Estimating Fiscal Multipliers by Combining Statistical Identification with Potentially Endogenous Proxies

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[a]The views expressed do not necessarily reflect the views of Sveriges Riksbank.

Motivation

- Proxy VARs have become popular tool to identify the effects of fiscal policy.
- Angelini et al. (2023): Different potentially valid proxy variables lead to contradictory conclusions about the size of fiscal multipliers:
  - Fiscal proxy SVAR in Mertens and Ravn (2014):
    $\rightarrow$ tax multiplier $>$ spending multiplier
  - Non-fiscal proxy SVAR in Caldara and Kamps (2017):
    $\rightarrow$ tax multiplier $<$ spending multiplier
- Some of the exogeneity assumptions of the proxy variables are violated.

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Research Questions

- Which proxy is correct and what is the spending and tax multiplier?
- More general: How can we deal with potentially invalid proxies?

Contribution

- Technical contribution:
    - Novel Bayesian moment-based proxy SVAR estimator.
    - Combination of non-Gaussian SVAR with potentially invalid proxy variables.
- Evidence on the effects of fiscal policy:
    - Spending multiplier $>$ tax multiplier.
    - Tax proxy is negatively correlated with output shocks.

Structural Vector Autoregression

$$y_t = \sum_{i=1}^{p} A_i y_{t-i} + u_t \qquad \text{and} \qquad u_t = B_0 \varepsilon_t$$

Independent non-Gaussian: Lanne et al. (2017), Gouriéroux et al. (2017), Maxand (2020), Keweloh (2021), Hafner et al. (2022), Hafner and Herwartz (2023), Hafner et al. (2023), Herwartz and Wang (2023a), Keweloh (2023), Herwartz and Wang (2024)

Statistical & traditional identification: Bruns and Lütkepohl (2022), Schlaak et al. (2023), Drautzburg and Wright (2023), Keweloh et al. (2023), Herwartz and Wang (2023b), Crucil et al. (2023), Braun (2023), Keweloh (2024), Carriero et al. (2024), Bacchiocchi et al. (2024)

Proxy: Stock and Watson (2012), Mertens and Ravn (2013), Angelini and Fanelli (2019), Caldara and Herbst (2019), Braun and Brüggemann (2022), Jentsch and Lunsford (2022)

Proxy variable

A proxy variable z_t for a target shock ε_{1t} is valid if

1. Relevant: $E[z_t \varepsilon_{1t}] \neq 0$
2. Exogenous: $E[z_t \varepsilon_{jt}] = 0$ for $j \neq 1$

Proxy SVAR approaches

	Frequentist	Bayesian
Augmented Proxy SVAR	Angelini and Fanelli (2019)	Caldara and Herbst (2019)
Moment-Based Proxy SVAR	Mertens and Ravn (2013)	**?**

Linear proxy variable

A linear proxy $z_t = \Phi \varepsilon_t + \eta_t$ with $\eta_t \sim N(0, \sigma^2)$ for a target shock ε_{1t} is valid if

1. Relevant: $E[z_t \varepsilon_{1t}] \neq 0 \quad \Longleftrightarrow \quad \Phi_1 \neq 0$
2. Exogenous: $E[z_t \varepsilon_{jt}] = 0$ for $j \neq 1 \quad \Longleftrightarrow \quad \Phi = [\Phi_1, 0, ..., 0]$

Augmented proxy SVAR estimator

The augment proxy SVAR can be written as

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = ... + \begin{bmatrix} B_0 & 0 \\ \Phi & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ \eta_t \end{bmatrix}, \tag{1}$$

see Caldara and Herbst (2019) or Angelini and Fanelli (2019).

Critique: The augmented proxy approach specifies the proxy DGP. Misspecification of the proxy DGP can lead to dependent shocks in the SVAR:

For a non-linear proxy variable generated by $z_t = \psi_t(\tilde{\Phi}_i \varepsilon_{it} + \tilde{\eta}_t)$ where ψ_t is a Bernoulli random variable, the misspecified linear augmented proxy SVAR with the linear proxy specification $z_t = \Phi_i \varepsilon_{it} + \eta_t$ leads to a measurment error

$$\eta_t = \begin{cases} (\tilde{\Phi}_i - \Phi_i)\varepsilon_{it} + \tilde{\eta}_t & , \text{ if } \psi_t = 1 \\ -\Phi_i \varepsilon_{it} & , \text{ else} \end{cases} .$$

Observation: The frequentist moment-based proxy approach does not rely on specifying the DGP of the proxy, see Mertens and Ravn (2013).

