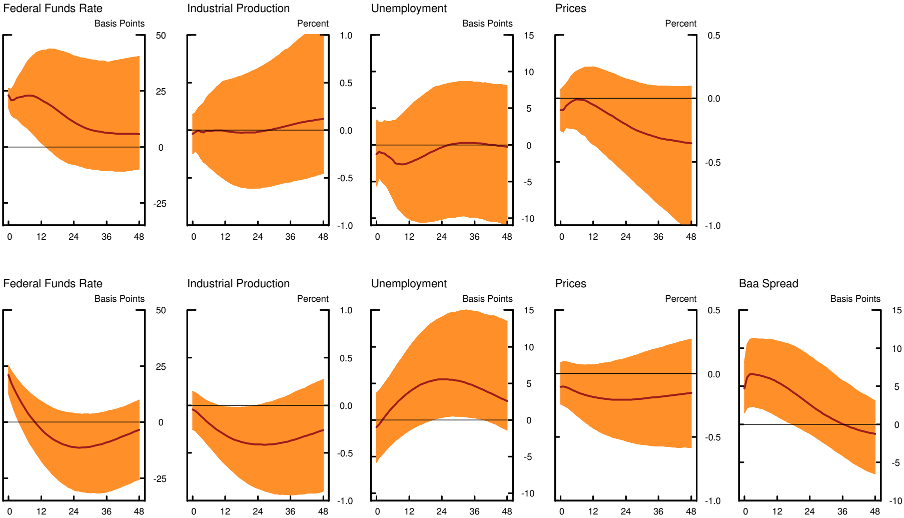
- Sample availability: 1991–2014. Focus on 1994I–2007VI:
  - No FOMC statements prior to 1994.
  - 5 pp drop in federal funds rate from 2007:VII to 2009:XI
  - Federal funds rate at the zero lower bound from 2009:XI.

Data & Model Specification

- Main results based on the estimation of two models.
- 4-equation model:
  1. federal funds rate;
  2. log of industrial production (IP);
  3. Unemployment rate;
  4. log of the producer price index.
- 5-equation model:
  5. Moody's seasoned Baa corporate bond yield minus yield on 10-year treasury.
- We use $p = 12$ lags in the VAR + constant.

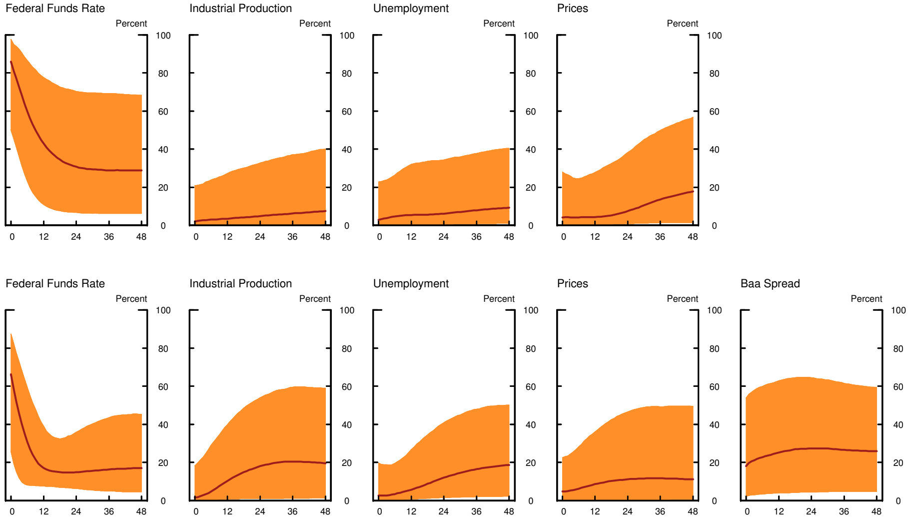
Responses to a Monetary Shock

4-Equation vs 5-Equation Models



Contribution to the FEV of Monetary Shocks

4-Equation vs 5-Equation Models



Systematic Component of Monetary Policy

Contemporaneous Elasticities

	4-Equation BP-SVAR	5-Equation BP-SVAR
$\psi_{0,cs}$		-1.18
		[-3.11 -0.35]
$\psi_{0,\pi}$	0.10	0.13
	[-0.08 0.33]	[-0.11 0.37]
ψ_{0,Δ_y}	0.06	0.03
	[-0.11 0.27]	[-0.15 0.25]
$\psi_{0,u}$	0.22	0.23
	[-0.64 1.19]	[-0.67 1.38]

