Identification of SVAR models by combining sign restrictions with external instruments

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SVARs are time series models to quantify causal relationships in macroeconomics:

- Aggregate effects of tax cuts?
- Impact of exogenous oil supply disruptions?
- Importance of migration for labor markets?

Main challenge: identification of similar events in the data ("shocks")

For the n variate vector of time series y_t:

$$y_t = \nu + \sum_{j=1}^{p} A_j y_{t-j} + u_t \qquad u_t \sim (0, \Sigma_u) \tag{1}$$

$$u_t = B\varepsilon_t \qquad \varepsilon_t \sim (0, I_n) \tag{2}$$

SVAR tools:

- Impulse response functions (IRFs)
- Forecast error variance decompositions (FEVDs)
- Historical decompositions

Identification problem

From $u_t = B\varepsilon_t$ and $\varepsilon_t \sim (0, I_n)$ it follows that

$$\Sigma_u = \mathsf{E}[u_t u_t'] = \mathsf{E}[B\varepsilon_t\varepsilon_t' B'] = BB'.$$

Let $\tilde{B} = BQ$ with Q s.t. $QQ' = I_n$:

$$\Sigma_u = BB' = BQQ'B' = \tilde{B}\tilde{B}'$$

Additional restrictions are necessary to identify B (or equivalently ε_t)

1. Exclusion restrictions (Sims; 1980; Bernanke; 1986; Blanchard and Quah; 1989)
2. Identification by distributional assumptions (Rigobon; 2003; Gourieroux et al.; 2017)
3. *Sign restrictions* (Faust; 1998; Canova and De Nicoló; 2002; Uhlig; 2005)
4. *External instruments* (Mertens and Ravn; 2012; Stock and Watson; 2012)

Identification by sign restrictions (SR) I

Typical use of sign restrictions involves

- Impose uncontroversial SR on (functions of) structural parameters
- Leave (functions of) structural parameters of interest unrestricted

SR yield set-identification: many models consistent with the same reduced form dynamics

Example: SVAR(12) for:

$$y_t = [\mathsf{gdp}_t, \mathsf{def}_t, \mathsf{comp}_t, \mathsf{EBP}_t, \mathsf{ffr}_t].$$

What is the effect of (contractionary) monetary policy (MP) $(\varepsilon_{1t} = \varepsilon_t^{mp})$?

SR of Uhlig (2005), for $h = 0, \ldots, 5$:

$$\frac{\partial \mathsf{def}_{t+h}}{\partial \varepsilon_t^{mp}} \leq 0, \qquad \frac{\partial \mathsf{ffr}_{t+h}}{\partial \varepsilon_t^{mp}} \geq 0$$

Identification by sign restrictions (SR) III

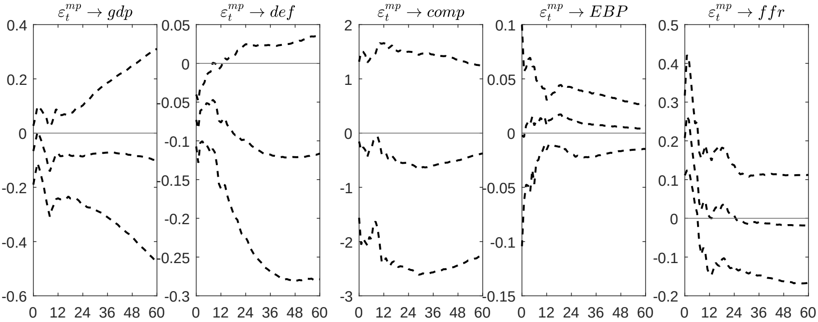

Figure: IRFs with 68% posterior credibility sets.

- SR often yield uninformative results
- Preview: we suggest to exploit information in external variables to sharpen identification

Idea: avoid direct restrictions exploiting external instruments ("proxies"). IV constraints:

$$\mathsf{E}[\varepsilon_{1t} m_t] \neq 0,$$
$$\mathsf{E}[\varepsilon_{it} m_t] = 0 \qquad i = 2, \dots, n.$$

Example: narrative MP shock Romer and Romer (2004) (R&R)

- Read FOMC minutes and construct series for intended changes in ffr_t
- m_t defined as the residual of regression on Greenbook forecasts