Goal: Develop a Bayesian moment-based proxy estimator not rely on specifying the DGP of the proxy.

Bayesian augmented proxy SVAR estimator

Caldara and Herbst (2019) write the joint likelihood of the data y and the proxy z as

$$p(y,z|B) = p(y|B)p(z|y,B). \tag{2}$$

The conditional likelihood of the proxy $p(z|y,B)$ is derived from the augmented proxy equation $z_t = \Phi_i \varepsilon_{it} + \eta_t$ and the distribution of the proxy noise term η_t.

Intuition: Re-weights the likelihood of the data y by putting more weight to the parameters that result in target shocks equal to a scaled version of the proxy.

Bayesian moment-based proxy SVAR (for simplification $n = 2$)

Define the proxy exogeneity moment condition

$$D(z, y, B) = \frac{1}{\sqrt{T}} \sum_{t=1}^{T} z_t e_{2t}(B) \quad \text{with} \quad e_t(B) := B^{-1} u_t. \tag{3}$$

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The joint likelihood of the data y and the proxy exogeneity moment condition $D(z)$ is

$$p(y, D(z)|B) = p(y|B)p(D(z)|y, B). \tag{4}$$

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The conditional likelihood of the proxy moment condition follows from the CLT:

$$D(z)|y, B_0 \sim \mathcal{N}(0, \sigma_z^2) \tag{5}$$

Intuition: Re-weights the likelihood of the data y by giving more weight to parameters that result in non-target shocks that are uncorrelated with the proxy.

Bayesian moment-based (potentially invalid) proxy SVAR(for simplification $n = 2$)

Generalize the proxy exogeneity moment condition

$$D(z, y, B, \mu) = \frac{1}{\sqrt{T}} \sum_{t=1}^{T} (z_t e_{2t}(B) - \mu) \quad \text{with} \quad e_t(B) := B^{-1} u_t. \tag{6}$$

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The joint likelihood of the data y and the proxy exogeneity moment condition $D(z)$ is

$$p(y, D(z)|B, \mu) = p(y|B) p(D(z)|y, B, \mu). \tag{7}$$

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$$D(z)|y, B_0, \mu_0 \sim \mathcal{N}(0, \sigma_z^2) \quad \text{with } \mu_0 = E[z_t \varepsilon_{2t}]. \tag{8}$$

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We propose a prior distribution for μ that reflects the belief in an exogenous proxy

$$\mu \sim N(0, \sigma_\mu^2), \quad \sigma_\mu^2 \sim IG(a, b). \tag{9}$$

Bayesian non-Gaussian SVAR

Anttonen et al. (2023): Independent and non-Gaussian shocks ε_{it} with density $f_i(\varepsilon_{it};\lambda_i)$ yield the likelihood

$$p(y|B,\lambda) = |det(B)|^{-T} \prod_{i=1}^{n} \prod_{t=1}^{T} f_i(e_{it}(B,y_t);\lambda_i). \tag{10}$$

We assume that each shock follows a skewed t-distribution such that the density function of the ith shock is given by

$$f_i(\varepsilon_{it};\lambda_i,q_i) = \frac{\Gamma(0.5+q_i)}{v(\pi q_i)^{0.5}\Gamma(q_i)(\frac{|\varepsilon_{it}+m|^2}{q_i v^2(\lambda \text{sign}(\varepsilon_{it}+m)+1)^2})^{0.5+q_i}}. \tag{11}$$

Summary: We combine a non-Gaussian SVAR with potentially invalid proxies.

Why?

- In a non-Gaussian SVAR with independent shocks, proxy variables are not required for identification.
- Our goal is to leverage prior knowledge of an exogenous proxy to enhance estimation precision.
- At the same time, we remain flexible and can disregard the proxy if the data provide evidence against its exogeneity.

