

Optimism Shock

on the Australian Business Cycle

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Introduction

In this research project, I...

- ▶ R package **bsvarSIGNS**
 - ▶ hopefully on CRAN next semester!
- ▶ Implements **Arias, Rubio-Ramírez, and Waggoner (2018)**
- ▶ Replicates US data
- ▶ Extends to Australian data and more

bsvarSIGNs

- ▶ Bayesian structural vector autoregression (bsvar)
- ▶ Simultaneous equations + autoregression
- ▶ Identified with many restrictions
 - ▶ zero restrictions
 - ▶ sign restrictions
 - ▶ narrative restrictions

Question

Does optimism shock drive business cycles?

- ▶ Theory suggests **yes** (Angeletos, Collard, and Dellas 2018)
- ▶ Optimistic → spend more and work harder → economic boom!
- ▶ What does the data say?

Optimism shock

- ▶ **Positively** affects stock prices
- ▶ **Zero** impact on productivity

$$\begin{bmatrix} u_t^{\text{productivity}} \\ u_t^{\text{stock prices}} \\ u_t^{\text{consumption}} \\ u_t^{\text{real interest rate}} \\ u_t^{\text{hours worked}} \end{bmatrix} = \begin{bmatrix} 0 & * & * & * & * \\ + & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \\ * & * & * & * & * \end{bmatrix} \begin{bmatrix} \varepsilon_t^{\text{optimism}} \\ \varepsilon_t^2 \\ \varepsilon_t^3 \\ \varepsilon_t^4 \\ \varepsilon_t^5 \end{bmatrix}$$

u_t reduced-form errors, ε_t structural shocks, $*$ = no restrictions

Penalty function approach

Beaudry, Nam, and Wang (2011)

- ▶ Studies optimism shock with penalty function approach (PFA).
- ▶ Concludes optimism shock **drives** business cycle
- ▶ Since significant boom in **consumption and hours worked**.

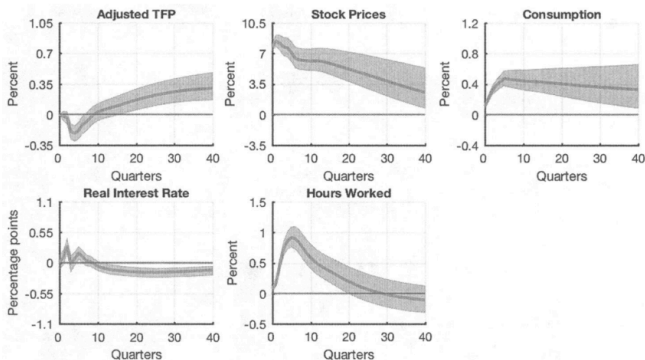


Figure 1: US optimism shock impulse responses with PFA

Original paper

Arias, Rubio-Ramírez, and Waggoner (2018)

- ▶ Proves PFA imposes **additional** restrictions
- ▶ Proposed an importance sampler that gives **true** solutions
- ▶ Concludes optimism shock does **not** drive business cycle

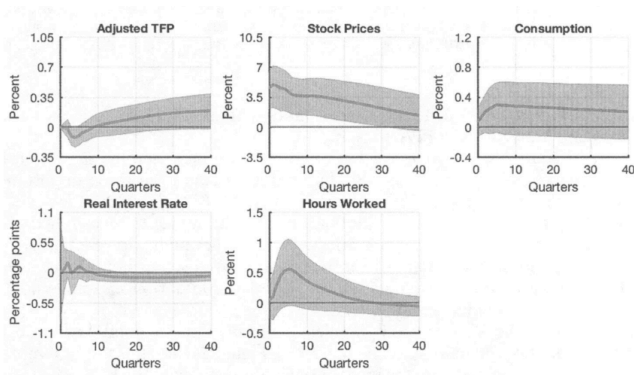


Figure 2: US optimism shock impulse responses with importance sampler

Importance sampler algorithm

Orthogonal reduced-form parameterization:

$$y_t' = x_t' B + e_t' Q' \text{chol}(\Sigma, \text{upper})$$

1. Sample (B, Σ, Q) conditional on the zero restrictions.
2. If the sign restrictions are satisfied, keep the draw and compute an importance weight, otherwise discard.
3. Repeat steps 1-2 until the desired number of samples is obtained.
4. Resample with replacement using the importance weights.