Identification by external instruments II

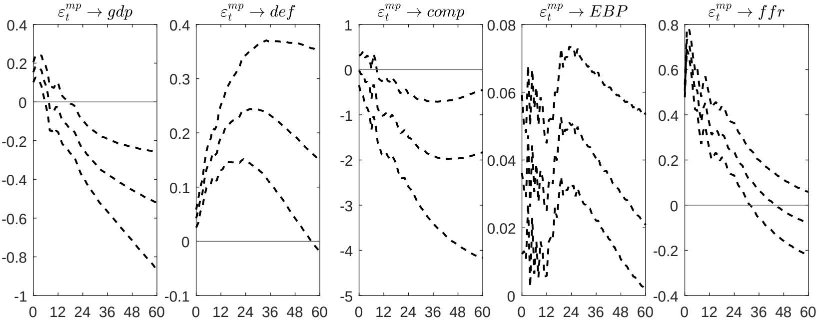

Figure: IRFs with 68% posterior credibility sets.

- Exogeneity questionable. R&R predicable by credit spreads (Caldara and Herbst; 2019)
- Preview: We exploit information without assuming exogeneity ("plausibly exogenous" (Conley et al.; 2012))

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We discuss novel ways to combine SR and IV, mitigating some of the mentioned flaws

Scenario 1: The proxy variables are credibly exogenous. Here, SR may be useful to:

- Impose SR on shocks identified by IV conditions. Why?
  - Disentangle shocks if $k > 1$ (e.g. Piffer and Podstawski (2017))
  - Overidentify the shocks (testable)
- Impose SR to identify *additional shocks* orthogonal to those identified by IV

Summary of our paper II

Scenario 2: proxy variables are only *plausible exogenous*. Our suggestion:

- Start with set identified SVAR based on SR
- Sharpen identification discarding models for which ε_t is unrelated to m_t (correlations, variance contributions)
- Note: exogeneity of m_t is not necessary

Sharpens identification w/o risk of imposing false IV constraints

Other features discussed in the paper:

- Proxy augmented SVAR model as unified framework to handle restrictions in both scenarios
- Bayesian inference by Markov Chain Monte Carlo (MCMC)
- Estimation of Bayes factors to quantify support for competing restrictions
- Applications: identifying oil market and monetary policy shocks

Literature related to *scenario 2:*

- combining SRs with narrative evidence:
  - Kilian and Murphy (2012)
  - Antolín-Díaz and Rubio-Ramírez (2018)
- restricting relation of set identified shock with external variables:
  - Uhrin and Herwartz (2016)
  - Ludvigson et al. (2017)

  Main differences: we suggest restrictions w/o thresholds and coherent Bayesian inference

Related literature II

Inference framework related to papers discussing Bayesian Proxy SVARs:

- Arias, Rubio Ramírez and Waggoner (2019) (ARW19)
- Caldara and Herbst (2019) (CH19)
- Giacomini et al. (2019)

Main differences:

- Posterior inference for an augmented B model.
  - ARW19: augmented A model ($B = \mathsf{A}^{-1}$)
  - CH19: hybrid model
- We cover estimation of Marginal Likelihoods and Bayes Factors

Proxy augmented SVAR I

Let m_t be a $k \times 1$ vector of external proxy variables:

$$\underbrace{\begin{pmatrix} y_t \\ m_t \end{pmatrix}}_{\tilde{y}_t} = \underbrace{\begin{pmatrix} c \\ c_m \end{pmatrix}}_{\tilde{c}} + \sum_{i=1}^{p} \underbrace{\begin{pmatrix} A_i & 0_{n\times k} \\ \Gamma_{1i} & \Gamma_{2i} \end{pmatrix}}_{\tilde{A}_i} \underbrace{\begin{pmatrix} y_{t-i} \\ m_{t-i} \end{pmatrix}}_{\tilde{y}_{t-i}} + \underbrace{\begin{pmatrix} B & 0_{n\times k} \\ \Phi & \Sigma_\eta^{1/2} \end{pmatrix}}_{\tilde{B}} \underbrace{\begin{pmatrix} \varepsilon_t \\ \eta_t \end{pmatrix}}_{\tilde{\varepsilon}_t}, \tag{3}$$

where $[\varepsilon_t, \eta_t]' \sim \mathcal{N}(0, I_{n+k})$

- m_t unpredictable if $\Gamma_{1i} = \Gamma_{2i} = 0$ (assumed in the following). Can be tested.
- Measurement error interpretation: $m_t = \Phi \varepsilon_t + \Sigma_\eta^{\frac{1}{2}} \eta_t$ and $\eta_t \perp \varepsilon_t$
- $\tilde{B}$ is identified up to orthogonal rotations of the form:

$$\tilde{B}_2 = \tilde{B} Q, \qquad Q = \mathsf{diag}(Q_1, Q_2) = \begin{pmatrix} Q_1 & 0 \\ 0 & Q_2 \end{pmatrix},$$

where Q_1 is $n \times n$ and Q_2 is $k \times k$.