Finite sample performance

$$\begin{bmatrix} u_{g,t} \\ u_{y,t} \\ u_{\tau,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0.15 & 1 & -0.5 \\ 0 & 1.5 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{g,t} \\ \varepsilon_{y,t} \\ \varepsilon_{\tau,t} \end{bmatrix}. \tag{12}$$

The variable z_t is a proxy variable for $\varepsilon_{\tau t}$. We consider two scenarios:

1. Exogenous proxy: $z_t = \varepsilon_{\tau,t} + \eta_t$
2. Endogenous proxy: $z_t = \varepsilon_{\tau,t} - 0.37\varepsilon_{y,t} + \eta_t$

Table 1: Median and MSE of estimated impact of $\varepsilon_{\tau t}$ ($T = 250$).

	exogenous proxy $z_{\tau t} = \varepsilon_{\tau t} + \eta_t$	endogenous proxy $z_{\tau t} = \varepsilon_{\tau t} - 0.37\varepsilon_{Yt} + \eta_t$
proxy (augmented)	$\begin{bmatrix} \underset{(0.008)}{0.00} & \underset{(0.009)}{-0.50} & \underset{(0.022)}{1.00} \end{bmatrix}'$	$\begin{bmatrix} \underset{(0.008)}{0.00} & \underset{(0.106)}{-0.81} & \underset{(0.363)}{0.42} \end{bmatrix}'$

Note: The true impact of the shock $\varepsilon_{\tau t}$ *is* $\begin{bmatrix} 0 & -0.5 & 1 \end{bmatrix}'$.

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non-Gaussian	$\begin{bmatrix} \underset{(0.017)}{0.00} & \underset{(0.021)}{-0.49} & \underset{(0.051)}{0.95} \end{bmatrix}'$	$\begin{bmatrix} \underset{(0.018)}{0.00} & \underset{(0.019)}{-0.48} & \underset{(0.046)}{0.95} \end{bmatrix}'$

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non-Gaussian proxy moment	$\begin{bmatrix} \underset{(0.007)}{0.00} & \underset{(0.009)}{-0.50} & \underset{(0.021)}{1.00} \end{bmatrix}'$	$\begin{bmatrix} \underset{(0.009)}{0.00} & \underset{(0.026)}{-0.59} & \underset{(0.081)}{0.82} \end{bmatrix}'$

Note: The true impact of the shock $\varepsilon_{\tau t}$ *is* $\begin{bmatrix} 0 & -0.5 & 1 \end{bmatrix}'$.

Table 2: Median and MSE of estimated impact of $\varepsilon_{\tau t}$ ($T = 800$).

	exogenous proxy $z_{\tau t} = \varepsilon_{\tau t} + \eta_t$	endogenous proxy $z_{\tau t} = \varepsilon_{\tau t} - 0.37\varepsilon_{Yt} + \eta_t$
proxy (augmented)	$\begin{bmatrix} \underset{(0.002)}{0.00} & \underset{(0.003)}{-0.50} & \underset{(0.007)}{1.00} \end{bmatrix}'$	$\begin{bmatrix} \underset{(0.002)}{0.00} & \underset{(0.103)}{-0.82} & \underset{(0.355)}{0.41} \end{bmatrix}'$
proxy (moments)	$\begin{bmatrix} \underset{(0.002)}{0.00} & \underset{(0.003)}{-0.50} & \underset{(0.007)}{1.00} \end{bmatrix}'$	$\begin{bmatrix} \underset{(0.002)}{0.00} & \underset{(0.102)}{-0.82} & \underset{(0.353)}{0.41} \end{bmatrix}'$
non-Gaussian	$\begin{bmatrix} \underset{(0.005)}{0.00} & \underset{(0.005)}{-0.49} & \underset{(0.012)}{0.99} \end{bmatrix}'$	$\begin{bmatrix} \underset{(0.005)}{0.00} & \underset{(0.005)}{-0.49} & \underset{(0.012)}{0.99} \end{bmatrix}'$
non-Gaussian proxy moment	$\begin{bmatrix} \underset{(0.002)}{0.00} & \underset{(0.003)}{-0.50} & \underset{(0.006)}{1.00} \end{bmatrix}'$	$\begin{bmatrix} \underset{(0.003)}{0.00} & \underset{(0.006)}{-0.52} & \underset{(0.017)}{0.96} \end{bmatrix}'$

Note: The true impact of the shock $\varepsilon_{\tau t}$ is $\begin{bmatrix} 0 & -0.5 & 1 \end{bmatrix}'$.

