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

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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

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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

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  - 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 parameters are $\phi = (B, \Sigma)$

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

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

$$r_{ij}^h = \left[C_h(B) A_0^{-1} \right]_{ij}$$

The impulse-response identified set

- Without identifying restrictions, knowledge of the reduced form parameter ϕ gives a set of observationally equivalent A_0's

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with Q ranging over space of all orthonormal matrices $\mathcal{O}$

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- Imposing identifying restrictions progressively restricts the space of feasible $Q's$ until $r(\phi, Q)$ is point identified

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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

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  - 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 $\Longrightarrow$ 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?

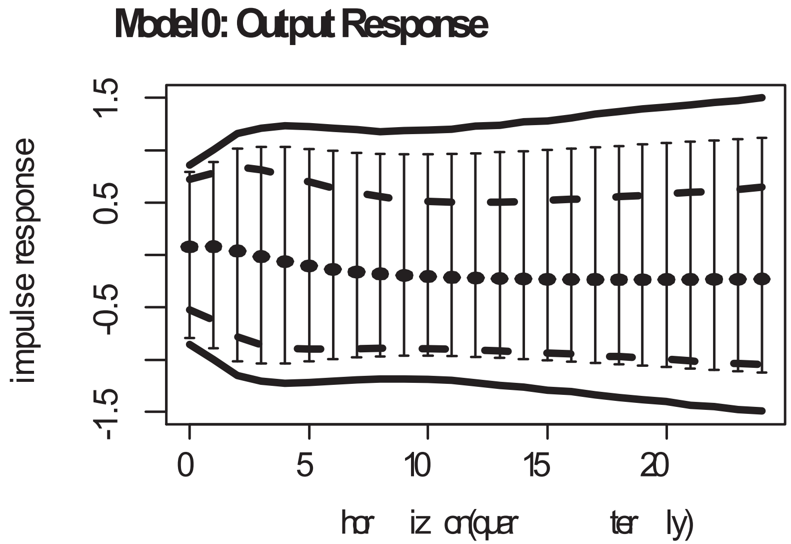
- Different combinations of restrictions

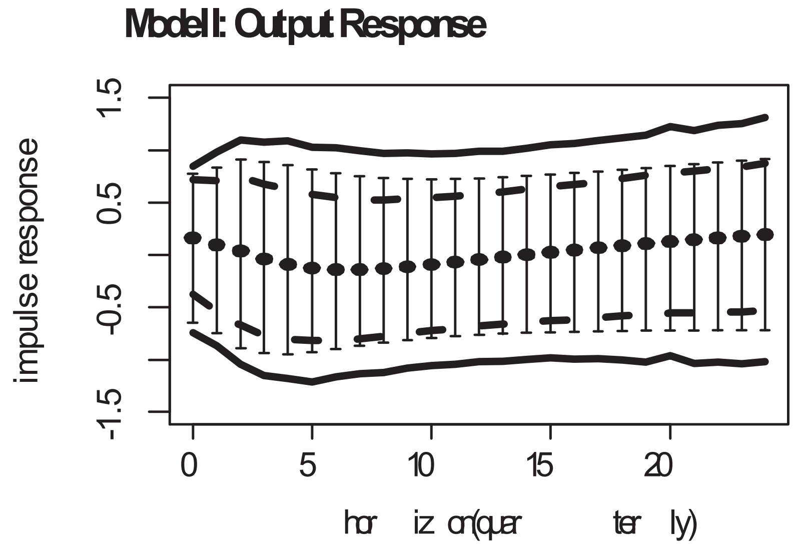
Models

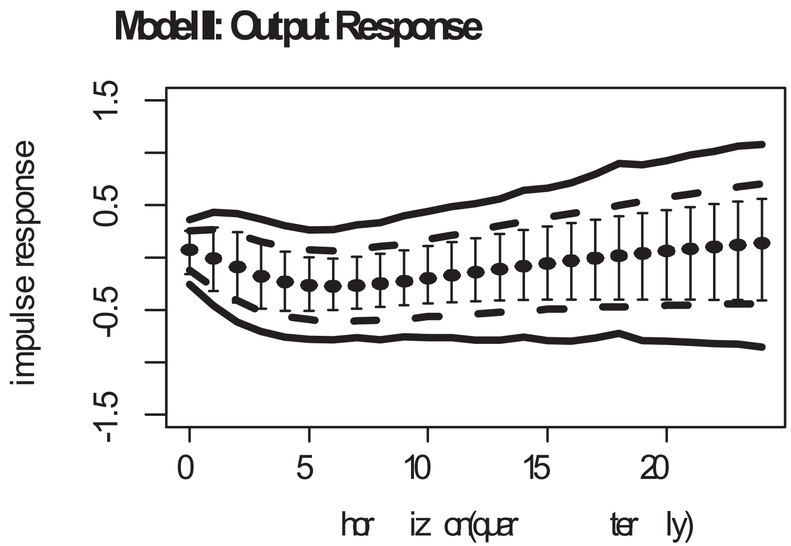
Restrictions	0	I	II	III	IV	V	VI	VII
(i) $a_{12} = 0$	-	-	x	-	-	x	x	-
(ii) $IR^0 = 0$	-	-	-	x	-	x	-	x
(iii) $CIR^\infty = 0$	-	-	-	-	x	-	x	x
(iv) sign restr.	-	x	x	x	x	x	x	x

