Flexible Priors and Restrictions for Structural Vector Autoregressions

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Motivation

- **What is a Structural VAR?**

  Structural VAR

$$\mathbf{A_0}\mathbf{y}_t = \mathbf{c} + \mathbf{A_1}\mathbf{y}_{t-1} + \cdots + \mathbf{A_p}\mathbf{y}_{t-p} + \boldsymbol{\Sigma}\boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \mathcal{I})$$

  Reduced-Form VAR

$$\mathbf{y}_t = \mathbf{d} + \mathbf{B_1}\mathbf{y}_{t-1} + \cdots + \mathbf{B_p}\mathbf{y}_{t-p} + \mathbf{u}_t, \quad \mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Omega})$$

- **On the importance of SVARs:**
  - Essential tool for understanding economic dynamics and policy impacts.
  - Useful to inform and validate DSGE models.

Problem Statement

Conventional approaches to estimate SVARs:

1. Rely on reduced-form representation of the VAR.
2. Separate estimation and identification steps.
3. Rely on algorithms that restrict the flexibility and scope of priors and identifying information.
4. Conditional on an estimated parameter vector, multiple theories (SVARs) derived from the same RFVAR share equal likelihood.

Our Solution and This Paper

New framework to apply a broad range of priors and restrictions on (functions of) structural parameters **drawing on a wealth of economic knowledge**.

1. **Leverages structural-form representation**.
2. Integrates estimation and identification in a single step.
3. Combines identifying information, eliminating separate algorithms.
    - **Acommodates rich set of priors and restrictions:**
        - Priors on structural parameters
        - Priors on (non-)linear functions of structural parameters
          $\rightarrow$ *sign, shape, narrative sign and relative magnitude priors*
        - (In-)equality restrictions
          $\rightarrow$ *zero and bound restrictions*
        - Combinations of the above
    - **Can be used to identify one, a subset or all shocks.**
4. Allows for Bayesian model comparison to evaluate different economic theories.

More Benefits of Our Approach

- Elicits **transparent and informative priors** on structural parameters
  $\Longrightarrow$ avoids imposition of unintended beliefs on structural objects of interest.

- Flexibly **tailors model dynamics to prior beliefs** $\Longrightarrow$ no rigid imposition.

- Does not rely on terative procedures $\Longrightarrow$ **scalable to complex models**.

Roadmap

1. **Methodology**

2. **Building Intuition: A Simple Simulation Study**

3. **Empirical Illustration: Replicating and Extending Belongia and Ireland (2021)**

4. **Summing Up**

Methodology

Structural VAR

Expanded Notation

$$\mathbf{A_0 y}_t = \mathbf{c} + \mathbf{A_1 y}_{t-1} + \cdots + \mathbf{A_p y}_{t-p} + \mathbf{\Sigma}\boldsymbol{\epsilon}_t, \tag{1}$$

- $\mathbf{y}_t$ is the $n \times 1$ vector of endogenous variables
- $\boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \mathcal{I})$ is a vector of mutually uncorrelated structural innovations
- WLOG diagonal elements of $\mathbf{A_0}$ normalized to 1
  $\Rightarrow$ diagonal elements of $\mathbf{\Sigma}$ = standard deviations of structural shocks

Compact Notation

$$\mathbf{A_0 y}_t = \mathbf{A}^{+}\mathbf{x}_t + \mathbf{\Sigma}\boldsymbol{\epsilon}_t, \tag{2}$$

where $\mathbf{x}_t = \left[\mathbf{1},\ \mathbf{y}'_{t-1},\ \ldots,\ \mathbf{y}'_{t-p}\right]'$, and $\mathbf{A}^{+} = [\mathbf{c},\ \mathbf{A_1},\ \ldots,\ \mathbf{A_p}]$.

An Example

Aggregate Demand

$$y_t = \alpha_{yr} r_t + \rho_y y_{t-1} + \rho_{yr} r_{t-1} + \sigma^{ad} \epsilon^{ad} \tag{3}$$

Monetary Policy

$$r_t = \alpha_{ry} y_t + \rho_{ry} y_{t-1} + \rho_r r_{t-1} + \sigma^{mp} \epsilon^{mp} \tag{4}$$

Structural Matrices

$$\mathbf{A_0} = \begin{bmatrix} 1 & -\alpha_{yr} \\ -\alpha_{ry} & 1 \end{bmatrix}, \; \mathbf{A_1} = \begin{bmatrix} \rho_y & \rho_{yr} \\ \rho_{ry} & \rho_r \end{bmatrix}, \; \mathbf{\Sigma} = \begin{bmatrix} \sigma^{ad} & 0 \\ 0 & \sigma^{mp} \end{bmatrix}$$

Likelihood

Let $\mathbf{Y}_T = [\mathbf{y}_1, \ldots, \mathbf{y}_T]'$ and $\theta = [\mathbf{A_0}, \mathbf{A}^+, \mathbf{\Sigma}]$, then the likelihood can be written as

$$p\left(\mathbf{Y}_T|\theta\right) = \frac{\left|det\left(\mathbf{A_0}\right)\right|^T}{\left(2\pi\right)^{\frac{nT}{2}}}\left|\mathbf{\Sigma}\right|^{-T} e^{-\frac{1}{2}\left(\mathbf{A_0}\mathbf{y}_t - \mathbf{A}^+\mathbf{x}_t\right)'\mathbf{\Sigma}^{-2}\left(\mathbf{A_0}\mathbf{y}_t - \mathbf{A}^+\mathbf{x}_t\right)} \tag{5}$$

Priors on Structural VAR Parameters

- **Overall dynamic behavior** $f_{sz}(\theta)$
  - Sims and Zha (1998) prior
- **Structural parameters** $f_{sparam}(\theta)$
  - Priors in the spirit of Baumeister and Hamilton (2019)
- **Priors on structural objects** $f_{sobj}(\theta)$
  - "Endogenous priors" as in Del Negro and Schorfheide (2008) and Christiano, Trabandt and Walentin (2011), also known as "system priors" in Andrle and Plasil (2018).
  - Can be applied to any **(linear and nonlinear) function of the structural parameters**, e.g., IRFs, HD, VD, shocks.
- **Overall prior density** is $f(\theta) = f_{sz}(\theta) f_{sparam}(\theta) f_{sobj}(\theta)$

An Aside: Behavioral Priors vs. Entropic Tilting

- **Objective:**
  - Incorporate additional information.
  - Maintain closeness to original beliefs or distributions.

- **Method:**
  - **Behavioral/Property/Endogenous/System Priors: Bayesian updating.**
    - Priors on complex functions, e.g., $f_{sobj}(\theta) \propto \exp\left(-\lambda \cdot \text{Penalty}(\theta)\right)$, λ= belief strength.
    - Penalty term reflects the deviation from the desired properties.
  - **Entropic Tilting:** e.g. Robertson, Tallman and Whiteman (2005)
    - Adjust distributions to satisfy moment conditions: $\mathbb{E}_Q[h(X)] = c$.
    - New set of weights to minimize Kullback-Leibler divergence: $\min_Q \mathbb{E}_Q\left[\log \frac{Q}{P}\right]$.