Let $\varepsilon_t = [\underset{1\times q}{\varepsilon'_{1t}} : \varepsilon'_{2t} : \underset{1\times k}{\varepsilon'_{3t}}]'$ and $B = [\underset{n\times q}{B_1} : B_2 : \underset{n\times k}{B_3}]$.

- ε_{3t} identified by k valid instruments m_t:

$$\begin{aligned} \mathsf{E}(m_{it}, \varepsilon_{i,t}) &\neq 0, \qquad i = n-k+1, \ldots, n, \\ \mathsf{E}(m_{it}, \varepsilon_{j,t}) &= 0, \qquad i \neq j, \end{aligned}$$

In SVAR: $\mathsf{E}(m_t \varepsilon_t) = \mathsf{E}((\Phi \varepsilon_t + \Sigma_\eta^{\frac{1}{2}} \eta_t)\varepsilon_t) = \Phi$, implying

$$\begin{aligned} \Phi &= [0_{k\times n-k}, \phi_2] \\ \mathrm{rk}(\phi_2) &= k \end{aligned}$$

"reliability matrix" $\Lambda = \Sigma_\eta^{-1}\phi_2\phi_2'$ gives strength of relation.

- If $k = 1$, ε_{3t} is point-identified. For $k > 1$, additional restrictions necessary
- SR can be used to:
  - Identify q additional shocks $\varepsilon_{1t} \perp \varepsilon_{3t}$
  - Disentangle ε_{3t} if $k > 1$, see e.g. Piffer and Podstawski (2017).
  - Rule out weak identification by SR on Λ (CH19, ARW19)
- Both types of SR may be overidentifying (testable)

Let m_t contain k "plausible exogenous" proxies targeting ε_{1t}

In addition to SR, we suggest for $i = 1, \dots, k$:

1. Correlation between m_{it} and ε_{1t} is positive:

$$\mathrm{Corr}(m_{it}, \varepsilon_{1t}) > 0 \iff \phi_{i1} > 0$$

2. ε_{1t} shows largest correlation with m_{it}:

$$\mathrm{Corr}(m_{it}, \varepsilon_{1t}) > \mathrm{Corr}(m_{it}, \varepsilon_{jt}) \iff \phi_{i1} > \phi_{ij},$$

for $j = 2, \dots, n$.

3. ε_{1t} explains the largest fractions of variance of m_{it}:

$$\psi_{i1} > \psi_{ij}, \qquad j = 2, \dots n.$$

   where $\psi_{ij} = \phi_{ij}^2 / \mathsf{Var}(m_{it})$.

4. ε_{1t} explains more variance of m_{it} than the sum of all other shocks:

$$\psi_{i1} > \sum_{j=2}^{n} \psi_{ij}.$$

Gaussian Likelihood:

$$p(\tilde{Y}|\alpha,\beta) \propto |\tilde{B}\tilde{B}|^{-\frac{T}{2}} \exp\left(-\frac{1}{2}\,\mathrm{tr}(\tilde{B}^{-1\prime}\tilde{B}^{-1}(\tilde{Y}-X\tilde{A})(\tilde{Y}-X\tilde{A})')\right).$$

- $\tilde{Y} = [\tilde{y}_1, \ldots, \tilde{y}_T]'$
- $X = [x_1, \ldots, x_T]'$ with $x_t = [1, \tilde{y}'_{t-1}, \ldots, \tilde{y}'_{t-p}]'$
- $\tilde{A} = [\tilde{c}, \tilde{A}_1, \ldots, \tilde{A}_p]$
- $\tilde{\alpha} = S_a\,\mathrm{vec}(\tilde{A})$ free parameters $\tilde{A}$
- $\beta = S_b\,\mathrm{vec}(\tilde{B})$ free parameters $\tilde{B}$

We specify the following prior distributions:

$$p(\alpha) \sim \mathcal{N}(\alpha_0, V_\alpha),$$
$$p(\beta) \sim \mathcal{N}(0, S_b(I_{n+k} \otimes V_\beta)S_b',)$$

This prior for β is uniform over the set of admissible models,

Hence, the posterior

$$p(\alpha, \beta|\tilde{Y}) = \frac{p(\tilde{Y}|\alpha, \beta)p(\alpha)p(\beta)}{p(\tilde{Y})}$$

is uniform over the set of admissible models.

