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Statistical Identification of Economic Shocks by Signs in Structural Vector Autoregression*

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Abstract

We propose a new frequentist approach to sign restrictions in structural vector autoregressive models. By making efficient use of non-Gaussianity in the data, point identification is achieved which facilitates standard asymptotic inference and, hence, the assessment of theoretically implied signs and labeling of the statistically identified structural shocks. We illustrate the benefits of our approach in an empirical application to the U.S. labor market.

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1 Introduction

The approach of identifying structural vector autoregressive (SVAR) models by sign restrictions, pioneered by Faust (1988), Canova and De Nicoló (2002), and Uhlig (2005), has become very popular in empirical macroeconomic research. Compared to most other approaches to identifying SVAR models, sign restrictions, only constraining the signs of the effects of the shocks based on economic theory or institutional knowledge, are less stringent, but still manage to convey economic intuition. Therefore, they have a great appeal in empirical research.

The key feature of sign-identified SVAR models is that the impulse response functions are only set identified, while other commonly employed approaches, such as short-run identification restrictions, achieve point identification. In other words, only bounds for the parameters of the impact multiplier matrix governing the impulse responses are obtained. Bayesian inference dominates the literature on sign-identified SVAR models, and it is not necessarily a problem from the Bayesian perspective that parameters are only set identified, since if a proper prior on all the parameters of the SVAR model is used, the resulting posterior distribution of the impulse response functions is well defined (see Poirier (1998)). Nevertheless, the lack of point identification is not a virtue, as it hampers learning from the data. It may also impede reporting the results of impulse response analysis, especially as the identified set may be very large, as discussed by Fry and Pagan (2011).

Besides set identification, another shortcoming of the traditional Bayesian approaches to sign restrictions, recently pointed out by Baumeister and Hamilton (2015), is that conventional (implicit) priors may be inadvertently informative about structural impulse responses. As a solution, Baumeister and Hamilton recommended that researchers impose explicit priors for the elements of the impact multiplier matrix, and identify their role in influencing posterior conclusions. However, the methodology outlined by Baumeister and Hamilton has recently been criticized on several grounds (see Kilian and Lütkepohl (2017, Chapter 13.7), Herrera and Rangaraju (2018), and Kilian and Zhou (2019)). For instance, it has been argued that it is inapplicable to many sign-identified SVAR models in the literature, and the priors in some applications have been ad hoc and inconsistent with extraneous evidence. In particular, it is unclear how exactly extraneous information, such as estimates of the parameters of interest reported in the previous literature should be translated into a prior density.

In this paper, we propose an alternative approach as a solution to the problems of the traditional procedure of identification by sign restrictions discussed above, where theoretically implied signs of the effects of shocks are used for economic identification (labeling) in a statistically identified SVAR model. In line with the recent advances in the statistical identification literature, our idea is to make use of non-Gaussianity of the structural errors of the SVAR model (see Kilian and Lütkepohl (2017, Chapter 14) for a textbook treatment of the relevant literature). In order to avoid making distributional assumptions, we estimate the SVAR model by the generalized method of moments (GMM) with moment conditions implied by non-Gaussianity, as in Lanne and Luoto (2021). Once the model has been estimated, we can check by inspection and by computing confidence intervals whether the elements in the columns of the impact matrix satisfy the theoretically implied signs. Subsequently, the shocks corresponding to the columns that do, can be labeled the shocks of interest.

This approach has two main benefits. First, it facilitates point identification, i.e, it produces a unique SVAR model with unique impulse response functions. Second, because of unique identification, any restrictions on the parameters can be tested in a straightforward manner using conventional asymptotic testing procedures. Moreover, as no signs are imposed, it is possible to assess the plausibility of the theoretically implied signs of the effects of the shocks, which is typically infeasible (see, e.g., the discussion in Kilian and Lütkepohl (2017, Chapter 13.5)). In particular, if none of the columns of the estimated impact matrix satisfies the sign constraints, we can conclude that identification by signs is not viable. Our approach is akin to the procedure of Canova and Paustian (2011), where some moments, including the robust sign restrictions, are employed for identification to facilitate the assessment of the remaining theoretically implied signs.