(In-)Equality Restrictions

- **Can be thought of as dogmatic priors**: Researcher has strong belief that specific (combinations of) structural parameters have certain values or lie in a given range.

- Our methodology allows us to impose:

  - **(Non-)linear range and inequality restrictions** on the structural VAR parameters, which exclude certain values of the parameter space.

  - **Linear equality restrictions**, handled via the techniques by **Binning and Maih (2015)**.

Deriving the Posterior

- Posterior combines the likelihood and the prior:

$$g\left(\theta|\mathbf{Y}_T\right) = \frac{p\left(\mathbf{Y}_T|\theta\right) f(\theta)}{p(\mathbf{Y}_T)} \propto p\left(\mathbf{Y}_T|\theta\right) f(\theta) \equiv \tilde{g}\left(\theta|\mathbf{Y}_T\right)$$

- Mode found by maximizing the posterior kernel $\tilde{g}\left(\theta|\mathbf{Y}_T\right)$ as with DSGE models.

- The posterior kernel can be initialized using a candidate parameter vector and standard maximization routines can be used to find its maximum.

- **Practitioners can first inspect the mode before moving to posterior sampling.**

Modeling Environment: RISE Toolbox - Maih (2015)

- Regime Switching DSGE + Optimal policy + 5th-order perturbation
- Regime Switching VAR + SVAR + Panel VAR + Proxy SVAR
- MLE, Bayesian Estimation, Indirect Inference
- Conditional forecasting for nonlinear models + Relative Entropy
- Uncertainty Quantification: GSA, HDMR, etc.
- PDF and HTML reporting systems
- Support for various time series frequencies: D-ly, W-ly, M-ly, Q-ly, H-ly, Y-ly, and undated

Building Intuition:
A Simple Simulation Study

Our DGP: A Toy Model

Aggregate Demand

$$y_t = \alpha_{yr} r_t + \rho_y y_{t-1} + \rho_{yr} r_{t-1} + \sigma^{ad} \epsilon^{ad} \tag{6}$$

Monetary Policy

$$r_t = \alpha_{ry} y_t + \rho_{ry} y_{t-1} + \rho_r r_{t-1} + \sigma^{mp} \epsilon^{mp} \tag{7}$$

Implementation

Structural VAR Model

$$\mathbf{A_0 y}_t = \mathbf{A_1 x}_t + \mathbf{\Sigma}\boldsymbol{\epsilon}_t, \tag{8}$$

with one lag and where $\mathbf{y}_t' = [y_t, r_t]'$ and $\epsilon_t' = \left[\epsilon_t^{ad}, \epsilon_t^{mp}\right]'$.

Structural Matrices

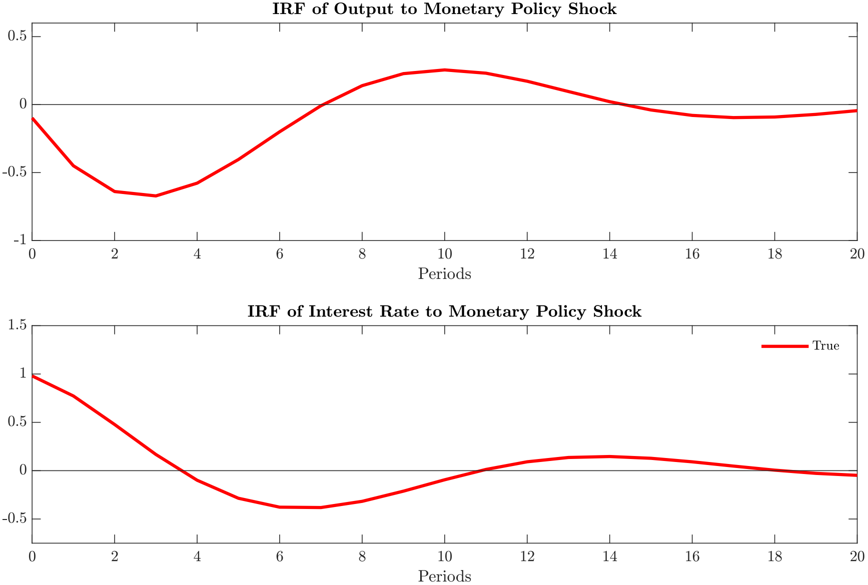
$$\mathbf{A_0} = \begin{bmatrix} 1 & -\alpha_{yr} \\ -\alpha_{ry} & 1 \end{bmatrix}, \ \mathbf{A_1} = \begin{bmatrix} \rho_y & \rho_{yr} \\ \rho_{ry} & \rho_r \end{bmatrix}, \ \mathbf{\Sigma} = \begin{bmatrix} \sigma^{ad} & 0 \\ 0 & \sigma^{mp} \end{bmatrix} \tag{9}$$

Parameterization

$$\mathbf{A_0} = \begin{bmatrix} 1 & 0.1 \\ -0.2 & 1 \end{bmatrix}, \ \mathbf{A_1} = \begin{bmatrix} 0.8 & -0.3 \\ 0.2 & 0.9 \end{bmatrix}, \ \mathbf{\Sigma} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{10}$$

- **Simulate data for $t = 200$ periods.**
- **Estimate a suite of SVARs**, using flat Sims and Zha (1998) priors.

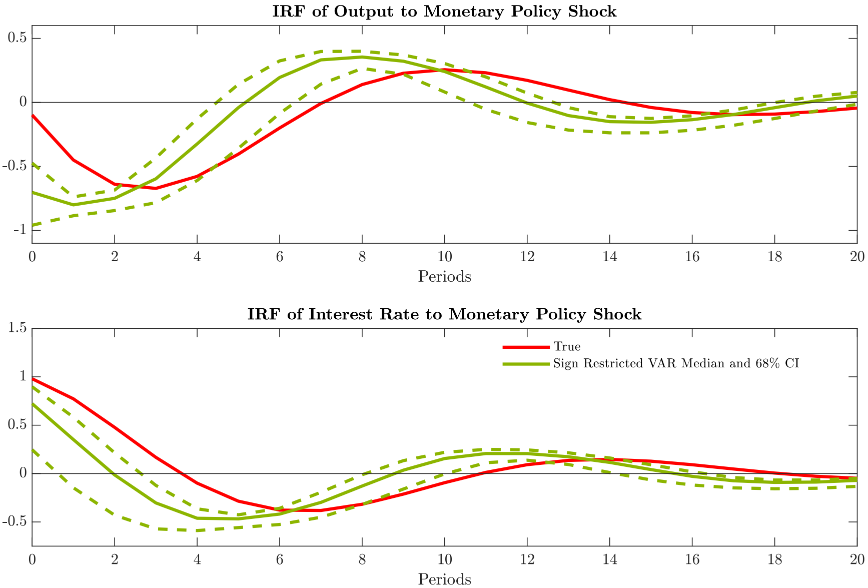
True IRFs


IRF of Output to Monetary Policy Shock
0.5
0
-0.5
-1
0 2 4 6 8 10 12 14 16 18 20
Periods
IRF of Interest Rate to Monetary Policy Shock
1.5
1
0.5
0
-0.5
True
0 2 4 6 8 10 12 14 16 18 20
Periods

