Discussion of Arias, Caldara, Rubio-Ramirez: The systematic component of monetary policy in SVARs: an agnostic identification procedure

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What the paper does

- A nice paper on an important topic that takes identification seriously
The take-away message

- Analysis of the effects of monetary policy shocks in SVARs crucially depends on identifying restrictions
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  2. Liquidity puzzle: monetary aggregates ↑ when policy rate ↑
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- Paper shows that one need not throw the baby out with the bathwater:
  - Imposing (zero and sign) restrictions only on the policy equation is enough to remove all three puzzles
The econometric challenges

- Set-identification of impulse responses
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- Paper addresses computational challenge: how to obtain Bayesian estimates of set-identified impulse responses using priors that are "conditionally agnostic" (on the reduced form parameters)
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- Useful general method for flexible use of identifying restrictions
- Potential for greater understanding effect of choice of identifying restrictions on policy conclusions and overturning conventional wisdom
What could go wrong...

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- "Problems" of standard Bayesian inference in set-identified models
  - Poirier (1998): priors in set identified models not updated and thus can entirely drive inference
  - Baumeister and Hamilton (2014): apparently agnostic priors (such as those in this paper) can be unintentionally informative for the object of interest (e.g. impulse-response)
The econometric set-up

- n-variable SVAR:

\[ A_0 y_t = a + \sum_{j=1}^{p} A_j y_{t-j} + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(0, I_n), \]
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- **Reduced-form VAR:**

\[ y_t = b + \sum_{j=1}^{p} B_j y_{t-j} + u_t, \quad u_t \sim \mathcal{N}(0, \Sigma) \]

where \( \Sigma = \Sigma_{tr} \Sigma_{tr}' = A_0^{-1} (A_0^{-1})' \)
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- Reduced-form parameters are \( \phi = (B, \Sigma) \)
The econometric framework

- Invert VAR into $MA(\infty)$ (restrict $\phi$ to ensure invertibility)

$$y_t = c + \sum_{j=1}^{\infty} C_j(B) A_0^{-1} \epsilon_t$$
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$$y_t = c + \sum_{j=1}^{\infty} C_j(B)A_0^{-1}\epsilon_t$$

- Impulse-response of variable $i$ to shock $j$ at horizon $h$ is

$$r_{ij}^h = [C_h(B)A_0^{-1}]_{ij}$$
The impulse-response identified set

- Without identifying restrictions, knowledge of the reduced form parameter $\phi$ gives a set of observationally equivalent $A'_0$s

\[ \{ A_0 = Q'S_{tr}^{-1} \} , \]

with $Q$ ranging over space of all orthonormal matrices $O$
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- This corresponds to a set of observationally equivalent impulse-responses $r_{ij}^h \equiv [C_h(B) \Sigma_{tr} Q]_{ij} = r(\phi, Q)$
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- Imposing identifying restrictions progressively restricts the space of feasible $Q'$s until $r(\phi, Q)$ is point identified
From "agnostic priors" to "ambiguous priors"

- Giacomini and Kitagawa (2015): use of multiple-prior Bayesian inference (≡ambiguous priors) instead of single-prior solves the problem
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- Giacomini and Kitagawa (2015): use of multiple-prior Bayesian inference (≡ambiguous priors) instead of single-prior solves the problem
- In practice: obtain an estimate of the impulse response identified set by adding simple optimization step to the algorithm in this paper
The robust Bayes approach

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- In a nutshell:
  - Instead of choosing one prior consider the class of all possible priors for $Q$
  - This gives a class of posteriors for the impulse response
  - Summarize this class by reporting posterior mean upper and lower bounds $\Rightarrow$ estimator of the identified set
A different conclusion?

- Aruoba & Schorfheide (2011)

\[
A_0 \begin{pmatrix} r_t \\ \Delta y_t \\ \pi_t \\ m_t \end{pmatrix} = c + A(L) \begin{pmatrix} r_t \\ \Delta y_t \\ \pi_t \\ m_t \end{pmatrix} + \begin{pmatrix} \epsilon_{rt} \\ \epsilon_{yt} \\ \epsilon_{\pi t} \\ \epsilon_{mt} \end{pmatrix}
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- Sign restrictions: \( \frac{\partial r_{t+h}}{\partial \epsilon_{rt}} \geq 0, \frac{\partial \pi_{t+h}}{\partial \epsilon_{rt}} \leq 0, \frac{\partial m_{t+h}}{\partial \epsilon_{rt}} \leq 0 \), for \( h = 0, 1 \)
A different conclusion?

- Different combinations of restrictions

**Models**

<table>
<thead>
<tr>
<th>Restrictions</th>
<th>0</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
<th>VI</th>
<th>VII</th>
</tr>
</thead>
<tbody>
<tr>
<td>(i) $a_{12} = 0$</td>
<td>-</td>
<td>-</td>
<td>x</td>
<td>-</td>
<td>-</td>
<td>x</td>
<td>x</td>
<td>-</td>
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<tr>
<td>(ii) $IR^0 = 0$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>x</td>
<td>-</td>
<td>x</td>
<td>-</td>
<td>x</td>
</tr>
<tr>
<td>(iii) $CIR^\infty = 0$</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>x</td>
<td>-</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>(iv) sign restr.</td>
<td>-</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
</tbody>
</table>

Note: "x" indicates the restriction is imposed
Results - Models 0-III

Model 0: Output Response

Model I: Output Response

Model II: Output Response

Model III: Output Response
Results - Models IV-VII

Model IV: Output Response

Model V: Output Response

Model VI: Output Response

Model VII: Output Response
Bottom line

- After removing effect of prior choice, a simple zero restriction on policy equation not enough to obtain decline in output
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- Important to isolate informativeness of identifying restrictions from arbitrary choice of (unintentionally informative?) priors
  \[\Rightarrow\] multiple prior Bayesian approach can help