Identifying VARs from Sparse Narrative Instruments

Dynamic Effects of U.S. Macroprudential Policies

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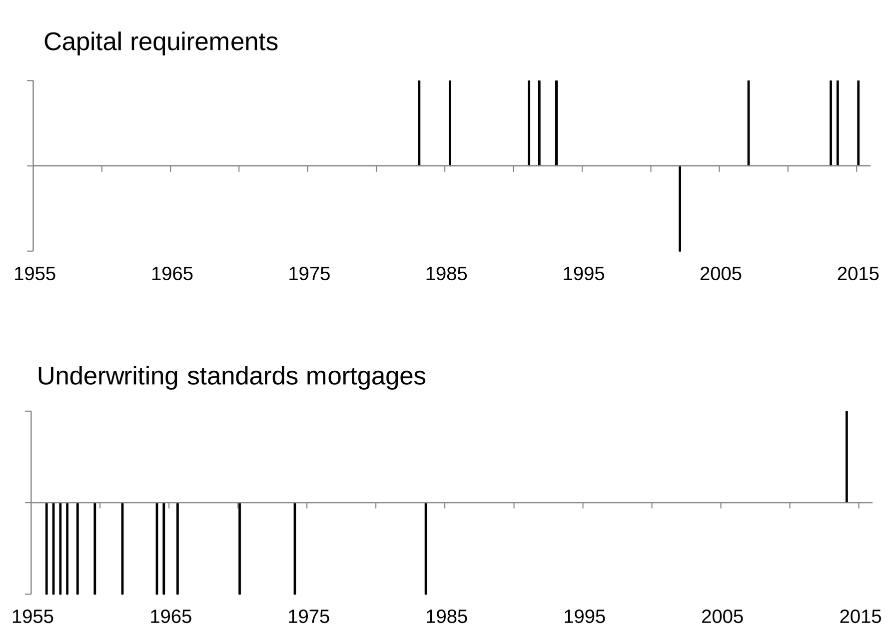
1. Summary

We adopt the proxy VAR approach to the case that the instrument is narrative (binary and sparse). In practice, policy measures are often rare, difficult to quantify, and imperfectly observable.

1. We propose two alternative identification schemes based on sign concordance and discriminant regression.
2. We combine them in a Bayesian version of the narrative proxy VAR.
3. We conduct a Monte Carlo study to compare the approach with standard proxy VARs and local projections.
4. We apply the narrative proxy VAR to U.S. policy measures on capital requirements and mortgage underwriting standards

Figure 1: *U.S. Macroprudential Policy Indices*



2. Assumptions

Consider the VAR

$$y_t = \sum_{s=1}^{p} B_s y_{t-s} + u_t, \qquad u_t^+ \sim N(0, \Sigma^+)$$
$$u_t = u_t^+ + \Gamma\theta_t \qquad \theta_t^+ \sim N(0,1)$$

The $n \times 1$ vector of residuals u_t embeds an 1×1 policy shock θ_t. Isolate the impact of θ_t from the transformation

$$A_0 u_t = \epsilon_t = \epsilon_t^+ + \begin{bmatrix} \gamma \\ 0_{n-1} \end{bmatrix} \theta_t, \qquad \epsilon_t \sim N(0, I_n)$$

Consider $\alpha^T u_t = \epsilon_{t,1}$, where α^T is the first row of A_0.

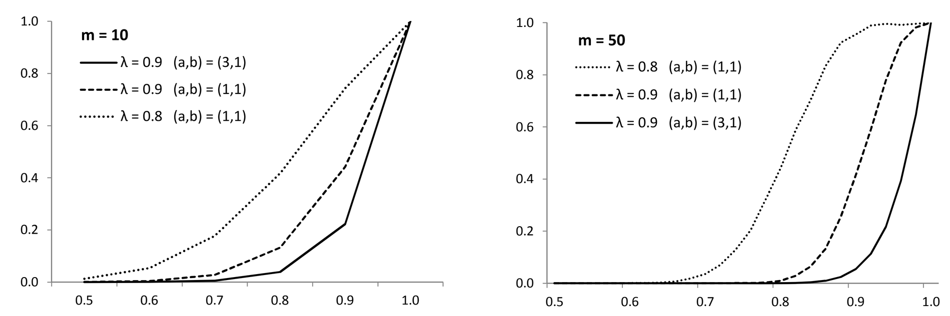
Instrument z_t takes the value $z_t = \mathrm{sign}(\theta_t)$ for a small number m of periods. It is zero otherwise, indicating the absence of information.