Experiment I : **Honoring Traditions**

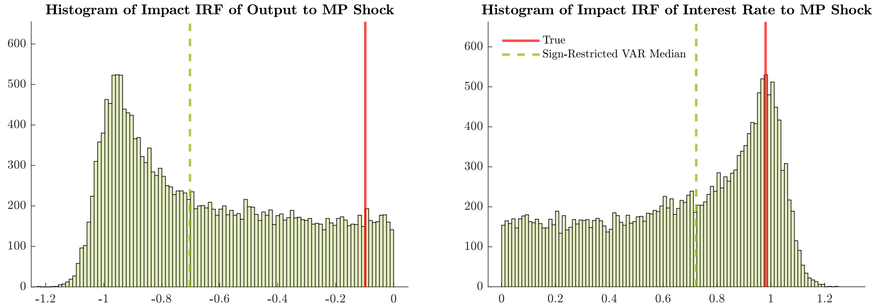
- **Conventional VAR with sign restrictions**
  - In the tradition of Faust (1998), Canova and De Nicolò (2002), Uhlig (2005).
- **Sign restrictions**
  - Output responds negatively, on impact, to MP shock.
  - Interest rate responds positively, on impact, to MP shock.
- **Implementation details**
  - Rubio-Ramírez, Waggoner and Zha (2010) algorithm to impose sign restrictions.

IRFs



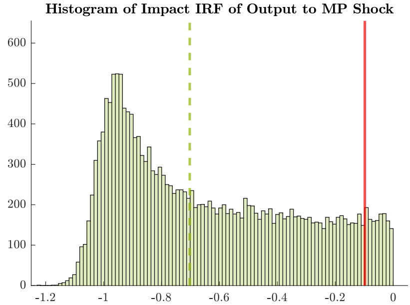
IRF of Output to Monetary Policy Shock
0.5
0
-0.5
-1
0
2
4
6
8
10
12
14
16
18
20
Periods
IRF of Interest Rate to Monetary Policy Shock
1.5
1
0.5
0
-0.5
True
Sign Restricted VAR Median and 68% CI
0
2
4
6
8
10
12
14
16
18
20
Periods

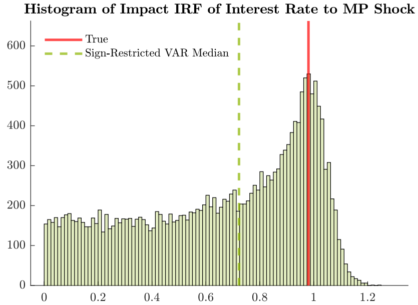
Histograms of Impact IRFs



- True impact IRF of interest rate assigned high density but different from median.
- True impact IRF of output not assigned high density and different from median.
- These *marginal* posterior distributions of the IRFs are not uniform as intended.

Histograms of Impact IRFs



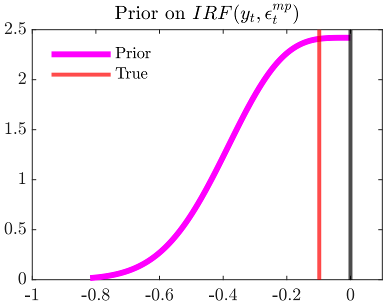


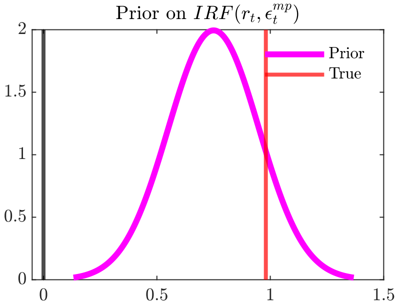
- True impact IRF of interest rate assigned high density but different from median.
- True impact IRF of output not assigned high density and different from median.
- These *marginal* posterior distributions of the IRFs are not uniform as intended.
- **Implications for structural parameters:** $\alpha_{yr} \in (-\infty, 0]$ **and** $\alpha_{ry} \in [0.01, 114.83]$ $\rightarrow$ **we do not learn anything about the structural parameters.**

Experiment II: **Innovating on the Approach**

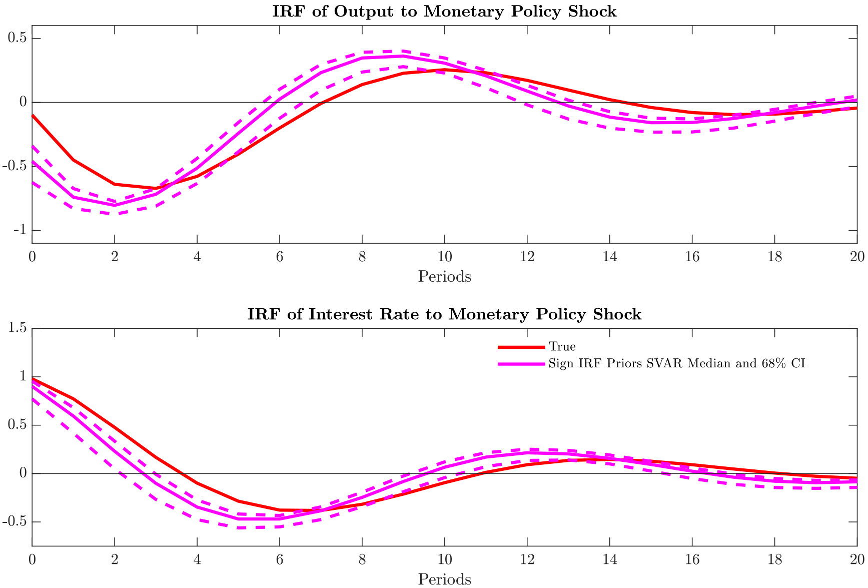
Structural VAR with endogenous prior on signs of impact IRFs.

$$-IRF(y_t, \epsilon_t^{mp}) \sim folded\ \mathcal{N}(0.2, 0.2) \qquad IRF(r_t, \epsilon_t^{mp}) \sim folded\ \mathcal{N}(0.75, 0.2)$$





IRFs


IRF of Output to Monetary Policy Shock
0.5
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1
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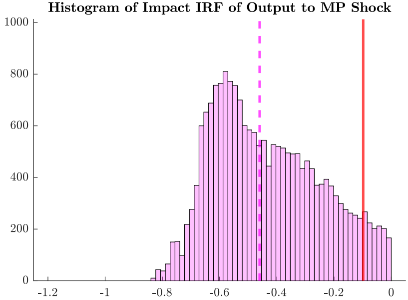
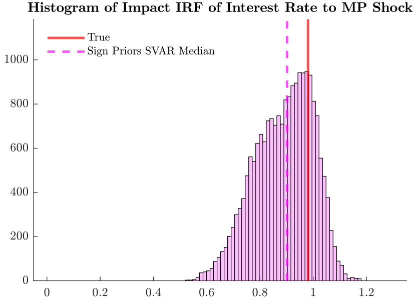
True
Sign IRF Priors SVAR Median and 68% CI
Periods

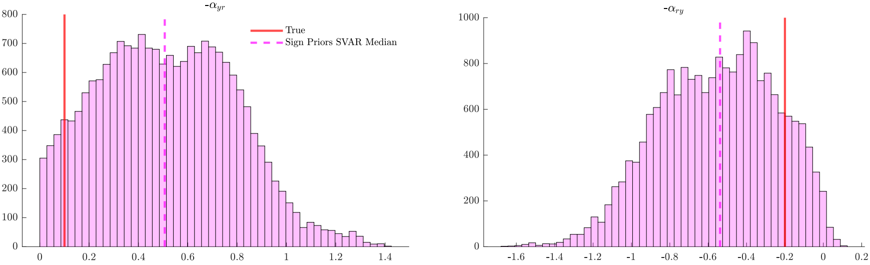
Histograms of Impact IRFs





- **Sign priors considerably reduce posterior range of IRFs.**
- True impact IRF of interest rate assigned high density and closer to median.
- True impact response of output is still in the tail of the posterior distribution.