Our procedure is frequentist, but it avoids the non-uniqueness problem that frequentist approaches to sign restrictions share with the traditional Bayesian approaches (see Granziera et al. (2018), and Gafarov et al. (2015, 2018)). It is closely related to the similar procedure in the Bayesian framework by Lanne and Luoto (2020). However, in that case, the SVAR model is statistically identified by assuming a specific non-Gaussian distribution for the structural errors, whereas the procedure considered in this paper is more robust in that no distributional assumptions are made. Another difference is that while the plausibility of the theoretically implied signs can be formally checked in the Bayesian setup, our frequentist procedure can only be seen as an informal approach to estimating a sign-identified SVAR model.

We illustrate our procedure by means of Hamilton and Baumeister's (2015) empirical application to the U.S. labor market. Clear deviations from Gaussianity of the structural shocks are detected, which facilitates statistical identification. Hence, we can quite accurately estimate the labor-supply and labor-demand elasticities of interest by the GMM, and compute point-identified responses of the real wage and employment to the labor-supply and labor-demand shocks. While the estimated responses of the real wage to both shocks are similar to those of Baumeister and Hamilton, we obtain responses of employment that are quite different from theirs. In particular, we find the effect of the labor-demand shock on employment much stronger than they did. This may partly be related to the fact that the long-run restriction underlying their prior is rejected at conventional significance levels.

The outline of the rest of the paper is as follows. In Section 2, we introduce the SVAR model and discuss its statistical identification and labeling the statistically identified shocks. Section 3 contains the empirical application to the U.S. labor market; in Subsection 3.1, we introduce Hamilton and Baumeister's (2015) model and discuss its estimation by the GMM under the assumption of non-Gaussian errors, while Subsection 3.2 contains the empirical results. Finally, Section 4 concludes.

2 Model

We consider the n-variate structural VAR(p) model

$$y_t = a + A_1 y_{t-1} + \cdots + A_p y_{t-p} + B u_t, \tag{1}$$

where y_t is a vector of time series of interest, a is an intercept term, $A_1, \ldots, A_p$ are $n \times n$ coefficient matrices, and the matrix B summarizing the contemporaneous structural relations of the errors is assumed nonsingular. In the literature, model (1) is often referred to as the B-model (see, e.g., Lütkepohl 2005, Chapter 9). An alternative SVAR formulation is obtained by left-multiplying (1) by the inverse of B:

$$Ay_t = a^* + A_1^* y_{t-1} + \cdots + A_p^* y_{t-p} + u_t, \tag{2}$$

where $A = B^{-1}$, $a^* = B^{-1}a$, and $A_j^* = B^{-1}A_j$ $(j = 1, \ldots, p)$, and it is this A-model formulation that we will consider in our empirical application.

In order to facilitate identification of matrix B (or its inverse A), two further assumptions have typically been made in the previous literature. First, u_t has been assumed to be a sequence of stationary random vectors with each component u_{it}, $i = 1, \cdots, n$, being independent in time and having zero mean and finite positive variance. Second, it has been assumed that the components u_{it} are mutually independent, and at most one of them has a Gaussian marginal distribution. Under these assumptions, matrix B (and hence its inverse A) is unique apart from permutation and multiplication by -1 of its columns (see Proposition 1 and its proof in Lanne et al. (2017)). Uniqueness up to permutation and multiplication by -1 of the columns of B means that the model remains the same after changing the order of the columns of B or multiplying any of them by -1 as long as the shocks u_{it} are reordered and scaled accordingly.

