Variance Maximizing Identification and the Plague of Confounding Shocks

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Variance-maximizing (VM) SVAR research

- Dominant long-run shocks (Technology/News)
  - **FORD (2014)** - Technology shock identification, improvements vs. long-run approach.
  - **Barsky and Sims (2011)** - Identify TFP "news"
- Dominant business-cycle shocks
  - **Levchenko and Pandalai-Nayar (2020)** - TFP "news" and separate "sentiment"/confidence shocks
  - **Angeletos, Collard, and Dellas (2020)** - analysis of the business cycle "anatomy".
  - **Giannone, Lenza, and Riechlin (2020)** - Euro-area cyclical shocks identified.

Questions, and a preview of our answers

- What are VM identifications really capturing in the presence of multiple shocks?
  - A combination of structural shocks, not just the largest.
- When do confounding shocks affect inference when using VM identifications?
  - For long-run identifications (technology shocks), a VM method in the frequency domain is most robust. But the issue does not appear large when applied to US data.
  - When identifying dominant business-cycle shocks, inference can be very difficult. "Hybrid" shocks with competing effects are identified.

The Max Share Approach

Find the shock that maximizes the forecast error variance of productivity at the ten-year horizon ($k = 40$ quarters).

$$y_{t+k} - \hat{y}_{t+k} = \sum_{\tau=0}^{k-1} D^{\tau} u_{t+k-\tau}$$

Standard intuition: technology will dominate at this horizon, vector α will capture this dominant shock.

$$\max \omega(\alpha) = \frac{e_i' \left(\sum_{\tau=0}^{k-1} D^{\tau} \alpha \alpha' D^{\tau\prime} \right) e_i}{e_i' \left(\sum_{\tau=0}^{k-1} D^{\tau} \Sigma_u D^{\tau\prime} \right) e_i}$$

Alternative: Spectral identification

Choose desired frequency of interest in the variance-covariance matrix on which the maximization problem is applied. Modification to the Max Share approach using the ∞-MA coefficient matrix (D).

$$S_{YY}(\omega) = D\left(e^{-i\tau\omega}\right)\Sigma_u D\left(e^{i\tau\omega}\right)' = \sum_{\tau=-\infty}^{\infty} \gamma(\tau)\, e^{-i\tau\omega}$$

We propose further modification to cutoff ∞ horizon and reduce bias:

$$D^k(e^{-i\tau\omega}) = \sum_{\tau=0}^{k-1} D^\tau e^{-i\tau\omega} \neq \sum_{\tau=0}^{\infty} D^\tau e^{-i\tau\omega}$$

Demonstrating confounding shocks with a simple 2-variable model

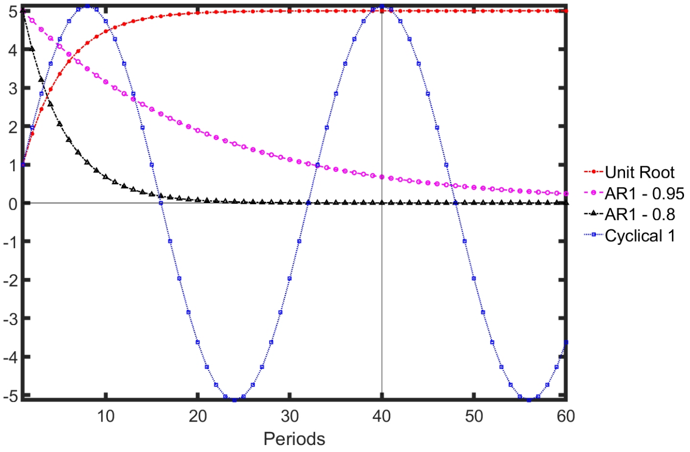

Figure: Example IRF data

IRF bias: Technology shock to labor productivity

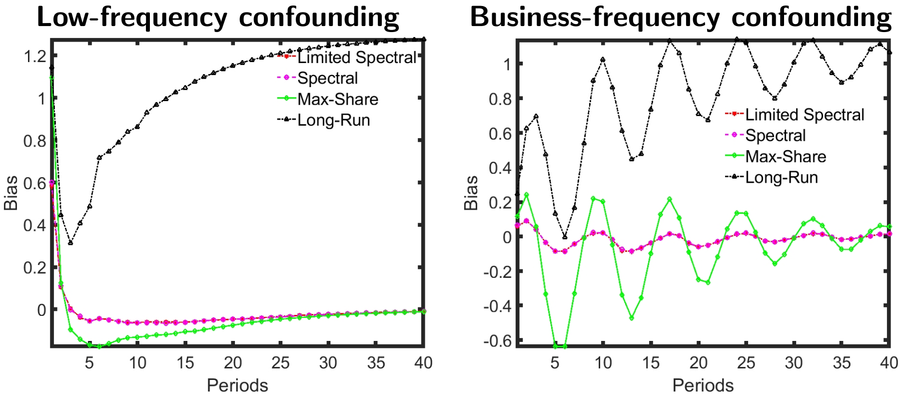

Figure: **IRF bias in the presence of low-frequency and business cycle shocks**

Note: Absolute bias of technology IRF on the presence of a confounding low, and a confounding business-cycle non-technology shock, respectively.