Histograms of Structural Parameters



- **Sign priors considerably reduce posterior range of the structural parameters.**

- True values of structural parameters within posterior distribution.

Experiment III: **Advancing Frontiers**

Structural VAR with parameter priors à la Baumeister and Hamilton (2018).

$$IRF(y_t, \epsilon_t^{mp}) = \frac{\alpha_{yr}}{1 - \alpha_{yr}\alpha_{ry}} \quad \text{and} \quad IRF(r_t, \epsilon_t^{mp}) = \frac{1}{1 - \alpha_{yr}\alpha_{ry}}$$

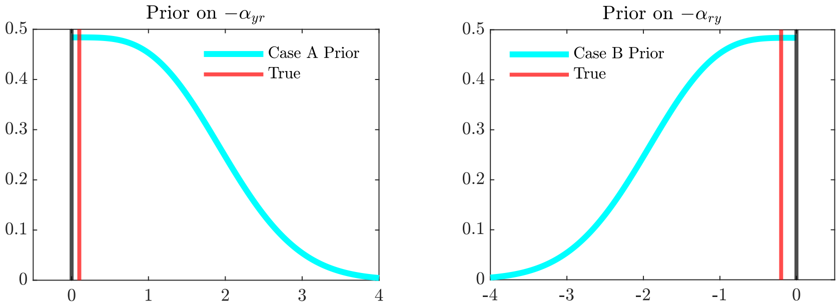
- **Case A: Prior on sensitivity of aggregate demand to interest rate**

$$a_{0,12} = -\alpha_{yr}$$
$$-\alpha_{yr} \sim folded\ \mathcal{N}(1,1) \tag{11}$$

- **Case B: Prior on monetary policy response to output**

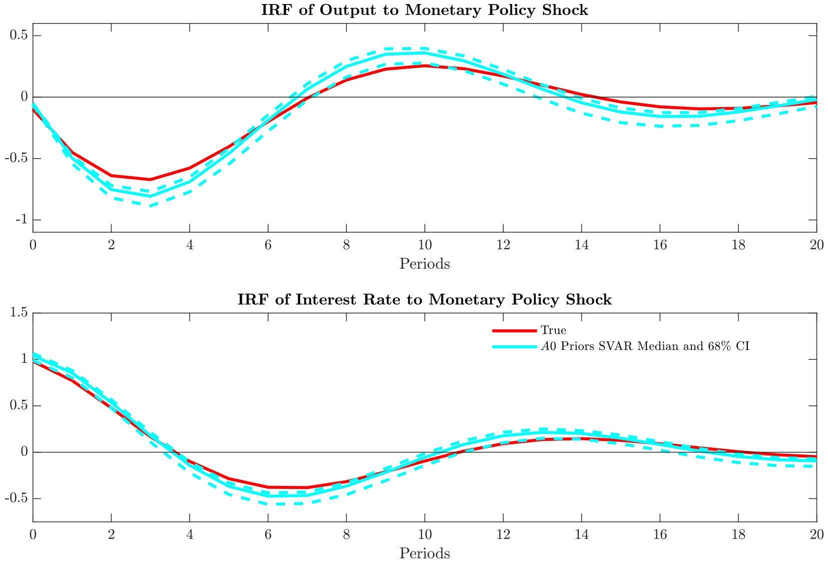
$$a_{0,21} = -\alpha_{ry}$$
$$\alpha_{ry} \sim folded\ \mathcal{N}(1,1) \tag{12}$$

Illustrating the Priors



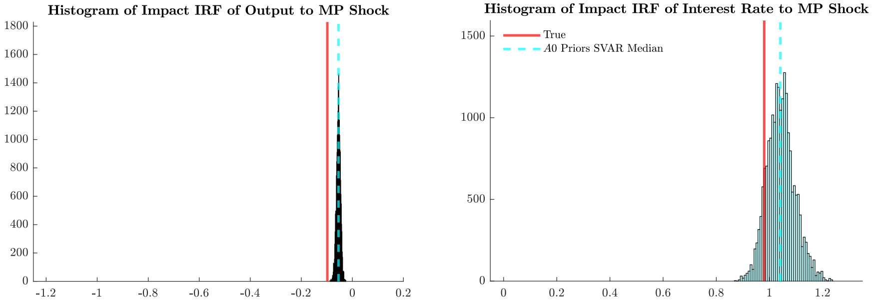
IRFs

Case A: $-\alpha_{yr} \sim \textit{folded}\ \mathcal{N}(1,1)$



Histograms of Impact IRFs

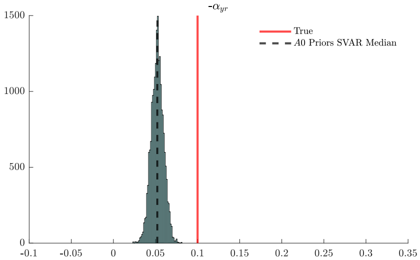
Case A: $-\alpha_{yr} \sim \textit{folded } \mathcal{N}(1,1)$

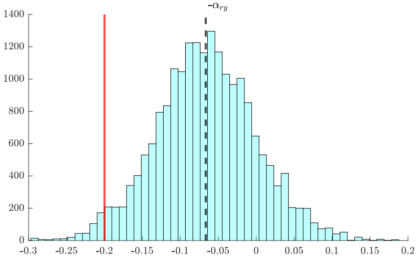


- **Prior on α_{yr} considerably reduces posterior range of IRFs.**
- True impact response of output is outside the posterior distribution, but close.