Lanne et al. (2017), and Lanne and Luoto (2020), inter alia, have assumed specific parametric error distributions, while Lanne and Luoto (2021), Keweloh (in press), and Lanne et al. (2021) have considered GMM estimation of the SVAR model based on co-kurtosis conditions. In this setup, the mutual independence and non-Gaussianity assumptions can be relaxed to some extent. In particular, Lanne et al. show that, with a suitable selection of moment conditions (see Section 3.1 for the condition needed in the case of the bivariate SVAR model), global and local identification in GMM estimation is achieved if the components of u_t are orthogonal, exhibit no excess co-kurtosis and at most one of them has zero excess kurtosis.

The structural shocks and their impulse responses are uniquely identified, but despite this statistical identification, the shocks cannot be labeled or given any economic interpretation without additional restrictions. Recently, Lanne et al. (2017) showed how conventional short-run and long-run identifying restrictions can be tested in this framework, and if not rejected, used for economic identification. Lanne and Luoto (2020), in turn, considered labeling the shocks by the theoretically implied signs of their effects on the variables included in the model. Their procedure is Bayesian, and the idea is to label the statistically identified shocks based on the posterior probabilities of the effects of the shocks satisfying the signs implied by economic theory.

In this paper, we propose a frequentist counterpart of the procedure of Lanne and Luoto (2020). However, compared to the latter, our frequentist procedure is quite informal. It is based on the idea that because the SVAR model is identified by non-Gaussianity, it is possible to assess the signs of the effects of the structural shocks by simple test procedures. For example, by computing confidence intervals for the elements of the impact matrix and checking whether positive or negative values are included in them, we can assess the the accordance of the theoretically implied signs with the data. This is facilitated by the fact that identification is indeed only statistical, and no signs are used to identify the structural shocks. If the shocks satisfy the sign constraints, they can be labeled accordingly.

3 Application to the U.S. labor market

3.1 GMM estimation

We demonstrate our approach to identification by signs in Baumeister and Hamilton's (2015) model of labor supply and labor demand:

$$\begin{aligned} \Delta n_t &= k^d + \beta^d \Delta w_t + b^d_{11}\Delta w_{t-1} + b^d_{12}\Delta n_{t-1} + b^d_{21}\Delta w_{t-2} \\ &\quad + b^d_{22}\Delta n_{t-2} + \cdots + b^d_{81}\Delta w_{t-8} + b^d_{82}\Delta n_{t-8} + u^d_t, \\ \Delta n_t &= k^s + \alpha^s \Delta w_t + b^s_{11}\Delta w_{t-1} + b^s_{12}\Delta n_{t-1} + b^s_{21}\Delta w_{t-2} \\ &\quad + b^s_{22}\Delta n_{t-2} + \cdots + b^s_{81}\Delta w_{t-8} + b^s_{82}\Delta n_{t-8} + u^s_t, \end{aligned} \tag{3}$$

where Δn_t is the growth rate of employment, Δw_t is the growth rate of real compensation per hour, β^d is the short-run wage elasticity of demand, and α^s is the short-run wage elasticity of supply. Baumeister and Hamilton identified the model by imposing sign restrictions, so they were able to label the first equation the demand equation and the second equation the supply equation, while we just estimate a bivariate SVAR(8) model and label the equations based on the estimated signs of the impact coefficients. The system can be written as

$$Ay_t = \mathbf{B}\mathbf{x}_{t-1} + u_t, \tag{4}$$

where $y_t = (\Delta w_t, \Delta n_t)'$, $\mathbf{x}_{t-1}$ is a $((2m+1)\times 1)$ vector containing the m lags of y_t and a constant, $\mathbf{B}$ is a $(2\times(2m+1))$ matrix collecting the coefficients of $\mathbf{x}_{t-1}$, and the components of the vector of structural disturbances $u_t = (u_t^d, u_t^s)'$ are orthogonal and exhibit no excess co-kurtosis. The (2×2) matrix

$$A = \begin{pmatrix} -\beta^d & 1 \\ -\alpha^s & 1 \end{pmatrix}$$

summarizes the simultaneous effects of Δw_t and Δn_t. The impact matrix of the structural shocks is obtained by inverting A:

$$A^{-1} = \frac{1}{-\beta^d + \alpha^s} \begin{pmatrix} 1 & -1 \\ \alpha^s & -\beta^d \end{pmatrix},$$

and the labor-supply and labor-demand shocks can be labeled by the estimated signs of β^d and α^s. In particular, if the estimate of α^s is positive, u_t^d can indeed be labeled the labor-demand shock, as it would then have impact effects of the same sign on both the real wage and employment. Likewise, if the estimate of β^d is negative, u_t^s is labeled the labor-supply shock with impact effects of opposite sign on the real wage and employment.

