Discussion: "Narrative Restrictions and Proxies" by Giacomini, Kitagawa & Read

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Outline

1. Robustness of narrative proxy approach
2. Inference with a weak proxy
3. Conclusion

Bivariate SVAR model with narrative signals

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} \Theta_{11} & \Theta_{12} \\ \Theta_{21} & \Theta_{22} \end{pmatrix} \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}, \quad t = 1, \dots, T.$$

- Shocks $(\varepsilon_{1t}, \varepsilon_{2t})$ are i.i.d. mean zero, variance 1, mutually independent.
- Narrative signals about ε_{1t} (for simplicity, no info about ε_{2t}):

$$Z_t = \begin{cases} 1 & \text{if we believe } \varepsilon_{1t} > 0, \\ 0 & \text{if sign unknown,} \\ -1 & \text{if we believe } \varepsilon_{1t} < 0. \end{cases}$$

- Data: (y_{1t}, y_{2t}, Z_t). Shocks are unobserved.
- Identified set for impulse responses Θ_{ij} is large if we ignore Z_t. How to model+exploit Z_t?

Bayesian inference when signals are perfect

- Assume first that signals are perfect:

$$\text{sign}(\varepsilon_{1t}) = Z_t \quad \text{whenever } Z_t \neq 0.$$

- This implies restrictions that can substantially sharpen inference about impulse responses:
  Antolín-Díaz & Rubio-Ramírez (2018); Ludvigson, Ma & Ng (2019); Giacomini, Kitagawa & Read (2021)

$$\text{sign}\left(\frac{\Theta_{22}y_{1t} - \Theta_{12}y_{2t}}{\Theta_{11}\Theta_{22} - \Theta_{12}\Theta_{21}}\right) = Z_t \quad \text{whenever } Z_t \neq 0.$$

- Subjective/robust Bayesian inference based on these restrictions imposes strong as'ns:
  - Signals are perfect and arrive randomly (likelihood function appears to impose that the event $\{Z_t \neq 0\}$ is independent of the shocks).
  - SVAR model assumes shocks are invertible (functions of only current and past data).

Proxy approach

- More generally, we could assume that the signal Z_t is a potentially imperfect proxy:

$$Z_t = F(\varepsilon_{1t}, u_t), \quad u_t \perp\!\!\!\perp (\varepsilon_{1t}, \varepsilon_{2t}),$$

where $F\colon \mathbb{R}^2 \to \{-1, 0, 1\}$ is unknown, and u_t is unobserved measurement error.

  - Example: $Z_t = \text{sign}(\varepsilon_{1t} + u_t) \times \mathbb{1}(|\varepsilon_{1t}| \geq 2)$.

- Yet, we assume that signals are not too inaccurate overall:

$$\text{Cov}(Z_t, \varepsilon_{1t}) > 0.$$

Proxy approach: Robust estimation

$$Z_t = F(\varepsilon_{1t}, u_t), \quad \text{Cov}(Z_t, \varepsilon_{1t}) > 0$$

- Consider estimation of the relative IR $\theta \equiv \Theta_{21}/\Theta_{11}$. Since

$$y_{2t} = \theta y_{1t} + (\Theta_{22} - \Theta_{21}\tfrac{\Theta_{12}}{\Theta_{11}})\varepsilon_{2t},$$

  we can estimate θ by 2SLS regression of y_{2t} on y_{1t}, with Z_t as IV.
  Romer & Romer (1989); Hamilton (2003); Budnik & Rünstler (2020)

- Appealing robustness properties:

  1. IV exclusion restriction holds even under misclassification and non-random signal arrival.
  2. Can allow shocks to be non-invertible with 2SLS version of Local Projection (or recursive VAR with Z_t ordered first). Stock & Watson (2018); Plagborg-Møller & Wolf (2021)

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Proxy approach: Weak identification

- Credible signals are usually only available for a small number K of periods $\Longrightarrow$ proxy Z_t is mostly zero $\Longrightarrow$ weak identification.
- G, K & R helpfully point out that the standard weak-IV robust SVAR procedure does *not* work if we model K as finite asymptotically. Montiel Olea, Stock & Watson (2021)
  - This procedure requires asy. normality of reduced-form sample moments.
  - But $T^{-1/2} \sum_{t=1}^{T} Z_t y_{1t} \xrightarrow{p} 0$, since $Z_t = 0$ for all but finite no. of obs.
  - Can fix the procedure if shocks are Gaussian, but this seems fragile.
- Should we therefore give up on the robustness afforded by the proxy approach?

Proxy inference in small samples

- Fundamentally, the setting with a sparse proxy Z_t is a small-sample problem. Can we apply weak-IV procedures that are geared towards small samples?
- Permutation Anderson-Rubin test: Under $H_0\colon \theta = \bar{\theta}$,

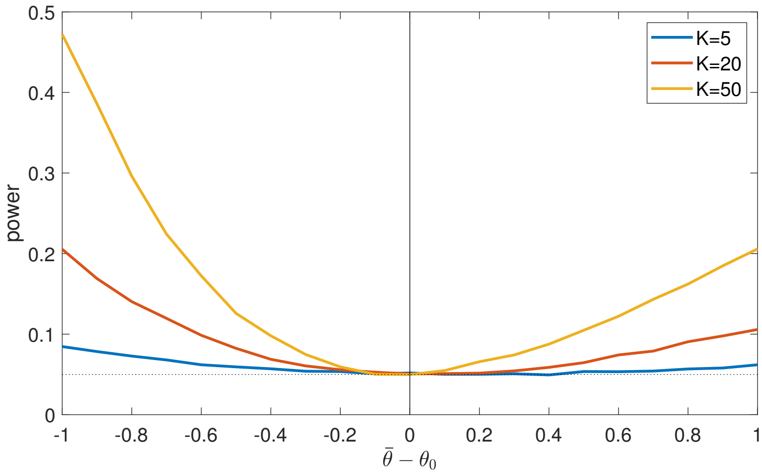
$$y_{2t} - \bar{\theta} y_{1t} = (\Theta_{22} - \Theta_{21} \tfrac{\Theta_{12}}{\Theta_{11}}) \varepsilon_{2t} \quad \Longrightarrow \quad (y_{2t} - \bar{\theta} y_{1t}) \perp\!\!\!\perp Z_t.$$

  Fisher permutation test of independence: Imbens & Rosenbaum (2005)

  1. Compute $|\widehat{\mathrm{Corr}}(y_{2t} - \bar{\theta} y_{1t}, Z_t)|$.
  2. Compute same statistic over all possible permutations of the IV data points $Z_1, \dots, Z_T$.
  3. Reject if original statistic exceeds 95th percentile of permutation distribution.

- Exact size in finite samples. Does not require shocks to be Gaussian.

Simulated size/power of nominal 5% permutation test



DGP: Same as G, K & R, except perfect signals arrive in first K periods where $\varepsilon_{1t} > 0$ (so uncond'l shock distribution is normal). $T = 500$. 5,000 simulations. 1,000 random permutations.

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Conclusion

- G, K & R are doing important work on understanding+improving narrative identification.
- Very helpful to point out the small-sample problem that (i) causes a weak proxy issue and (ii) cannot be tackled with the usual inference procedure based on asy. normality.
- My opinion: It would be a shame to give up on the proxy approach, as it is robust to misclassification, non-random signal arrival, and non-invertibility.
- My suggestion: Use small-sample weak-IV robust procedures, such as permutation test.
  - Power may be low, which seems inevitable given nature of restrictions.
  - May want to relax shock independence assumptions (also true for other approaches).