Business cycle anatomy revisited

Many recent papers have begun to apply VAR Spectral methods to pick out business-cycle shocks (Angeletos et al. 2020; Levchenko and Pandalai-Nayar, 2018; Giannone et al. 2020).

- There are many different business-cycle shocks! More possibilities for capturing multiple drivers than technology.
- Does one shock dominate as a driver of main real macro-aggregates (Angeletos et al. 2020).
- Is there really a dichotomy for the drivers of real and nominal variables?

Targeting business cycle drivers

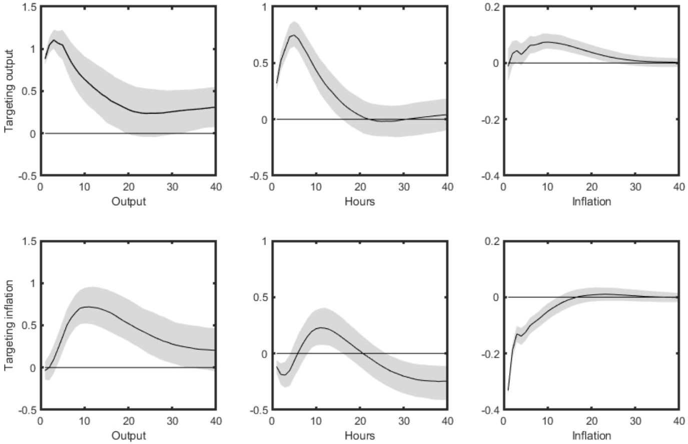

Figure: Targeting Output and Inflation at Business-cycle Frequencies

Note: 16th and 86th percentile error bands. First row shows impulse responses to the shock which maximises the variance of output at business-cycle frequencies (6-32 quarters). The second targets inflation. The VAR consists of US data on labor productivity, hours-worked, the investment to GDP ratio, the consumption to GDP ratio, the consumption expenditure deflator (inflation), and the 10-year US treasury yield.

Simple NK model with supply and demand shock

A simple model demonstrates how the Spectral methodology can produce these results:

$$y_t = \frac{-1}{\sigma}\left(R_t - E_t[\pi_{t+1}]\right) + E_t[y_{t+1}] + \eta_t$$

$$\pi_t = \kappa MC_t + \beta E_t[\pi_{t+1}]$$

$$MC_t = (\sigma + \chi) y_t - (1 + \chi) a_t$$

$$R_t = (\phi_t) y_t + \phi_\pi \pi_t$$

Where y_t is output, R_t is the nominal interest rate, π_t is inflation, MC is marginal costs. η represents a demand (preferences) shock, while a_t reflects a supply-side technology shock. σ is the inter-temporal elasticity of substitution, χ is the Frisch elasticity of labor supply. κ is the slope of the Phillips curve, and is a function of the probability of not being able to reset prices each period (θ) and the discount rate (β) :$\kappa = (1-\theta)(1-\beta\theta)/\theta$

Hybrid supply-demand shock estimated

Simulating the data for 250 periods and then separately identifying the dominant business-cycle driver of output and inflation

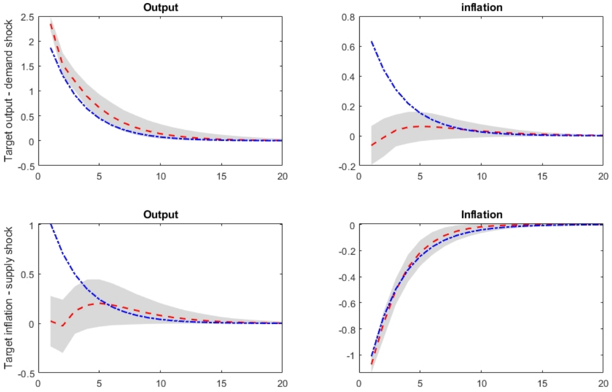

Figure: Targeting Output and Inflation at Business-cycle Frequencies

Note: 16th and 86th percentile error bands. The first row shows impulse responses to the shock which maximises the variance of output produced by the simple New Keynesian model at business-cycle frequencies (6-32 quarters). The second targets inflation. Blue lines indicate the true IRF of the demand shock (top row) and supply shock (bottom row).

Conclusions

- Use Spectral and Limited Spectral for identifying technology shocks, although Max Share works as well in many cases, and much better than long-run restriction.

- Confounding shocks can lead to misleading results, especially at business-cycle frequencies. Use deductive reasoning to interpret.