We estimate the SVAR model by the efficient GMM based on the following moment conditions:

$$E\left(u_t \otimes \mathbf{x}_{t-1}\right) = 0_{2k\times 1} \tag{5a}$$

$$E\left(u_t^d\right)^2 - d_{11} = 0 \tag{5b}$$

$$E\left(u_t^s\right)^2 - d_{22} = 0 \tag{5c}$$

$$E(u_t^d u_t^s) = 0 \tag{5d}$$

where $\otimes$ denotes the Kronecker product, and d_{ii} $(i = 1, 2)$ are the diagonal elements of $D = E(u_t u_t')$. Conditions (5a), implicitly assume that the lag length 8 is sufficient to make the components of the error term u_t serially uncorrelated, while conditions (5b) and (5c) concern the variances of the elements of u_t, and condition (5d) makes the errors orthogonal.

In addition, we impose either of the following asymmetric co-kurtosis conditions:

$$E(\left(u_t^d\right)^3 u_t^s) = 0 \tag{6a}$$

$$E((u_t^s)^3 u_t^d) = 0 \tag{6b}$$

as well as the symmetric co-kurtosis condition of the form

$$E(\left(u_t^d\right)^2 (u_t^s)^2) - d_{11}d_{22} = 0. \tag{7}$$

As shown by Lanne et al. (2021), when standard GMM regularity conditions hold, moment conditions (5a)–(5d), either (6a) or (6b), and (7) guarantee local and global point identification in the bivariate SVAR model, as long as at most one of the structural shocks has zero excess kurtosis. Conditions (6a) and (6b) are particularly informative in the presence of skewness, while they are redundant under Gaussianity, and the selection between them can be made by minimizing the relevant moment selection criterion (RMSC) suggested by Hall et al. (2007). Finally, we use Hansen's (1982) J-test of over-identifying restrictions to confirm that the selected set of moment conditions is in accordance with the data.

As Lanne et al. (2021) show, the SVAR model is identified only up to permutation and multiplication by -1 of the columns of A, and therefore, additional restrictions are, in general, needed to facilitate statistical inference. However, because in this particular application the elements on the first row are fixed, so is the ordering of the columns as well as their signs. Hence, the GMM estimator is consistent and asymptotically normally distributed, which facilitates standard asymptotic inference.

3.2 Empirical results

In this section, we report the estimation results based on Baumeister and Hamilton's (2015) quarterly data set spanning the period 1970:Q1–2014:Q2.[1] We start out by estimating a reduced-form eighth-order vector autoregressive (VAR(8)) model for $(\Delta n_t, \Delta w_t)'$ by ordinary least squares. The residuals exhibit clear non-normality, indicating that at least one of the structural errors must be non-Gaussian, which guarantees point identification.[2]

[1]The data were kindly provided by Christiane Baumeister on her website at https://sites.google.com/site/cjsbaumeister/research.

[2]The values of the Jarque-Bera test statistic for non-normality of the residuals are 11.192 and 11.852, with asymptotic p values 0.015 and 0.011, respectively, indicating non-Gaussianity at the 5% significance

Table 1: GMM estimates of β^d and α^s.

Parameter	Estimate	Standard Error	95% Confidence Interval
β^d	–0.317	0.151	[–0.021, –0.613]
α^s	0.514	0.283	[–0.041, 1.069]

The entries are the GMM estimates of the short-run demand and supply elasticities, and their asymptotic standard errors and 95% confidence intervals.