The Effects of Fiscal Policy

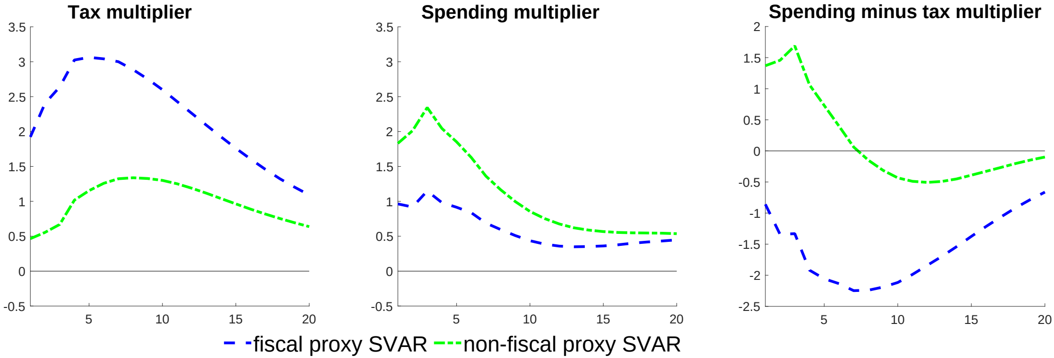
Quarterly data from 1950 to 2006 analogous to Mertens and Ravn (2014) with

$$\begin{bmatrix} \tau_t \\ g_t \\ y_t \end{bmatrix} = \gamma X_t + \sum_{i=1}^{4} A_i \begin{bmatrix} \tau_{t-i} \\ g_{t-i} \\ y_{t-i} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} \varepsilon_{\tau,t} \\ \varepsilon_{g,t} \\ \varepsilon_{y,t} \end{bmatrix}$$

Proxies:

- Tax proxy $z_{\tau,t}$ used in fiscal proxy VAR in Mertens and Ravn (2014):
$$E[z_{\tau,t}\varepsilon_{g,t}] = 0 \text{ and } E[z_{\tau,t}\varepsilon_{y,t}] = 0$$
- TFP proxy $z_{y,t}$ used in non-fiscal proxy VAR in Caldara and Kamps (2017):
$$E[z_{y,t}\varepsilon_{\tau,t}] = 0 \text{ and } E[z_{y,t}\varepsilon_{g,t}] = 0$$
- Military spending $z_{g,t}$ proxy for spending shocks:
$$E[z_{g,t}\varepsilon_{\tau,t}] = 0 \text{ and } E[z_{g,t}\varepsilon_{y,t}] = 0$$