Historgrams of Structural Parameters

Case A: $-\alpha_{yr} \sim \textit{folded } \mathcal{N}(1,1)$

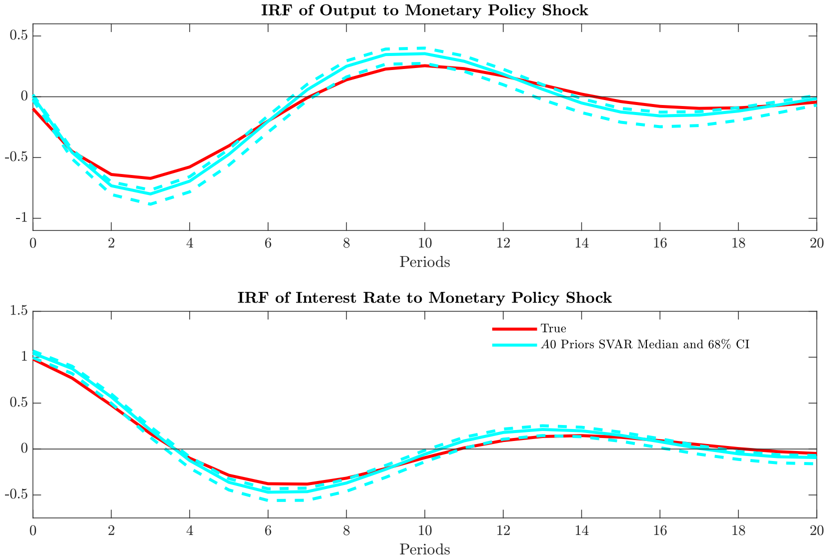




- **Prior on α_{yr} considerably reduces posterior range of structural parameters.**
  - $-\alpha_{yr}$: from $[0, 1.4]$ to $[0.025, 0.075]$
  - $-\alpha_{ry}$: from $[-1.6, 0.2]$ to $[-0.3, 0.2]$
- True sensitivity of AD to interest rate α_{yr} outside of distribution, but close.

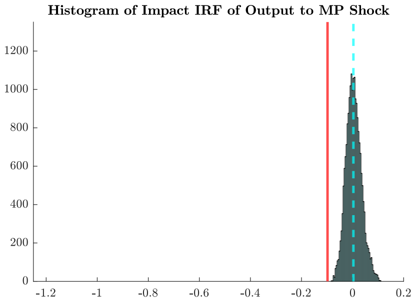
IRFs

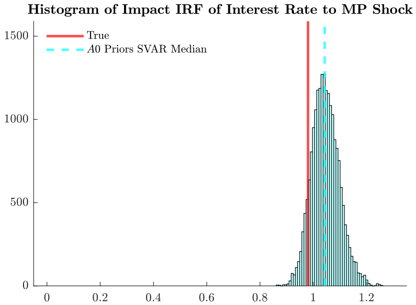
Case B: $\alpha_{ry} \sim \textit{folded } \mathcal{N}(1,1)$



Histograms of Impact IRFs

Case B: $\alpha_{ry} \sim \textit{folded}\ \mathcal{N}(1,1)$

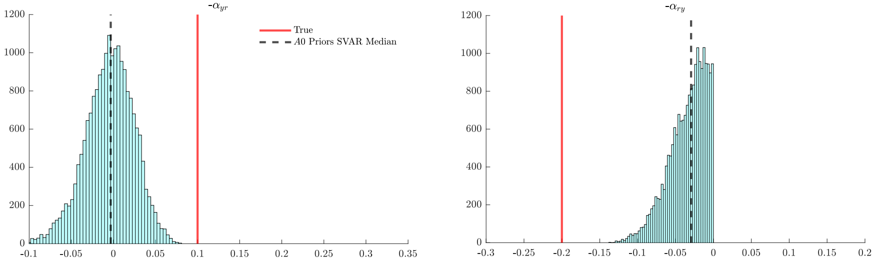




- **Prior on α_{ry} considerably reduces posterior range of IRFs.**
- Truth still outside the posterior distribution.

Histograms of Structural Parameters

Case B: $\alpha_{ry} \sim \textit{folded}\ \mathcal{N}(1,1)$



- **Prior on α_{ry} considerably reduces posterior range of structural parameters:**
    - $-\alpha_{yr}$: from $[0, 1.4]$ to $[-0.1, 0.075]$
    - $-\alpha_{ry}$: from $[-1.6, 0.2]$ to $[-0.15, 0]$
- True response of MP to output α_{ry} outside of distribution, but close.

Experiment IV: **Harmonizing Echoes**

Put all prior information on the table!

- **Prior on the sensitivity of aggregate demand to interest rate**

$$-\alpha_{yr} \sim folded\ \mathcal{N}(1,1) \tag{13}$$

- **Prior on the monetary policy response to output**

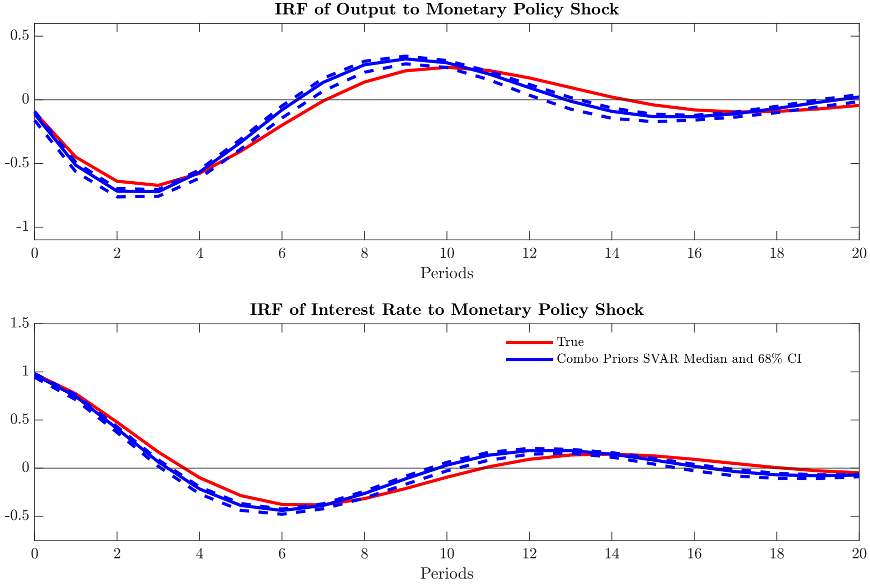
$$\alpha_{ry} \sim folded\ \mathcal{N}(1,1) \tag{14}$$

- **Signs of impulse responses**

$$-IRF(y_t, \epsilon_t^{mp}) \sim folded\ \mathcal{N}(0.2, 0.2) \tag{15}$$

$$IRF(r_t, \epsilon_t^{mp}) \sim folded\ \mathcal{N}(0.75, 0.2) \tag{16}$$

IRFs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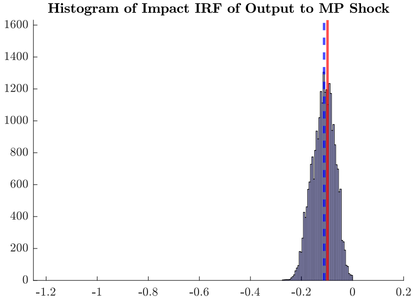
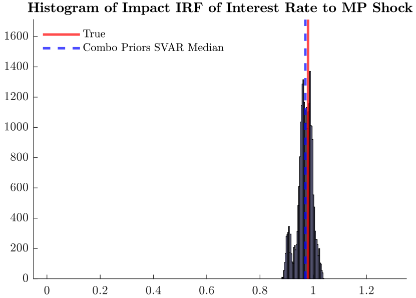
Periods

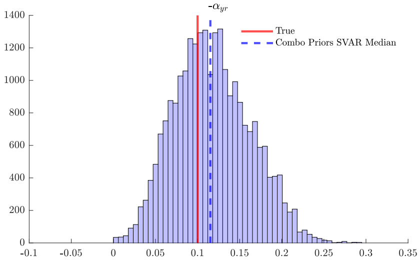
Histograms of Impact IRFs

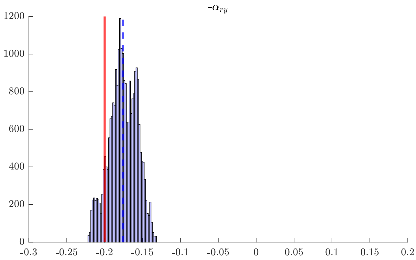




- **True values of impact IRFs within posterior distribution and with high density.**

Histograms of Structural Parameters





- **True values of structural parameters within posterior distribution and close to median.**

Key Takeaways

- Sign priors and priors on structural parameters can give extremely helpful identifying information.