To avoid the problems caused by potential misspecification of the SVAR model we do not entertain any specific non-Gaussian distributions for the structural errors, but follow Lanne et al. (2021) and estimate the SVAR model by the efficient GMM based on moment conditions (5a)–(5d) and (7). In addition, condition (6b) is included because it (coupled with the rest of the conditions) yields a smaller value of the RMSC than condition (6a).[3] With 39 moment conditions and 38 parameters, Hansen's (1982) J-test of over-identification restrictions can be used as a general specification test. The p-value of the J-test equals 0.998, indicating the validity of the moment conditions.

GMM estimation yields estimates of the coefficients of two equations for Δn_t with the same explanatory variables, so additional information is needed to label the equations in model (3) (or, equivalently, the shocks). To that end, we use the theoretically implied signs of the short-run labor-supply and labor-demand elasticities, and label the equation with a positive (negative) coefficient estimate of Δw_t the supply (demand) equation. The resulting estimates of the labor-supply elasticity α^s and labor-demand elasticity β^d along with their asymptotic standard errors are reported in Table 1. According to asymptotic t-tests, both parameters are significantly different from zero at the 10% significance level, but only the parameter β^d at the 5% level. In particular, only negative values are included in the 95% asymptotic confidence interval of β^d. The point estimate of β^d is in accordance with the range based on microeconometric studies (from –0.75 to –0.15) referred to by Baumeister

level. Following, Kilian and Demiroglu (2000), we reconfirmed this conclusion by bootstrap. The corresponding bootstrapped (based on 10,000 replications) 5% (1%) critical values equal equal 8.880 and 5.941 (18.626 and 13.028), respectively, likewise indicating rejection of normality at the 5%, but not at the 1% significance level.

[3]The values of the RMSC equal –240.9 and –241.6, respectively, when conditions (6a) and (6b) are included.

and Hamilton (2015), but not with their empirical result (their posterior estimate of β^d (mode) lies close to unity in absolute value). Also, while our 95% confidence interval for α^s has a lot of overlap with the estimates reported in microeconometric and macroeconometric studies referred to by Baumeister and Hamilton, the most of the probability mass of their posterior distribution of α^s lies even below the minimum of the estimates in the microeconometric literature (0.15).

The estimated impact matrix is

$$\hat{A}^{-1} = \frac{1}{0.831} \begin{pmatrix} 1 & -1 \\ 0.514 & 0.317 \end{pmatrix},$$

and hence, we can indeed label the first shock u_t^d, whose effect on both employment and wages is of the same sign, the labor-demand shock and the second shock u_t^s with effects of opposite sign on employment and wages, the labor-supply shock. This interpretation is reinforced by the finding that the 95% confidence interval of the impact effect of the labor-demand shock consists of only positive values. While the lower bound of the corresponding confidence interval ([–0.073, 0.772]) for the labor-supply shock is slightly below zero, the 68% confidence interval only contains positive values.[4]

The impulse responses of the labor-demand and labor-supply shocks along with their 95% and 68% confidence bands up to 20 quarters are depicted in Figure 1. The shocks are normalized such that the labor-demand shock causes a 1% increase in the real wage on impact, while the impact effect of the labor-supply shock on the real wage is a 1% decrease. The responses of the real wage are in accordance to Baumeister and Hamilton's (2015) posterior results, albeit our impulse responses to the labor-supply shock remain significantly negative at the 5% significance level. In contrast, the impulse responses of employment depicted in the lower panel of Figure 1 differ markedly from the results of Baumeister and Hamilton. Specifically, we find the effect of the labor-demand shock much stronger than Baumeister and Hamilton, while the effect of the labor-supply shock turns out insignificant at the 5% level at all horizons. The former finding is not surprising, however,

[4]The confidence bands for the impulse response functions are computed by the delta-method. The covariance matrix of the GMM estimator is estimated using the Newey-West HAC estimator with an automatic bandwidth selection procedure of Newey and West (1994).