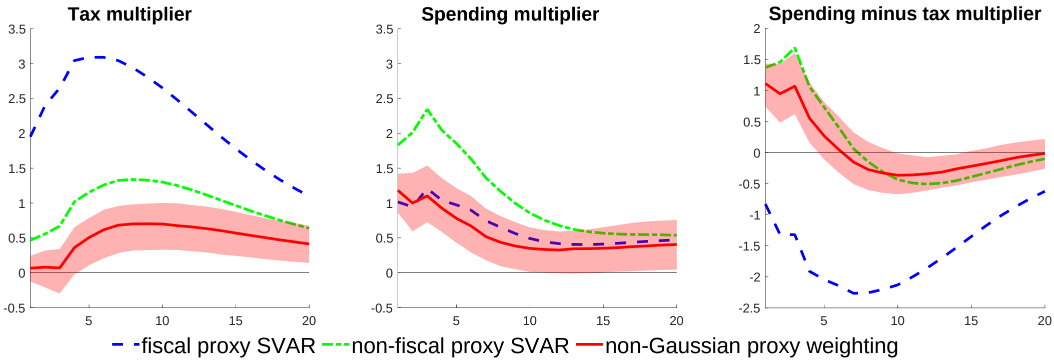
Figure 1: Output multipliers



Fiscal proxy VAR: Gaussian SVAR with the tax proxy and $b_{23} = 0$

Non-fiscal proxy VAR: Gaussian SVAR with the TFP proxy and $b_{21} = 0$

Figure 2: Comparison of output multipliers



Fiscal proxy VAR: Gaussian SVAR with the tax proxy and $b_{23} = 0$

Non-fiscal proxy VAR: Gaussian SVAR with the TFP proxy and $b_{21} = 0$

Non-Gaussian proxy weighting: Non-Gaussian SVAR with three proxies and shrinkage

Figure 3: Posterior of the exogeneity moment conditions

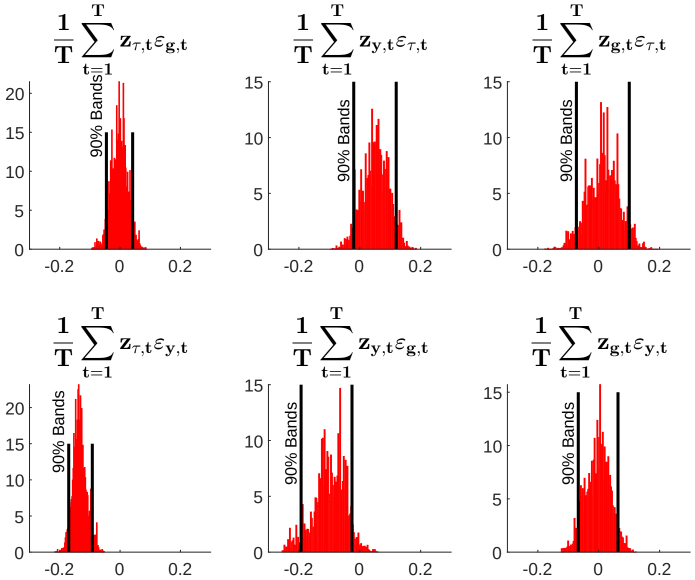
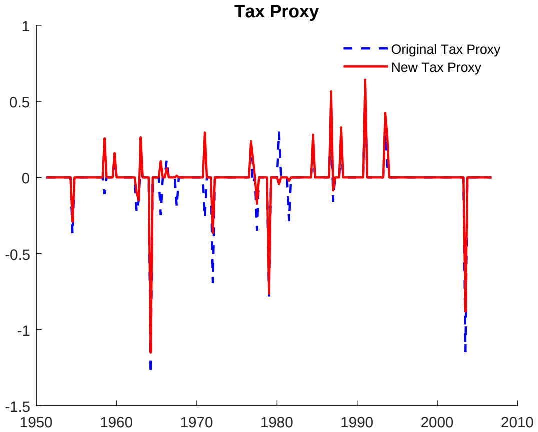
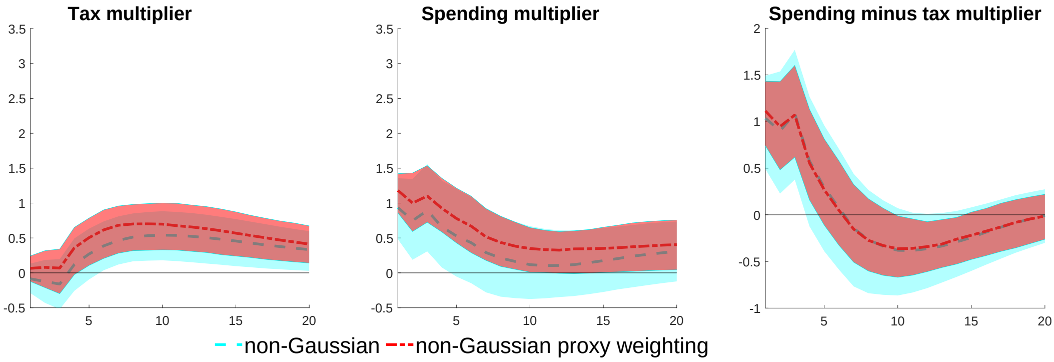


Figure 4: New tax proxy



Note: The new tax proxy is the residual of the regression $z_{\tau,t} = \beta_0 + \beta_1 \varepsilon_{g,t} + \beta_2 \varepsilon_{y,t} + u_t$.

Figure 5: Comparison of output multipliers



Non-Gaussian VAR: Non-Gaussian SVAR without proxies

Non-Gaussian proxy weighting: Non-Gaussian SVAR with three proxies and shrinkage

Summary

- Question: How can we deal with potentially invalid proxies?
$\rightarrow$ We propose a novel approach to include potentially invalid proxies into a Bayesian non-Gaussian SVAR using a shrinkage approach. Including valid proxies increases the performance of the non-Gaussian estimator.
- Question: Which proxy is valid / what is the spending and tax multiplier?
$\rightarrow$ We find that increasing government spending is a more effective tool to stimulate the economy than reducing taxes. We find that the tax proxy is negatively correlated with output shocks and the TFP proxy is negatively correlated with government spending shocks.

Thank you!

References

Angelini, G., G. Caggiano, E. Castelnuovo, and L. Fanelli (2023). Are fiscal multipliers estimated with proxy-svars robust? Oxford Bulletin of Economics and Statistics 85(1), 95–122.

Angelini, G. and L. Fanelli (2019). Exogenous uncertainty and the identification of structural vector autoregressions with external instruments. Journal of Applied Econometrics 34(6), 951–971.

Anttonen, J., M. Lanne, and J. Luoto (2023). Statistically Identified SVAR Model with Potentially Skewed and Fat-Tailed Errors. Journal of Applied Econometrics.