Cumulative Elasticities

Romer and Romer (2004) Revisited

- We reexamine narrative identification of monetary policy shocks of Romer and Romer (2004).
- Augmented RR regression:

$$
\begin{aligned}
\Delta r_\tau \quad = \quad & \alpha + \beta_0 f_\tau + \beta_{cs} cs_\tau^{5d} + \beta_1 \tilde{u}_{\tau,0} + \beta_2 \tilde{x}_{\tau,0} + \\
& \sum_{i=-1}^{2} \gamma_i \Delta \tilde{y}_{\tau,i} + \sum_{i=-1}^{2} \phi_i \tilde{\pi}_{\tau,i} + \\
& + \sum_{i=-1}^{2} \lambda_i (\Delta \tilde{y}_{\tau,i} - \Delta \tilde{y}_{\tau-1,i}) + \sum_{i=-1}^{2} \theta_i (\tilde{\pi}_{\tau,i} - \tilde{\pi}_{\tau-1,i}) + \varepsilon_t.
\end{aligned}
$$

- Two main changes:
  1. cs_τ^{5d}: average Baa spread 5 days prior to FOMC meeting.
  2. Sample period consistent with BP-SVAR analysis.

Romer and Romer Regressions

	(1)	(2)
Baa Spread (β_{cs})		-0.12
		(0.05)
Unemployment Rate	-0.06	-0.09
	(0.04)	(0.03)
Output Growth	0.09	0.08
	(0.02)	(0.02)
Inflation	0.25	0.21
	(0.05)	(0.05)
Output Growth (Revision)	0.04	-0.02
	(0.04)	(0.04)
Inflation (Revision)	-0.10	-0.08
	(0.09)	(0.09)
Adj. R^2	0.66	0.68

Hybrid VARs

- RR embed their measure of monetary policy shocks into a standard VAR by replacing the federal funds rate with the cumulated series of narrative shocks.

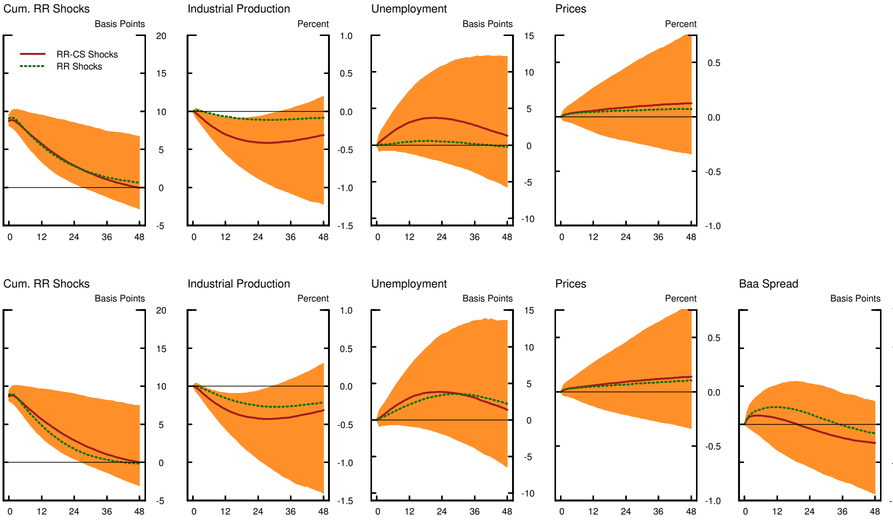
  See also Coibion (2012); Barakchian & Crowe (2013); Ramey (2016)

- Use hybrid VARs to trace the effects of two shocks:
  - RR shocks: residuals from regression (1);
  - RR-CS shocks: residuals from regression (2).

- Estimate hybrid SVARs with and without Baa spread.

Responses to Monetary Policy Shock

Hybrid VARs



Concluding Remarks

- We propose a framework for Bayesian analysis of Proxy SVARs.
- Application to monetary policy:
  - Monetary policy shocks are important drivers of business and financial conditions.
  - Monetary policy rule responds to corporate credit spreads.
- Results on the interaction between monetary policy and financial conditions replicable under the Romer & Romer identification.

  Romer & Romer (2004)

A Posterior Sampler

- Block Metropolis-Hastings (MH) Algorithm. Sample:
  1. (Φ, Σ) using a *mixture* of $p(\Phi, \Sigma | Y_{1:T})$ and a random-walk type proposal. Weight RW more heavily if shrinking toward proxy.
  2. Ω using independence MH step, proposal: prior.
  3. (β, σ_ν) using random-walk MH step.

- Efficacy depends on the similarity $p(\Phi, \Sigma | Y_{1:T})$ and $p(\Phi, \Sigma | Y_{1:T}, M_{1:T})$.

- Really different? Use Sequential Monte Carlo sampler.
  Bognanni & Herbst (2014)

- Sign and Zero Restrictions? Do (1) and (2) jointly.
  Arias et al (2016)

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Bayesian Proxy SVAR

Estimation via Sequential Monte Carlo

- Goal: simulate from posterior $p(\theta|\mathbf{Y}_{1:T}, M_{1:T})$,
  $\theta = [A_0, A_+, \beta, \sigma_\nu]$.