- Even information about parameters that do not directly enter the equation of the shock of interest can be very powerful in terms of identification.

- **Combining prior information can be very helpful and is, in fact, advisable.**

- **Priors on (functions of) structural parameters are an improvement over sign restrictions used in conventional VAR approaches.**

Bayesian Model Comparison

Table: **(Log) Marginal Data Densities**

	$\mathbf{p}(\alpha_{\mathbf{yr}})$	$\mathbf{p}(\alpha_{\mathbf{ry}})$	**endo**	**combo**	$\alpha_{\mathbf{yr}} = \mathbf{0}$	$\alpha_{\mathbf{ry}} = \mathbf{0}$
Reciprocal IS	570.9	**601.2**	577.5	587.4	565.8	565.7
Meng and Wong's Bridge	571.1	**601.4**	577.6	587.5	565.9	565.9
Ulrich Mueller	576.5	**607**	582.7	590.7	570.8	571
Laplace	583.7	**617.5**	580.7	600	573	574.2
Sims, Waggoner and Zha	572.5	**602.8**	578.2	588.1	567.4	567.4
Laplace MCMC	578.3	**612.4**	579.9	591.7	572.9	575.2
Chib and Jeliazkov	582.5	**616.8**	584.3	595.7	576.7	578.8
Modified Harmonic Mean	570.8	**601.1**	577.4	587.3	565.7	565.6

Empirical Illustration:

Replicating and Extending Belongia and Ireland (2021)

Belongia and Ireland (2021)

Structural VAR Model à la Baumeister and Hamilton (2018)

$$\mathbf{A_0}\mathbf{y}_t = \mathbf{A}^{+}\mathbf{x}_t + \mathbf{\Sigma}\boldsymbol{\epsilon}_t, \tag{17}$$

with four lags and where $\mathbf{y}_t' = [p_t, y_t, r_t]'$ and $\epsilon_t' = \left[\epsilon_t^{as}, \epsilon_t^{ad}, \epsilon_t^{mp}\right]'$.

- p_t inflation: year-over-year percentage changes in PCE
- y_t output gap: p.p. difference between real GDP and CBO's potential GDP.
- r_t: mix of effective FFR and Wu and Xia (2016) shadow FFR

Contemporaneous Structural Parameters Matrix $\mathbf{A_0}$

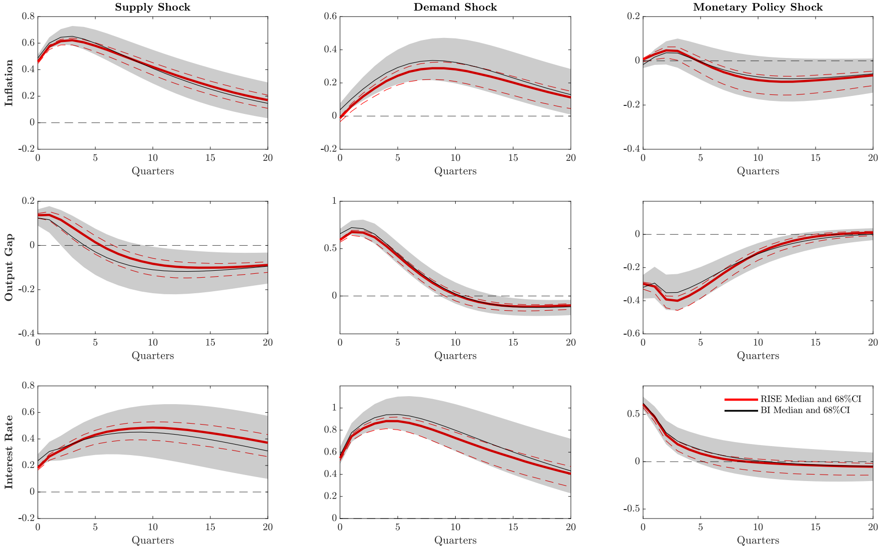
$$\mathbf{A_0} = \begin{bmatrix} 1 & -\alpha_{py} & 0 \\ -\alpha_{yr} & 1 & \alpha_{yr} \\ -\alpha_{rp} & -\alpha_{ry} & 1 \end{bmatrix} \tag{18}$$

Replication in RISE

- Sample 1968:Q1 - 2017:Q4. Sims and Zha (1998) prior with $\lambda_1 = 1$ and $\lambda_3 = 1$.
- **Restrictions**
  - $a_{0,21} = -a_{0,23}$ (related to α_{yr})
  - $a_{0,13} = 0$ (no contemporaneous relationship between π_t and r_t in Phillips curve)
- **Priors on elements in $\mathbf{A_0}$**:
  similar to original Student-t priors ($sc = 0.3$, $df = 2$), with larger prior variance

Parameter	Structural Equation	Mode	Scale
		Logistic Distribution	
$-\alpha_{py} = a_{0,12}$	Phillips Curve	-0.5	0.6
$-\alpha_{yr} = a_{0,21}$	Aggregate Demand	-1	0.6
$\alpha_{yr} = a_{0,23}$	Aggregate Demand	1	0.6
$-\alpha_{rp} = a_{0,31}$	MP Response to Inflation	-0.375	0.6
$-\alpha_{ry} = a_{0,32}$	MP Response to Output Gap	-0.125	0.6