1. Draw $\alpha^{(i)}$ from $p\left(\alpha|\theta_{-\alpha},\tilde{Y}\right) \sim \mathcal{N}(\bar{\alpha},\bar{V}_\alpha)$

$$\begin{aligned}\bar{V}_\alpha^{-1} &= V_\alpha^{-1} + S_a((BB')^{-1} \otimes X'X)S_a',\\ \bar{\alpha} &= \bar{V}_\alpha\left(V_\alpha^{-1} + S_a\,\mathrm{vec}(X'\tilde{Y}(BB')^{-1})\right).\end{aligned}$$

2. Draw $\beta^{(i)}$ from $p\left(\beta|\theta_{-\beta},\tilde{Y}\right)$ by an Accept Reject Metropolis Hastings algorithm (AR-MH) (Chib and Greenberg; 1995).

Let $p^\star(\beta)$ be a proposal that satisfies $p\left(\beta|\theta_{-\beta}, \tilde{Y}\right) \leq c_{AR} \times p^\star(\beta)$ in some region of the parameter space:

1. *Accept-reject sampling*: $\beta^\star \sim p^\star(\beta)$ accepted with probability $p\left(\beta^\star|\theta_{-\beta}, \tilde{Y}_o\right) / \left(c_{AR} \times p^\star(\beta)\right)$
2. *MH step:* Correct mistakes made in AR step if $p\left(\beta^\star|\theta_{-\beta}, \tilde{Y}\right) > c_{AR} \times p^\star(\beta^\star)$

We choose $p^\star(\beta)$ following ARW(18,19).

1. Draw $\tilde{B}^\star = \text{chol}(\Sigma)Q$ where $\Sigma \sim i\mathcal{W}(T, (\tilde{Y} - X\tilde{A})'(\tilde{Y} - X\tilde{A}))$ and $Q \sim$ uniform subject to exclusion and SR
2. Density $p^\star(\beta)$ implied for β can be computed based on the change of variable theorem given in ARW18

To test competing restrictions we use Bayes Factors (Kass and Raftery; 1995)

$$\mathsf{BF}_{12} = \frac{p(\tilde{Y}|H_1)}{p(\tilde{Y}|H_2)}.$$

- $p(\tilde{Y}|H_{1/2})$ are the Marginal Likelihoods (ML)
- Directly quantifies the posterior odds of model H_1 over H_2
- Not new to SVAR literature (Woźniak and Droumaguet; 2015; Lütkepohl and Woźniak; 2018)

Ingredients:

- $p(\theta|\tilde{Y}) = p^{\dagger}(\theta|\tilde{Y})/p(\tilde{Y})$
- importance density $q(\theta)$
- $f(\theta)$ s.t. $\int f(\theta)p(\theta|\tilde{Y})q(\theta)d\theta > 0$

Key identity:

$$1 = \frac{\int f(\theta)p(\theta|\tilde{Y})q(\theta)d\theta}{\int f(\theta)q(\theta)p(\theta|\tilde{Y})d\theta}$$

$$p(\tilde{Y}) = \frac{\mathsf{E}_q(f(\theta)p^{\dagger}(\theta|\tilde{Y}))}{\mathsf{E}_p(f(\theta)q(\theta))}$$

Given $\theta^{(i)} \sim q(\theta)$ and $\theta^{(j)} \sim p(\theta|\tilde{Y})$, Bridge Sampling estimator:

$$\hat{p}(\tilde{Y}) = \frac{\frac{1}{L}\sum_{i=1}^{L} f(\theta^{(i)})p^{\dagger}(\theta^{(i)}|\tilde{Y})}{\frac{1}{M}\sum_{j=1}^{M} f(\theta^{(j)})q(\theta^{(j)})}$$

- An optimal choice of $f(\theta)$ is given by Meng and Wong (1996)
- We choose $q(\theta) = q(\alpha)q(\beta)$ trained by MCMC output.