- Methodology: Sequential Monte Carlo (SMC) sampler.
  Herbst & Schorfheide (2014, 2015), Bognanni & Herbst (2015)

- SMC methods more robust to irregular likelihoods.

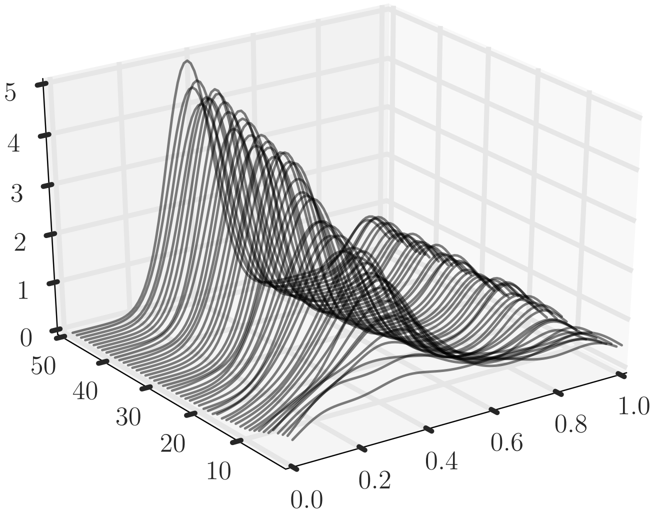
- Does not require conjugate priors.

- Works by building succesive particle approximations starting from prior, slowly adding information until characterizing the posterior:

$$\pi_n(\theta) \propto [p(M_{1:T}|\mathbf{Y}_{1:T}, \theta)]^{\phi_n} p(\theta|\mathbf{Y}_{1:T}), \quad \phi_0 = 0, \ldots, \phi_N = 1$$

SMC in One Picture

From Uniform Prior to Bimodal Posterior



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Predictability of Surprise Changes in FFR

- Romer and Romer (2004) type predictive regression.

	(1)	(2)
Unemployment	0.02	0.02
	(0.02)	(0.02)
Output Gap	0.01	0.00
	(0.01)	(0.01)
Output Growth	0.01	0.00
	(0.01)	(0.01)
Inflation	−0.01	−0.02
	(0.02)	(0.02)
Output Growth (Revision)	−0.02	0.00
	(0.02)	(0.02)
Inflation (Revision)	−0.03	0.02
	(0.04)	(0.04)
$Prob > F$	0.04	0.27
Adj. R^2	0.24	0.16

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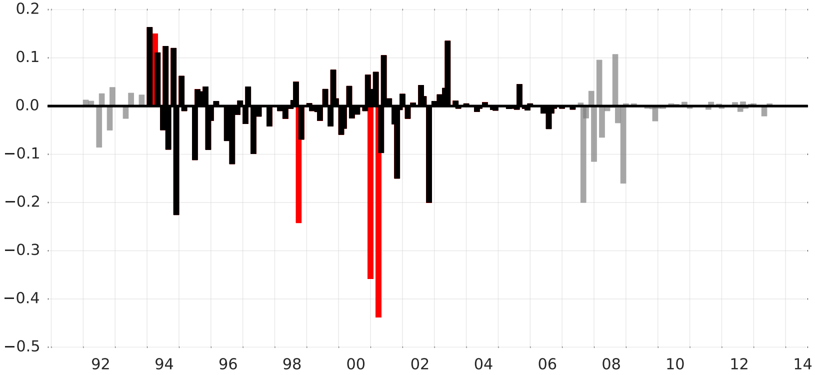
The Proxy

High Frequency Identification of Policy Surprises



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Systematic Component of Monetary Policy

Cumulative Elasticities

$$\psi_x = \sum_{l=0}^{p} \psi_{l,x}, \ \psi_\pi = \sum_{l=0}^{p} \sum_{i=0}^{l} \psi_{i,\pi}, \ \psi_{\Delta ip} = \sum_{l=0}^{p} \sum_{i=0}^{l} \psi_{i,\Delta ip}$$

	4-Equation BP-SVAR	5-Equation BP-SVAR
ψ_{cs}		-0.22
		[-0.35 -0.09]
ψ_π	0.15	0.13
	[-0.15 0.52]	[-0.12 0.39]
ψ_{Δ_y}	0.35	0.06
	[0.06 0.67]	[-0.14 0.32]
ψ_u	-0.01	-0.06
	[-0.09 0.06]	[-0.16 0.04]
ψ_r	0.97	0.96
	[0.94 1.01]	[0.92 1.01]

Contemp. Elasticities