Estimated IRFs after Posterior Sampling



Posterior of Coefficients

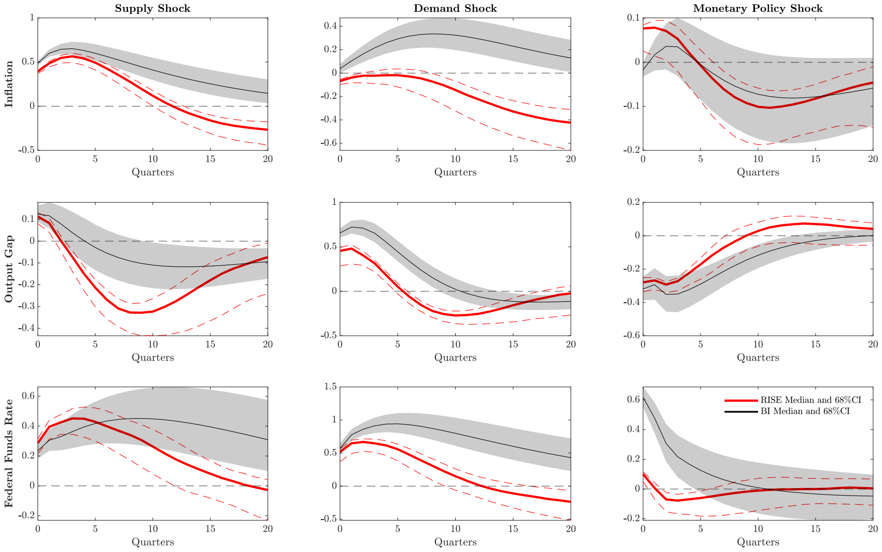
Laboratory: An Augmented VAR

- Extend VAR of Belongia and Ireland (2021) with
  - commodity price index
  - total reserves
  - non-borrowed reserves

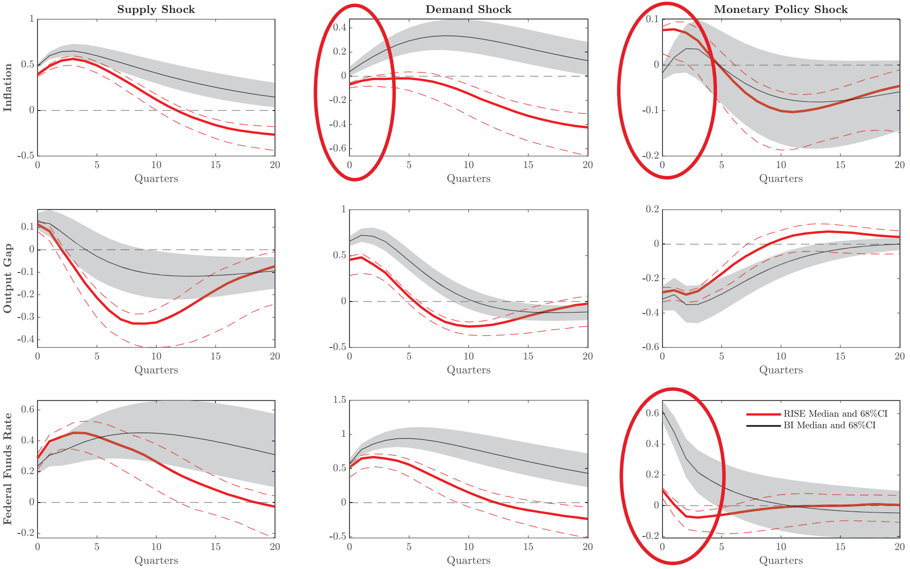
  from Uhlig (2005).

- Sample: 1968:Q1 - 2007:Q4.

IRFs: Belongia and Ireland (2021) Variables



IRFs: Belongia and Ireland (2021) Variables



Uhlig (2005) Variables

Combining Prior Information

- **Problem**: Extending the dataset affects the identification of all shocks.
- **Solution**: Add information on top of **Belongia and Ireland (2021) priors**.
- **Uhlig (2005) inspired sign priors**
  - A contractionary monetary policy shock reduces the commodity price index, total reserves, non-borrowed reserves **from 0 to 2 quarters after shock**.
  - Our prior for these IRFs is $\sim \mathcal{N}(-0.5, 0.25)$.
- **Add "DSGE-model-inspired" shape priors for responses to MP shock**
  - inflation negative in $h = 1$ and $h = 3 \sim$ *truncated* $\mathcal{N}(-0.2, 0.25, -20, 0)$
  - inflation back to zero at $h = 4 \sim \mathcal{N}(0, 0.25)$
  - output gap at $h = 2 \sim \mathcal{N}(-0.1, 0.25)$
  - output gap trough at $h = 4 \sim \mathcal{N}(-0.2, 0.25)$
  - output gap at $h = 6 \sim \mathcal{N}(-0.1, 0.25)$

What We Are Up Against

- Priors on VAR dynamics.
- Linear restrictions on structural VAR parameters.
- Priors on individual parameters of the structural form.
- Priors on signs and shapes of the IRFs.

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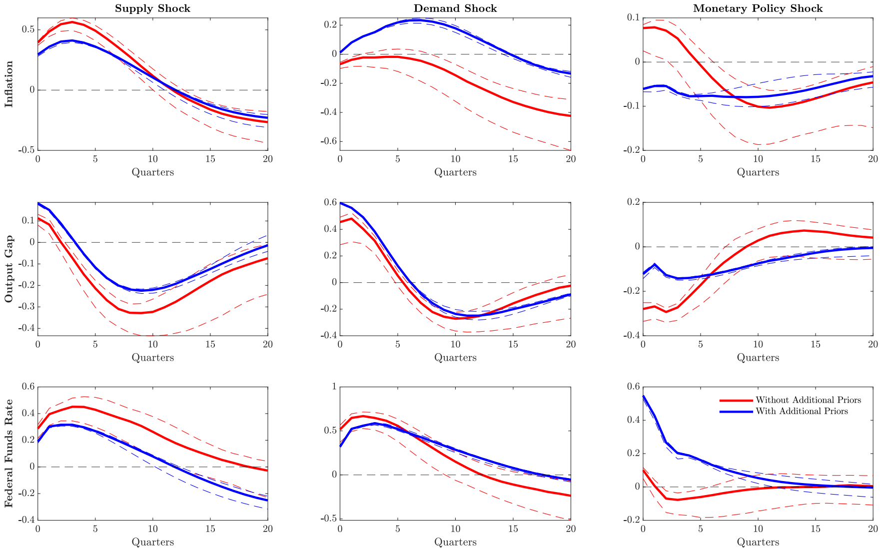
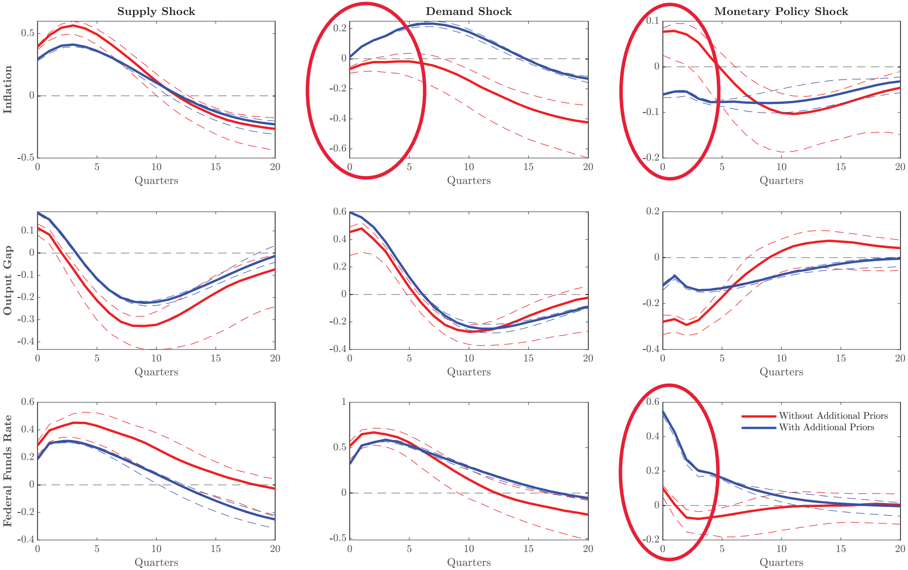
- Priors on VAR dynamics.
- Linear restrictions on structural VAR parameters.
- Priors on individual parameters of the structural form.
- Priors on signs and shapes of the IRFs.