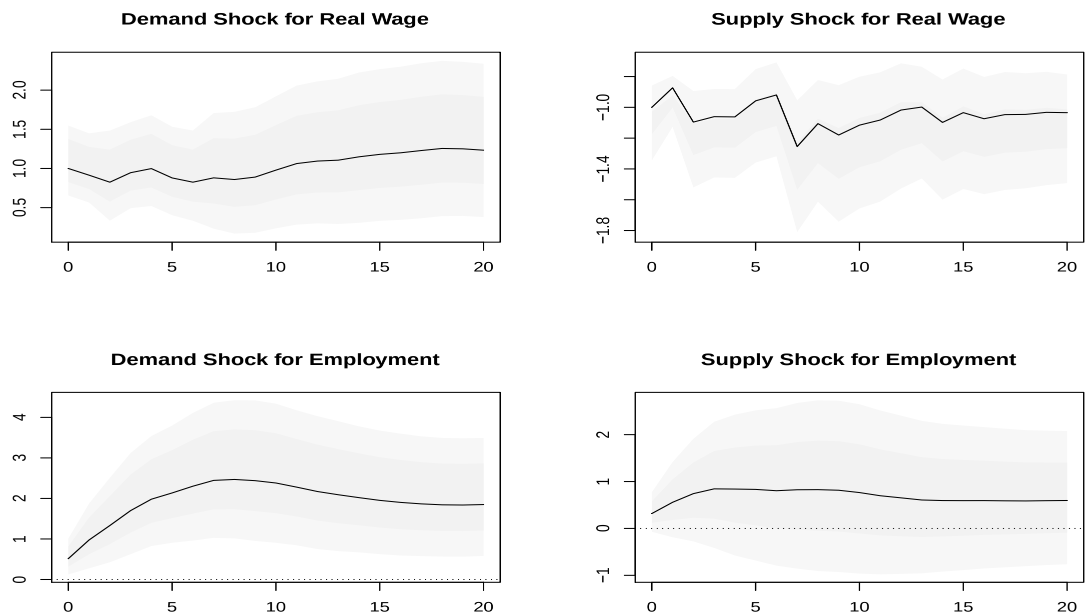

Figure 1: Impulse responses of the labor-supply and labor-demand shocks in the SVAR model. Each row contains the impulse responses of one shock on both variables. The lighter and darker shaded areas are, respectively, the 95% and 68% confidence bands.

as Baumeister and Hamilton's results were strongly driven by a relatively tight prior on the restriction on the long-run labor-demand elasticity, as pointed out in the Introduction. One advantage of our approach is that any restrictions on the parameters can be tested in a straightforward manner, and it turns out that Baumeister and Hamilton's long-run restriction does not seem to accord with the data, as it is rejected at the 5% significance level (the p-value of the Wald test is 0.029).

4 Conclusion

The traditional Bayesian and frequentist approaches to sign-identified SVAR models only achieve set identification. Moreover, as pointed out by Baumeister and Hamilton (2015), inter alia, the Bayesian impulse responses based on sign restrictions inadvertently depend on (implicit) informative priors. In this paper, we propose a frequentist solution to these shortcomings. In particular, we recommend making efficient use of the statistical properties of the data, specifically non-Gaussianity, to facilitate point identification, which, in turn, makes it possible to conduct standard inference. Subsequently, standard confidence intervals of the impulse responses can be used to provide the statistically identified shocks with an economic interpretation (label).

Our approach can be seen an informal frequentist alternative to Lanne and Luoto's (2020) Bayesian procedure, where the statistically identified shocks are labeled formally by assessing their posterior probabilities of satisfying theoretically implied sign constraints. In addition, in this paper, we estimate the SVAR model by the generalized method of moments, while Lanne and Luoto (2020) specified probability distributions for the structural shocks.