Replication

Same US data, different code

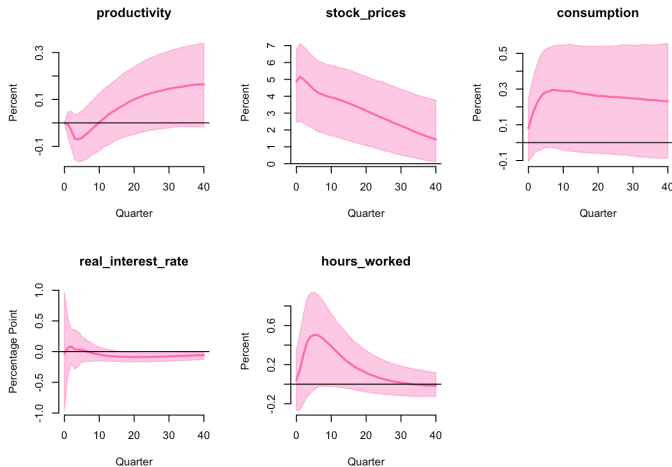


Figure 3: US optimism shock impulse responses using bsvarSIGNs

Extension 1: Australian data

No significant impact

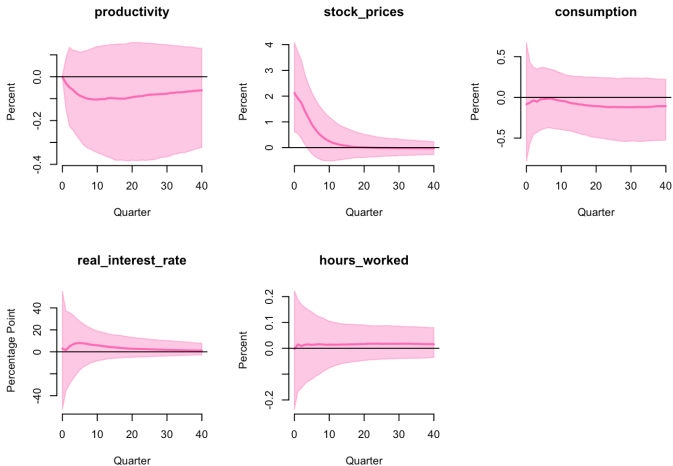


Figure 4: Australian optimism shock impulse responses using bsvarSIGNs

Extension 2: narrative restriction

Antolín-Díaz and Rubio-Ramírez (2018)

- ▶ Algorithm to impose narrative restrictions
- ▶ **Sign** of structural shocks
- ▶ ...

Assume additionally that the optimism shock

- ▶ is **negative** when Covid-19 hits Australia in 2020 Q1

$$\varepsilon_{2020Q1}^{\text{optimism}} < 0$$

Extension 2: Covid-19

A pessimism shock



Figure 5: ASX 200 index

Extension 2: pseudo proof

(To my knowledge) no paper has combined the two algorithms¹

Both papers use importance sampler

- ▶ Suppose the importance weights are w_1 and w_2
- ▶ To **combine** the two algorithms, resample with weights w
- ▶ Where $w = w_1 \times w_2$

A more rigorous proof (with no guarantee of correctness) is available *here*

¹Arias, Rubio-Ramírez, and Waggoner (2018) and Antolín-Díaz and Rubio-Ramírez (2018)