- $q(\alpha) \sim \mathcal{N}(\mu_\alpha, V_\alpha)$
- $q(\beta) \sim p_q(\beta; v_q, S_q)$ where:

$$p_q(\beta; v_q, S_q) = c_q |\tilde{B}\tilde{B}'|^{-v_q/2} \exp\left(-\frac{1}{2}\operatorname{tr}((\tilde{B}\tilde{B}')^{-1} S_q)\right)$$

  - $v_q = T$ and S_q posterior mean of $\tilde{U}\tilde{U}'$
  - Draws generated by AR-MH algorithm
  - c_q estimated using Chib and Jeliazkov (2005)

- Reliability formally assessed by (asymptotic) MSE

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Causes of oil-prices remain controversial:

- Mostly demand shocks (Kilian; 2009; Kilian and Murphy; 2012, 2014; Antolín-Díaz and Rubio-Ramírez; 2018)
- Both demand and supply shocks (Baumeister and Hamilton; 2019; Caldara et al.; 2019)
- Difference caused by restrictions used for the oil supply elasticity

We investigate if there is additional information from using the narrative supply shocks of Kilian (2008) (K08) and Caldara et al. (2019) (CCI) as IV.

SVAR with $p = 24$ lags for $y_t = [\Delta\mathsf{prod}_t, \mathsf{rea}_t, \mathsf{rpo}_t, \mathsf{i}_t]'$ where:

- $\Delta\mathsf{prod}_t$: percentage change in world oil production
- $\Delta\mathsf{wip}_t$: global industrial production (Baumeister and Hamilton; 2019) (BH19)
- rpo_t: log of the real oil price.
- i_t a measure of oil inventories (Kilian and Murphy; 2014) (KM14)

Sample periods: $1974\text{M}1$ to $2018\text{M}10$.

The following drivers are identified: $\varepsilon_t = [\varepsilon_t^s, \varepsilon_t^{ad}, \varepsilon_t^{od}, \varepsilon_{4t}]$, where

1. ε_t^s: Supply shock
2. ε_t^{ad}: Aggregate demand (AD) driven shock
3. ε_t^{od}: Oil market specific demand (OD) shocks

Identifying restrictions considered:

- SR: Sign Restrictions proposed in K&M:

$$\begin{pmatrix} \Delta\text{prod}_t \\ \Delta\text{wip}_t \\ \text{rpo}_t \\ \text{i}_t \end{pmatrix} = \begin{pmatrix} - & + & + & \star \\ - & + & - & \star \\ + & + & + & \star \\ \star & \star & + & \star \end{pmatrix} \begin{pmatrix} \varepsilon_t^s \\ \varepsilon_t^{ad} \\ \varepsilon_t^{od} \\ \varepsilon_{4t} \end{pmatrix}.$$

- Restrictions on supply elasticities ($\eta_1 = B_{12}/B_{32}$, $\eta_2 = B_{13}/B_{33}$) and demand elasticity ($\eta_3 = B_{11}/B_{31}$)
  - KM14: $\eta_{1/2} \in (0, 0.024)$
  - BH19: $\eta_{1/2} \sim t_{0,\infty}(0.1, 0.2, 3)$, $\eta_3 \sim t_{-\infty,0}(-0.1, 0.2, 3)$
- NEW: IV restrictions for ε_t^s based on K08 and CCI shocks

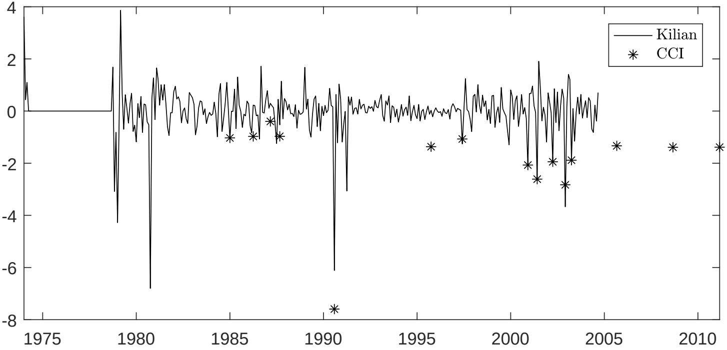

Figure: External instruments used for oil supply shock ε_t^s

External instruments for supply shocks II

	$\log \hat{p}(\tilde{Y})$	mse
H_1 K08	2072.766	0.016
H_2 K08	2229.924	0.015
H_1 CCI	2273.755	0.015
H_2 CCI	2495.343	0.015

Table: Marginal Likelihoods

Marginal Likelihoods favor unpredictability of both instruments:

- H_1: $\Gamma_{1i} = \Gamma_{2i} \neq 0$
- H_2: $\Gamma_{1i} = \Gamma_{2i} = 0$

Are we safe to combine SR with IV constraints (K08)?