3. Sign concordance (SC) criterion

Find α such that the sign of the policy shock corresponds to the instrument, sign$(\epsilon_{1,t}) = z_t$, for a sufficiently high number of observations.

- Draw uninformative α and count nr of correct signs $m\varphi = \sum \epsilon_{1,t} z_t > 0$
- Keep draw if $m\varphi$ is sufficiently high. $m\varphi$ follows a binomial distribution. Define acceptance weights from a prior belief on the probability of correct sign, π = $\mathbb{E}(m\varphi)$, e.g. a uniform over $(\lambda > 0.5, 1)$.

$$m\varphi \sim \mathrm{Binom}(\varphi; m, \pi)$$
$$\pi \quad \sim \mathrm{Uniform}(\lambda, 1)$$



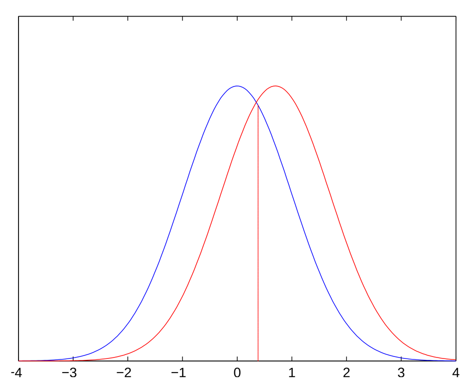
4. Discriminant (DC) regression

Find α to maximize the (sign-adjusted) difference in means of the policy shock for $z_t \neq 0$ and $z_t = 0$, $\mathbb{E}(\epsilon_{1,t} z_t | z_t \neq 0) - \mathbb{E}(\epsilon_{1,t} z_t | z_t = 0)$. This task amounts to discriminant analysis, a simple version of which can be implemented from the regression

$$z_t = \alpha_0 \delta_t + \alpha^T u_t,$$

where $\delta_t = -1$ if $z_t = -1$ and $\delta_t = 1$ otherwise.

$$\epsilon_{1,t} | z_t = 0 \sim N(0, \sigma_{11}^+)$$
$$\epsilon_{1,t} | z_t = 1 \sim N(\gamma, \sigma_{11}^+)$$
$$j > 1\!: \epsilon_{j,t} \sim N(0, \sigma_{jj}^+)$$



5. Further Considerations

1. Combine by estimating α from DC regression and applying SC prior.
2. Estimate the mean policy shock from $\gamma = \mathbb{E}(\epsilon_{1,t} z_t | z_t \neq 0)$.
3. Monte Carlo simulations: with sparse narrative indicators ...
   ... the narrative proxy VAR is more robust to measurement error than the standard proxy VAR, while efficiency losses remain limited.
   ... the standard proxy VAR overestimates confidence bounds
   ... local projections are clearly more inefficient

6. Application

Use indices from Figure 1 to assess impact of macroprudential policy measures in the U.S. from a quarterly VAR over 1958 Q1 - 2016 Q4. DC and SC give similar results, but their combination is most efficient. Please see the paper (ECB Working Paper 2353) for the average size of policy shocks.

