

Reconciling narrative monetary policy disturbances with structural VAR model shocks?[☆]

Martin Kliem^a, Alexander Kriwoluzky^{b,c}

^aDeutsche Bundesbank, Economic Research Center, Wilhelm-Epstein-Str. 14, 60431 Frankfurt am Main, Germany

^bUniversity of Bonn, Department of Economics, Kaiserstrasse 7-9, 53113 Bonn, Germany

^cCorresponding author. e-mail: a.kriwoluzky@uni-bonn.de

Abstract

Structural VAR studies disagree with narrative accounts about the history of monetary policy disturbances. We investigate whether employing the narrative monetary shock account as a proxy variable in a VAR model aligns both shock series. We find that it does not.

Keywords: vector autoregression model, monetary policy shocks, narrative identification

JEL: E31, E32, E52

1. Introduction

The history of monetary policy shocks is important and widely used for policy analysis. This time series is essential for the historical decomposition of key macro variables such as output and prices since it uncovers the historical contribution of monetary policy to the business cycle. The sequence of monetary policy disturbances is moreover important for conducting counterfactual analyses to explore the role of monetary policy. Yet while the importance of monetary policy shocks is widely recognized, there is strong disagreement about its composition in the empirical literature.¹

One strand of the empirical literature estimates the monetary policy shocks using a structural vector autoregressive (VAR) model (e.g. Sims, 1992; Christiano et al., 1996; Bernanke and Mihov, 1998). Another strand of the literature identifies monetary policy disturbances outside of a time series model, e.g., based on careful reading of documents pertaining to monetary policy decisions. This is referred to as the narrative approach and was pioneered by Romer and Romer (1989).² The

[☆]We would like to thank Jörg Breitung, Sandra Eickmeier, Norbert Metiu, and Gernot Müller for their helpful comments on the paper. The views expressed by the authors in this paper are their own and do not necessarily reflect those of the Deutsche Bundesbank.

¹Ilzetzki and Jin (2013) document the differences for structural monetary policy shock time series as well as structural fiscal policy shock time series with corresponding narrative accounts. In this paper, we only consider monetary policy shock time series.

²Similarly, other studies focus on financial market data outside the model to uncover a measure of monetary policy shocks. In particular, these papers measure surprise changes in the target federal funds rate (e.g. Kuttner, 2001; Gürkaynak et al., 2005) or measure market announcement movements (e.g. Cochrane and Piazzesi, 2002; Faust et al., 2004).

two strands of the literature result in discrepancies about the history of monetary policy shocks. Rudebusch (1998) even argues that the fact that the identified VAR model shocks are not in line with the narrative account casts doubt on the VAR method in general.

In the present paper, we attempt to reconcile the monetary policy shocks identified with a common structural VAR model and the narrative measures by Romer and Romer (2004). To achieve this, we employ the method suggested by Mertens and Ravn (2013b,a).³ The method incorporates the narrative monetary policy shocks into the VAR model by treating them as a proxy for the structural monetary policy shocks. Hence, this method offers an identification scheme for monetary policy shocks which seems promising to reconcile both strands of the literature. The otherwise standard VAR model also includes industrial production, the intended change in the federal funds rate, the price level, commodity prices, and a monetary aggregate. We find that the correlation between the narrative measures and the identified VAR model shocks are higher in comparison to the recursive identification scheme. However, the discrepancy between both shock series is still large.

We propose two explanations for the misalignment of the narrative account and the VAR model shock series. One is that the narrative time series by Romer and Romer (2004) is plagued with measurement error. The other is a potential misspecification of the VAR model. We then analyze how each source affects the results. To that end, we build on the findings by Coibion (2012). He focuses on the differences between the impulse response functions of the recursively identified VAR model and the impulse response functions of the narrative monetary policy shock. Coibion (2012) shows that three sources account for the difference: the response of the federal funds rate, the importance of two brief periods in 1982, and the selection of the lag length of the VAR model. Coibion (2012) provides alternative measures of the narrative monetary shock time series which account for potential sources of measurement errors. We analyze these alternative narrative accounts as well as a different lag length of the VAR model within our setup. Our results show that the alternative narrative accounts by Coibion (2012) have a smaller measurement error and that the misalignment between the monetary policy shock time series is sensitive to the lag selection.