	$\log \hat{p}(\tilde{Y})$	mse
IV	2229.924	0.015
IV+SR	2229.495	0.015
IV+SR+BH	2230.548	0.015
IV+SR+KM	2229.603	0.014

Table: Marginal Likelihoods

- Bayes Factor favoring IV over IV+SR: $\exp(2229.924 - 2229.495) \approx 1.53$
- Bayes Factor favoring BH19 over KM14 $\exp(2230.548 - 2229.6) \approx 2.5$

$\rightarrow$ no strong evidence against combining IV with SR

The drivers of oil prices: SR vs combined identification (K08)

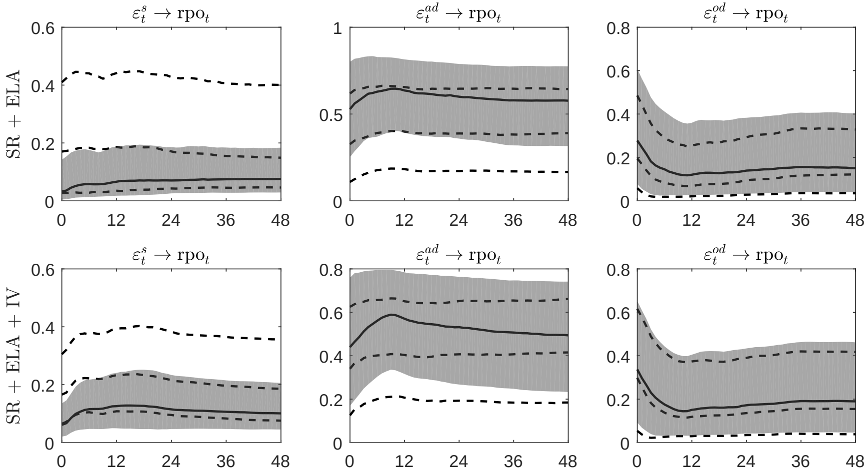

Figure: FEVDs with 68% posterior credibility sets. Shaded indicates KM14 restrictions, dashed BH19. In line with Montiel-Olea et al. (2018), K08 only weakly informative.

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Identify effect of monetary policy (MP) on credit markets

- Recursive identification as Christiano et al. (2005) not possible
- Sign restrictions as in Uhlig (2005) not informative
- IV difficult:
  - HFI (Gertler and Karadi; 2015): information effect contaminate shock
  - Narrative shocks (R&R) not credibly exogenous

Our approach: Combine R&R with SR without assuming exogeneity (scenario 2) monthly SVAR(12) for

$$y_t = [\mathsf{gdp}_t, \mathsf{def}_t, \mathsf{comp}_t, \mathsf{EBP}_t, \mathsf{ffr}_t]$$

- gdp_t: gross domestic product
- def_t: GDP deflator
- comp_t: commodity prices
- EBP_t: excess bond premium (Gilchrist and Zakrajšek; 2012)
- ffr_t: federal funds rate

Sample period: 1974M1-2007M12.

- *R1*: SR
  1. Uhlig (2005): $\frac{\partial \mathsf{def}_{t+h}}{\partial \varepsilon_t^{mp}} \leq 0$, $\frac{\partial \mathsf{ffr}_{t+h}}{\partial \varepsilon_t^{mp}} \geq 0$, $h = 0, \ldots, 5$
  2. Arias, Caldara and Rubio-Ramirez (2019):

$$r_t = \sum_{i=1}^{n-1} \xi_i u_{it} + \sigma_\xi \varepsilon_t^{mp}, \tag{4}$$

  where $\xi_i = -\mathsf{a}_{0,n1}^{-1} \mathsf{a}_{0,i1}$ and $\sigma_\xi = \mathsf{a}_{0,n1}^{-1}$ and $\mathsf{A}_0 = B^{-1}$.
  Restriction: $\xi_{1/2} > 0$

- *R2*: IV restrictions using R&R as instrument

- *R3*: R1 plus: ε_t^{mp} explains more of the variance in R&R than the sum of all other shocks