Figure 4: *Standardised IRF Capital Requirements*

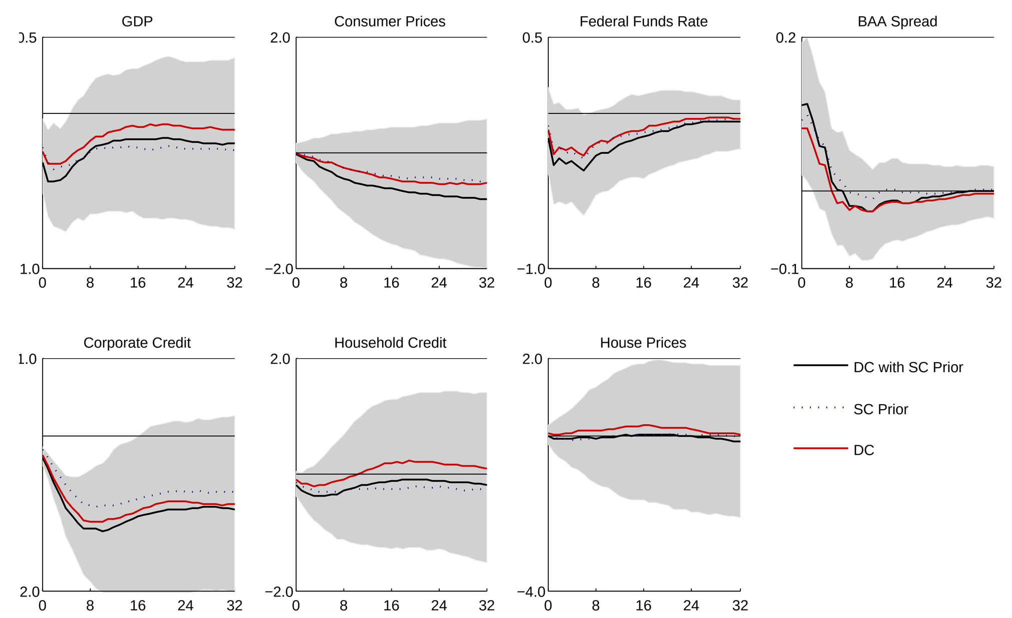


Figure 5: *Standardised IRF Underwriting Standards*

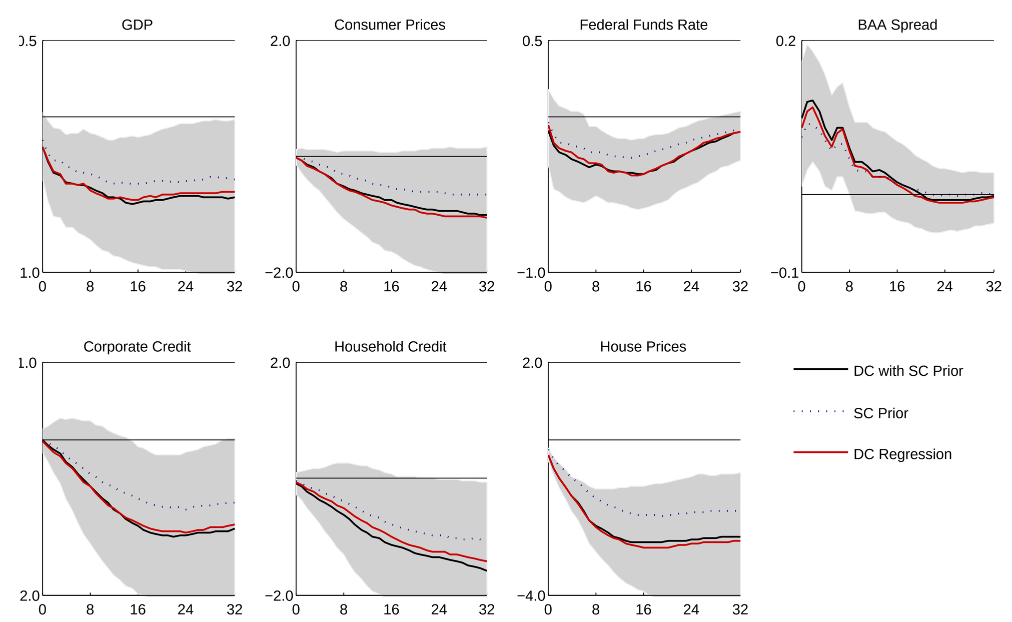
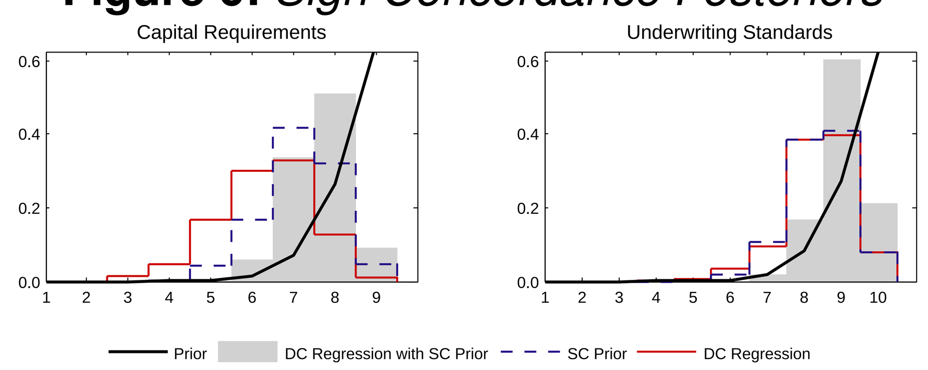


Figure 6: *Sign Concordance Posteriors*



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