We illustrate our approach in Baumeister and Hamilton's (2015) model of U.S. labor supply and labor demand. While they estimated the model with priors of labor-demand and labor-supply elasticities based on ranges of estimates obtained in the previous literature as well as a tight prior on a restriction on the the long-run labor-demand elasticity, we estimate a statistically identified SVAR model by the GMM. To some extent, our empirical results differ from those of Baumeister and Hamilton. In particular, the estimates of the labor-demand and labor-supply elasticities accord with the ranges of estimates obtained in the previous literature (unlike those of Baumeister and Hamilton). Moreover, we found a much stronger effect of the labor-demand shock on employment, presumably because, according to our results, Baumeister and Hamilton's long-run restriction on the labor-demand elasticity does not accord with the data.

References

Baumeister, C., and Hamilton, J. D. (2015). Sign restrictions, structural vector autoregressions, and useful prior information. *Econometrica*, 83, 1963–1999.

Canova, F., and De Nicoló, G. (2002). Monetary disturbances matter for business cycle fluctuations in the G7. *Journal of Monetary Economics*, 49,1131–1159.

Canova, F., and Paustian, M. (2011). Business cycle measurement with some theory, *Journal of Monetary Economics*, 58, 345–361.

Faust, J. (1998). The robustness of identified VAR conclusions about money. *Carnegie-Rochester Conference Series on Public Policy*, 49, 207–244.

Fry, R., and Pagan, A. (2011). Sign restrictions in structural vector autoregressions: A critical review. *Journal of Economic Literature*, 49, 938–960.

Gafarov, B., Meier, M., and Montiel Olea J. L. (2015). Projection inference for set-identified SVARs, Manuscript, Columbia University.

Gafarov, B., Meier, M., and Montiel Olea J. L. (2018). Delta-method inference for a class of set-identified SVARs, *Journal of Econometrics*, 203, 316–327.

Granziera, E., Moon, H. R., and Schorfheide, F. (2018). Inference for VARs identified with sign restrictions, *Quatitative Economics*, 9, 1087–1121.

Hall, A.R., Inoue, A., Jana, K., and Sin, C. (2007). Information in generalized method of mometns estimator in misspecified models. *Journal of Econometrics*, 138, 488–512.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 50, 1029–1054.

Herrera, A. M., and Rangaraju, S. K. (2020). The effect of oil supply shocks on U.S. economic activity: what have we learned? *Journal of Applied Econometrics*, 35, 141–159.

Keweloh, S. A. (in press). A generalized method of moments estimator for structural vector autoregressions based on higher moments. *Journal of Business and Economic Statistics*, forthcoming.

Kilian, L., and Demiroglu, U. (2000). Residual-based tests for normality in autoregressions: Asymptotic theory and simulation evidence. *Journal of Business and Economic Statistics*, 18, 40–50.

Kilian, L., and Lütkepohl, H. (2017). *Structural vector autoregressive analysis*. Oxford: Oxford University Press.

Kilian, L., and Zhou, X. (2019). Oil supply shock redux? Manuscript, University of Michigan.

Lanne, M. Liu, K., and Luoto, J. (2021). Identifying structural vector autoregression via large economic shocks. Manuscript, University of Helsinki.

Lanne, M., and Luoto, J. (2020). Identification of economic shocks by inequality constraints in Bayesian structural vector autoregression. *Oxford Bulletin of Economics and Statistics*, 82, 425–452.

Lanne, M., and Luoto, J. (2021). GMM estimation of non-Gaussian structural vector autoregression, *Journal of Business and Economic Statistics*, 39, 69–81.

Lanne, M., Meitz, M., and Saikkonen, P. (2017). Identification and estimation of non-Gaussian structural vector autoregressions. *Journal of Econometrics*, 196, 288–304.

Lütkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis*. Berlin: Springer-Verlag.

Newey, W. K., and West, K. D. (1994). Automatic lag selection in covariance matrix estimation. *Review of Economic Studies*, 61, 631–653.

Poirier, D. J. (2013). Revising Beliefs in Nonidentified Models, *Econometric Theory*, 14, 483–509.

Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics*, 52, 381–419.