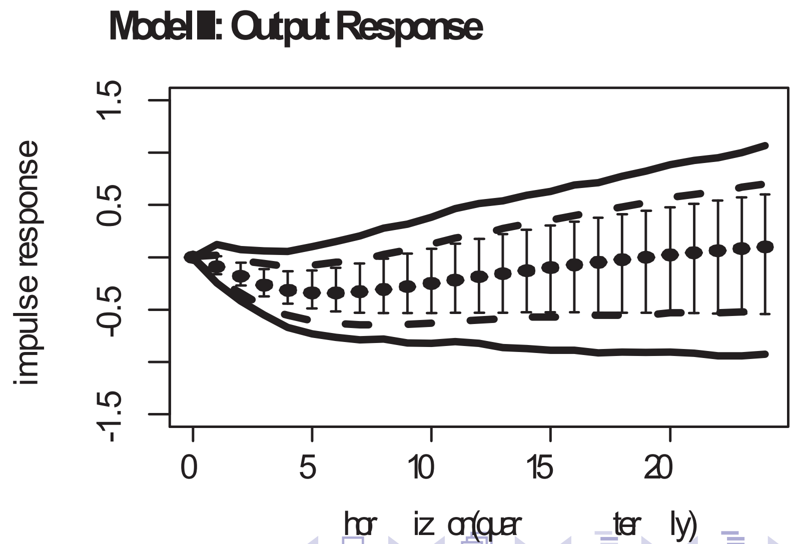
Note: "x" indicates the restriction is imposed

Results - Models 0-III

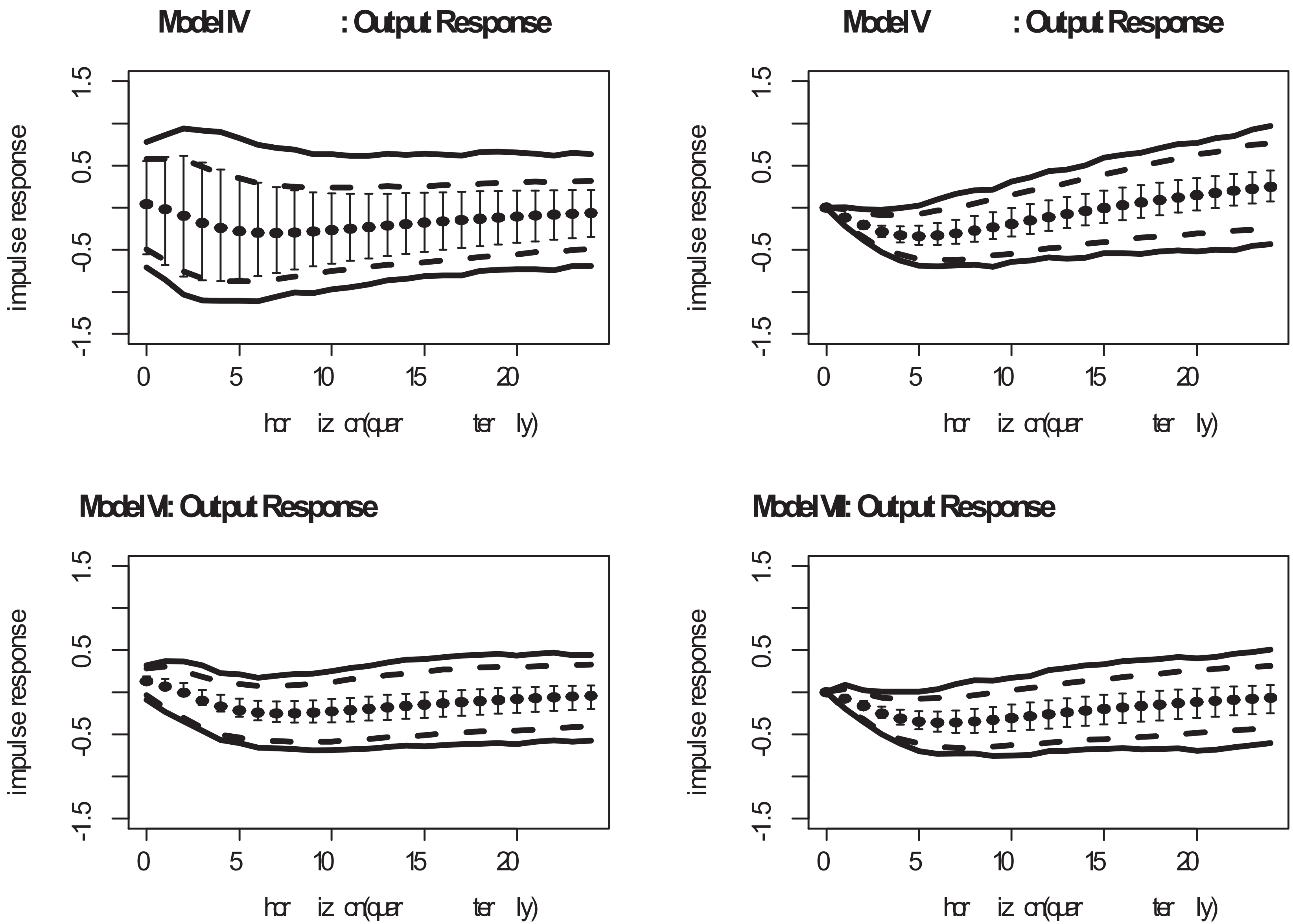








Results - Models IV-VII



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- Important to isolate informativeness of identifying restrictions from arbitrary choice of (unintentionally informative?) priors $\Longrightarrow$ multiple prior Bayesian approach can help