Extension 2: history

Historical values of optimism shock

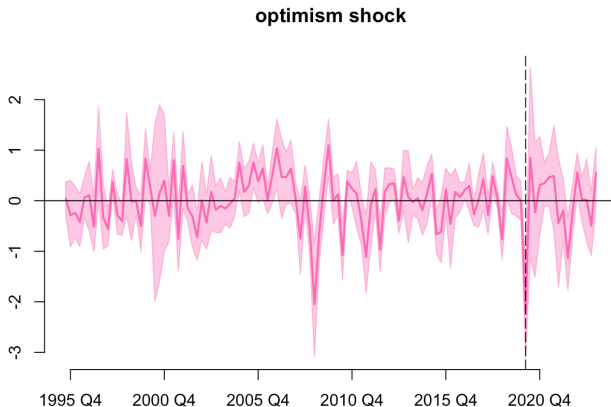


Figure 6: Australian optimism shock

Extension 2: result

Still no significant impact

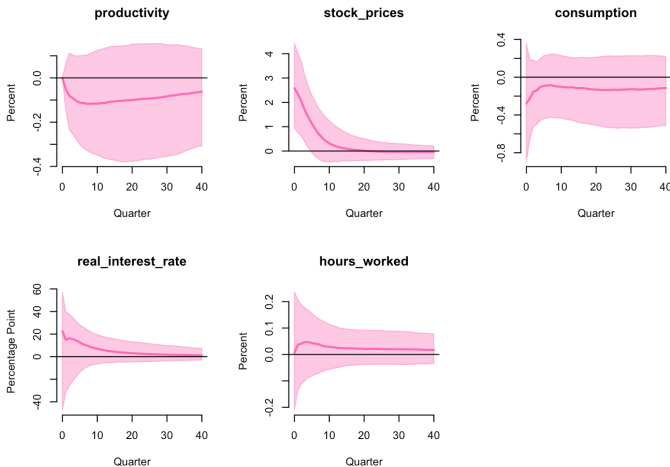


Figure 7: Australian optimism shock impulse responses with narrative restriction

Summary

- ▶ Optimism shock does **not** drive business cycle
- ▶ Result holds for both US and Australia
- ▶ Result is robust to restriction on Covid-19

Appendix: simulation study

Suppose the true structural model is

$$\begin{bmatrix} -1 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} -1 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\right)$$

equivalently, we can simulate 1,000 observations from the reduced-form

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix}, \begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix}\right)$$

Putting zero and sign restrictions on the inverse of the structural matrix

$$\begin{bmatrix} -1 & 1 \\ 1 & 0 \end{bmatrix}^{-1} = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} \Rightarrow \begin{bmatrix} 0 & + \\ + & + \end{bmatrix}$$

Posterior mean of 1,000 draws of the structural matrix is

$$\begin{array}{cc} & \begin{bmatrix} \cdot, 1 \end{bmatrix} & \begin{bmatrix} \cdot, 2 \end{bmatrix} \\ \begin{bmatrix} 1, \cdot \end{bmatrix} & -0.9613 & 1.0448 \\ \begin{bmatrix} 2, \cdot \end{bmatrix} & 0.9614 & 0.0000 \end{array}$$

References

- Angeletos, George-Marios, Fabrice Collard, and Harris Dellas. 2018. “Quantifying Confidence.” *Econometrica* 86 (5): 1689–1726.
- Antolín-Díaz, Juan, and Juan F Rubio-Ramírez. 2018. “Narrative Sign Restrictions for SVARs.” *American Economic Review* 108 (10): 2802–29.
- Arias, Jonas E, Juan F Rubio-Ramírez, and Daniel F Waggoner. 2018. “Inference Based on Structural Vector Autoregressions Identified with Sign and Zero Restrictions: Theory and Applications.” *Econometrica* 86 (2): 685–720.
- Beaudry, Paul, Deokwoo Nam, and Jian Wang. 2011. “Do Mood Swings Drive Business Cycles and Is It Rational?” National Bureau of Economic Research.