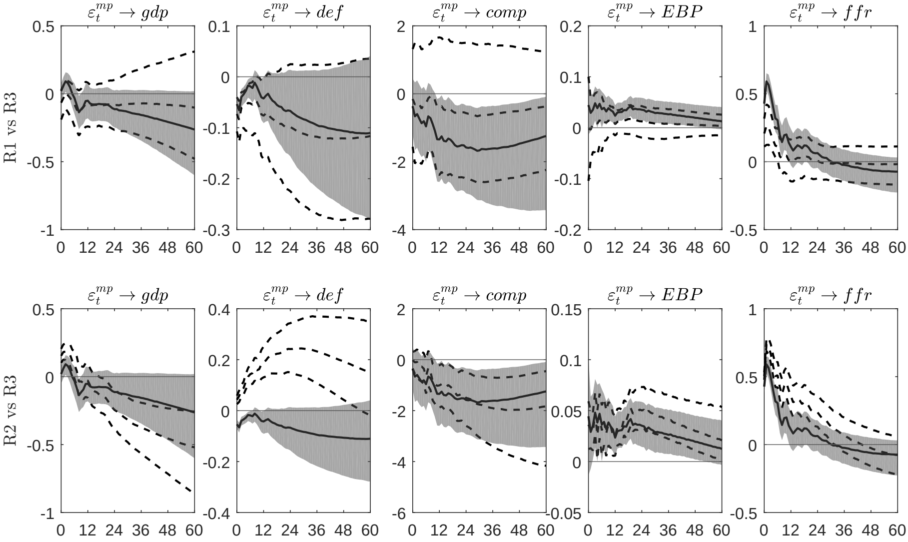

Figure: IRFs with 68% posterior credibility sets. Sample: 1974M1-2007M12.

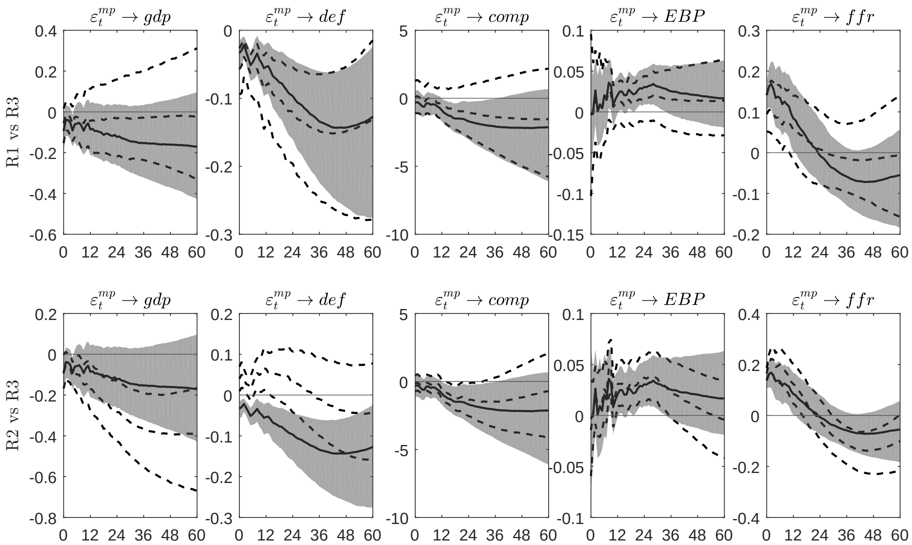

Figure: IRFs with 68% posterior credibility sets. Sample: 1983M1-2007M12 (great moderation).

Marginal likelihoods combining SR with exogeneity constraints

Model	$\log \hat{p}(\tilde{Y})$	mse
74-07: IV	-3185.279	0.027
74-07: IV+SR	-3189.565	0.029
83-07: IV 3	-2167.876	0.032
83-07: IV+SR 4	-2169.905	0.031

Table: Marginal Likelihoods IV vs IV + SR$(h = 0)$

If we assume R&R is a valid instrument:

- BF 74-07: $\exp(-3185.3 - (-3189.6)) \approx 72.6$
- BF 83-07: $\exp(-2167.9 - (-2169.95)) \approx 7.6$

$\rightarrow$ particularly for the sample 74-07, SR would be at odds with IV constraints.

- We suggest to combine sign restrictions with the information proxy variables. We distinguish between:
  - scenario 1: proxies exogenous
  - scenario 2: proxies "plausible exogenous"
- Discuss Bayesian inference and Marginal Likelihood estimation
- Empirical application demonstrate usefulness of the proposed methodology

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