2. Data and the VAR model setup

2.1. Data

Throughout the paper, we use the data set of Romer and Romer (2004).⁴ All data are of monthly frequency, non-seasonally-adjusted, and cover the time span from January 1966 to December 1996. In our analysis, we follow Romer and Romer (2004) and use the change in the log of the non-seasonally-adjusted index of industrial production (Δx_t) as the output measure and the change in the log of the non-seasonally-adjusted producer price index ($\Delta \pi_t$). Additionally, as suggested by Romer and Romer (2004), we employ the change in the intended federal funds rate instead of the actual federal funds rate and employ their measure of monetary policy shocks as

³The approach in these papers is also related to Stock and Watson (2008, 2012) and shares some ideas with e.g. Hamilton (2003), Kilian (2008), Nevo and Rosen (2012), and Evans and Marshall (2009).

⁴The data set is available at http://www.aeaweb.org/aer/data/sept04_data_romer.zip.

narrative account. The construction of this time series by Romer and Romer (2004) is based on a specific monetary policy reaction function,

$$\Delta i_t = f(X_t) + \varepsilon_{m,t}, \quad (1)$$

where Δi_t denotes the change in the intended federal funds rate around FOMC meetings and X_t denotes the various regressors, e.g. inflation, output, unemployment, and Greenbook forecasts. Romer and Romer construct their new measure of monetary policy shocks, m_t , from the residuals $\varepsilon_{m,t}$ by transforming them into monthly values. Figure 1 plots this new monetary policy measure as a solid line.⁵

Next to output, prices, and the policy rate, the VAR model includes the change in the log of the index of world commodity prices ($\Delta \pi_t^c$) and the change in the log of the money stock ΔM_t . The former time series is part of the data set used by Romer and Romer (2004), the latter is the change in the log of non-seasonally-adjusted nominal M2 taken from the FRED II database of the Federal Reserve Bank of St. Louis. These data are chosen to reduce the potential misspecification of the VAR model as discussed in e.g. Sims (1992).

2.2. The VAR model setup

We specify the endogenous variables of the VAR model (y_t) in the following way:

$$y_t = \left[\Delta x_t \quad \Delta \pi_t \quad \Delta \pi_t^c \quad \Delta i_t \quad \Delta M_t \right]' \quad (2)$$

The VAR model with n endogenous variables is given by:

$$y_t = B_0 + D_0 d_t + B(L)y_{t-1} + u_t, \quad u_t \sim \mathcal{N}(0, \Sigma_u), \quad (3)$$

where $B(L)$ denotes the reduced form VAR model coefficients, B_0 the intercept, and D_0 monthly dummies coefficients. Following Romer and Romer (2004), we use 36 lags of y_t for the VAR model setup. u_t denotes the $n \times 1$ vector of reduced form errors with the corresponding variance-covariance matrix Σ_u . The reduced form errors u_t are related to the structural errors ε_t as follows:

$$u_t = A\varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, I). \quad (4)$$

The identification issue in VAR models arises, because it is not possible to determine A uniquely from $\Sigma_u = AA'$. One way to identify the VAR model is to employ a recursive identification scheme, i.e. to assume that the intended federal funds rate is not affected contemporaneously by shocks to output or prices, but by shocks to the monetary aggregate. The recursive identification scheme is computed by taking the Cholesky decomposition (\tilde{A}) of the variance-covariance matrix. Given the Cholesky decomposition, the structural shocks can be computed using equation (4). Figure 1 plots the monetary policy shocks estimated on the basis of the five variable VAR model as dashed lines. This figure illustrates the common criticism with respect to structural VARs that the identified shocks are not in line with descriptive records (e.g. Rudebusch, 1998). Given our specific identification scheme, the correlation between the monetary shock accounts is approximately 0.3556.