Bacchiocchi, E., A. Bastianin, T. Kitagawa, and E. Mirto (2024). Partially identified heteroskedastic svars. arXiv preprint arXiv:2403.06879.

Braun, R. (2023). The importance of supply and demand for oil prices: evidence from non-gaussianity.

Braun, R. and R. Brüggemann (2022). Identification of svar models by combining sign restrictions with external instruments. Journal of Business & Economic Statistics (just-accepted), 1–38.

Bruns, M. and H. Lütkepohl (2022). Heteroskedastic proxy vector autoregressions: Testing for time-varying impulse responses in the presence of multiple proxies.

Caldara, D. and E. Herbst (2019). Monetary policy, real activity, and credit spreads: Evidence from bayesian proxy svars. American Economic Journal: Macroeconomics 11(1), 157–92.

Caldara, D. and C. Kamps (2017). The analytics of svars: a unified framework to measure fiscal multipliers. The Review of Economic Studies 84(3), 1015–1040.

Carriero, A., M. Marcellino, and T. Tornese (2024). Blended identification in structural vars. Journal of Monetary Economics, 103581.

Crucil, R., J. Hambuckers, and S. Maxand (2023). Do monetary policy shocks affect financial uncertainty? a non-gaussian proxy svar approach. A Non-gaussian Proxy SVAR Approach (June 5, 2023).

Drautzburg, T. and J. H. Wright (2023). Refining set-identification in vars through independence. Journal of Econometrics.

Gouriéroux, C., A. Monfort, and J.-P. Renne (2017). Statistical Inference for Independent Component Analysis: Application to Structural VAR Models. Journal of Econometrics 196(1), 111–126.

References iv

Hafner, C. M. and H. Herwartz (2023). Dynamic score-driven independent component analysis. Journal of Business & Economic Statistics 41(2), 298–308.

Hafner, C. M., H. Herwartz, and S. Maxand (2022). Identification of structural multivariate garch models. Journal of Econometrics 227(1), 212–227.

Hafner, C. M., H. Herwartz, and S. Wang (2023). Causal inference with (partially) independent shocks and structural signals on the global crude oil market. Technical report, Université catholique de Louvain, Institute of Statistics, Biostatistics and ....

Herwartz, H. and S. Wang (2023a). Consistent statistical identification of svars under (co-) heteroskedasticity of unknown form. Available at SSRN 4577627.

Herwartz, H. and S. Wang (2023b). Point estimation in sign-restricted svars based on independence criteria with an application to rational bubbles. Journal of Economic Dynamics and Control, 104630.

References v

Herwartz, H. and S. Wang (2024). Statistical identification in panel structural vector autoregressive models based on independence criteria. Journal of Applied Econometrics.

Jentsch, C. and K. G. Lunsford (2022). Asymptotically valid bootstrap inference for proxy svars. Journal of Business & Economic Statistics 40(4), 1876–1891.

Keweloh, S. A. (2021). A Generalized Method of Moments Estimator for Structural Vector Autoregressions Based on Higher Moments. Journal of Business & Economic Statistics 39(3), 772–782.

Keweloh, S. A. (2023). Structural vector autoregressions and higher moments: Challenges and solutions in small samples. arXiv preprint arXiv:2310.08173.

Keweloh, S. A. (2024). Uncertain short-run restrictions and statistically identified structural vector autoregressions.

Keweloh, S. A., S. Hetzenecker, and A. Seepe (2023). Monetary policy and information shocks in a block-recursive svar. Journal of International Money and Finance, 102892.

Lanne, M., M. Meitz, and P. Saikkonen (2017). Identification and Estimation of Non-Gaussian Structural Vector Autoregressions. Journal of Econometrics 196(2), 288–304.

Maxand, S. (2020). Identification of independent structural shocks in the presence of multiple gaussian components. Econometrics and Statistics 16, 55–68.

Mertens, K. and M. O. Ravn (2013). The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States. American Economic Review 103(4), 1212–47.

Mertens, K. and M. O. Ravn (2014). A Reconciliation of SVAR and Narrative Estimates of Tax Multipliers. Journal of Monetary Economics 68, S1–S19.

Schlaak, T., M. Rieth, and M. Podstawski (2023). Monetary policy, external instruments, and heteroskedasticity. Quantitative Economics 14(1), 161–200.

Stock, J. H. and M. Watson (2012). Disentangling the Channels of the 2007-09 Recession. Brookings Papers on Economic Activity 43(1), 81–156.