Not a problem for our procedure!

IRFs with Added Priors: Belongia and Ireland (2021) Variables



IRFs with Added Priors: Belongia and Ireland (2021) Variables



Uhlig (2005) Variables

Summing Up

Summing Up

- We offer a comprehensive and user-friendly framework for **estimating and identifying SVARs in one step and with one coherent and efficient algorithm**.

- Framework is flexible enough to accommodate all available sources of information that have been proposed in the literature jointly.

- **Added benefit of:**

  1. Openly acknowledging uncertainty about prior information.
  2. Conducting proper posterior inference.
  3. Tailoring model dynamics to prior beliefs without rigid imposition.

- The proposed method will be available in the RISE toolbox (see Maih, 2015), simplifying the estimation of structural VARs for practitioners.

Thank You!

References I

Andrle, M. and Plasil, M. (2018). Econometrics with System Priors. *Economics Letters*, **172**, 134–137.

Baumeister, C. and Hamilton, J. D. (2018). Inference in Structural Vector Autoregressions When the Identifying Assumptions are Not Fully Believed: Re-evaluating the Role of Monetary Policy in Economic Fluctuations. *Journal of Monetary Economics*, **100** (C), 48–65.

— and — (2019). Structural Interpretation of Vector Autoregressions with Incomplete Identification: Revisiting the Role of Oil Supply and Demand Shocks. *American Economic Review*, **109** (5), 1873–1910.

Belongia, M. T. and Ireland, P. N. (2021). A Classical View of the Business Cycle. *Journal of Money, Credit and Banking*, **53** (2-3), 333–366.

Binning, A. and Maih, J. (2015). *Applying Flexible Parameter Restrictions in Markov-Switching Vector Autoregression Models*. Working Papers No 12/2015, Centre for Applied Macro- and Petroleum Economics (CAMP), BI Norwegian Business School.

Canova, F. and De Nicolò, G. (2002). Monetary Disturbances Matter for Business Fluctuations in the G-7. *Journal of Monetary Economics*, **49** (6), 1131–1159.

Christiano, L. J., Trabandt, M. and Walentin, K. (2011). Introducing Financial Frictions and Unemployment into a Small Open Economy Model. *Journal of Economic Dynamics and Control*, **35** (12), 1999–2041.

Del Negro, M. and Schorfheide, F. (2008). Forming Priors for DSGE Models (and How it Affects the Assessment of Nominal Rigidities). *Journal of Monetary Economics*, **55** (7), 1191–1208.

Faust, J. (1998). The Robustness of Identified VAR Conclusions About Money. *Carnegie-Rochester Conference Series on Public Policy*, **49** (1), 207–244.

Maih, J. (2015). *Efficient Perturbation Methods for Solving Regime-Switching DSGE Models*. Working Paper 2015/01, Norges Bank.

References II

Robertson, J. C., Tallman, E. W. and Whiteman, C. H. (2005). Forecasting Using Relative Entropy. *Journal of Money, Credit and Banking*, **37** (3), 383–401.

Rubio-Ramírez, J. F., Waggoner, D. F. and Zha, T. (2010). Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference. *The Review of Economic Studies*, **77** (2), 665–696.

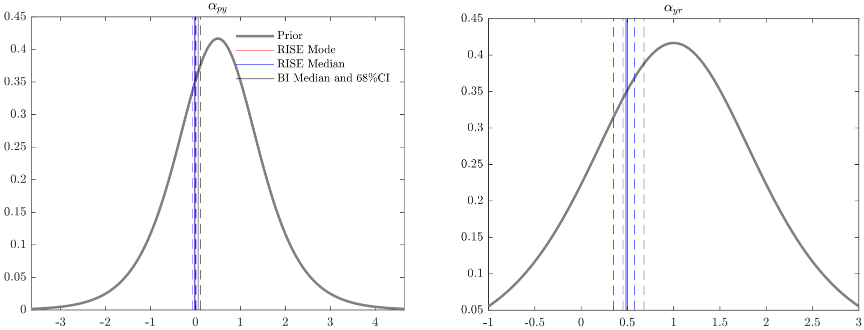
Sims, C. A. and Zha, T. (1998). Bayesian Methods for Dynamic Multivariate Models. *International Economic Review*, **39** (4), 949–968.

Uhlig, H. (2005). What are the Effects of Monetary Policy on Output?: Results from an Agnostic Identification Procedure. *Journal of Monetary Economics*, **52** (2), 381–419.

Wu, J. C. and Xia, F. D. (2016). Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound. *Journal of Money, Credit and Banking*, **48** (2-3), 253–291.

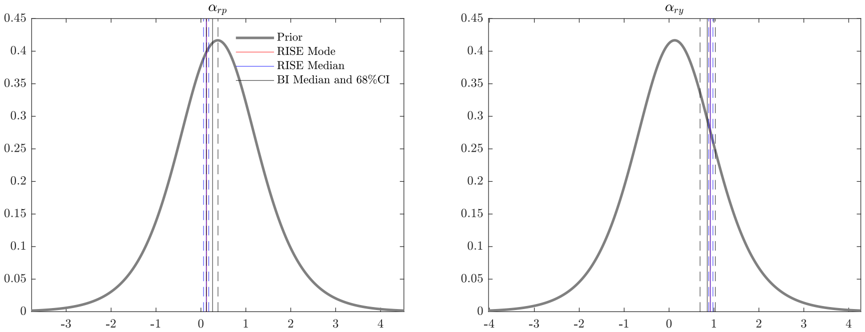
Estimated Contemporaneous Coefficients

Phillips Curve and Aggregate Demand



Estimated Contemporaneous Coefficients

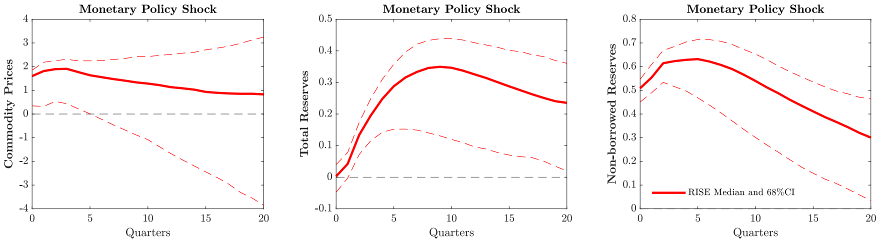
Monetary Policy Rule - Response to Inflation and Output Gap



Back

IRFs

Uhlig (2005) Variables



IRFs with Added Priors

Uhlig (2005) Variables