⁵Throughout the paper, when comparing shock accounts with each other, we re-scale each series by its standard deviation for better illustration.

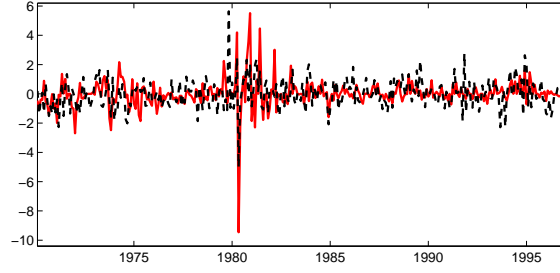


Figure 1: Shock comparison. The solid line represents the scaled narrative shock by Romer and Romer (2004), the dashed line represents the identified VAR model shock, the correlation between the two is 0.3556.

3. The proxy VAR model

In the following paragraphs, we will outline the method of Mertens and Ravn (2013b) to keep this paper self-contained. We start by partitioning the first row (a_1) of the impulse matrix (A) in (4), the reduced form innovations, and the structural innovations as follows:

$$\begin{aligned} a_1 &= \begin{bmatrix} a_{11} & a'_{21} \\ 1 \times 1 & n-1 \times 1 \end{bmatrix}' & (5) \\ \epsilon_t &= \begin{bmatrix} \epsilon_{1,t} & \epsilon'_{2,t} \\ 1 \times 1 & n-1 \times 1 \end{bmatrix}' \\ u_t &= \begin{bmatrix} u_{1,t} & u'_{2,t} \\ 1 \times 1 & n-1 \times 1 \end{bmatrix}' \end{aligned}$$

The first part ($\epsilon_{1,t}$ and $u_{1,t}$) is associated with the monetary policy shock, the second part comprises the additional shocks. Corresponding to the definition of a_1 , the monetary policy instrument is ordered first in the proxy VAR model.⁶ The narrative shock series (m_t) is assumed to be a proxy variable which is correlated with $\epsilon_{1,t}$,

$$E[m_t \epsilon_{1,t}] = \Phi, \quad \Phi \neq 0, \quad (6)$$

and uncorrelated with the remaining structural shocks:

$$E[m_t \epsilon_{2,t}] = 0. \quad (7)$$

Assumption (6) stresses the difference to the narrative approach. The narrative approach assumes the narrative shock series to be perfectly correlated with the structural shock. By employing the notation $\Sigma_{AB} \equiv E[AB]$, Mertens and Ravn show that using relationships (4)-(7), the additional restrictions for the identification of the structural shock $\epsilon_{1,t}$ can be derived as:

$$a_{21} = \Sigma_{mu'_1}^{-1} \Sigma_{mu'_2} a_{11} \quad (8)$$

Mertens and Ravn suggest using the following procedure to estimate the effects of $\epsilon_{1,t}$ on y_t using m_t as a proxy variable:

⁶This is only due to notation. The order of the variables in the proxy VAR model does not affect the results.

1. Estimate the VAR model in equation (3).
2. Regress the VAR model's residuals u_t on the proxy variable m_t to estimate $\Sigma_{mu'}$.
3. Given $\Sigma_{mu'}$ and Σ_u , calculate a_1 using equation (8) and the fact that $\Sigma_u = AA'$. A more detailed description of the calculation is given in Appendix Appendix A.

In order to estimate the quality of the proxy variable, Mertens and Ravn assume the following relationship between m_t and $\epsilon_{1,t}$:

$$m_t = E[D_t](\Gamma\epsilon_{1,t} + v_t), \quad (9)$$

where v_t denotes the measurement error, D_t is an indicator dummy variable tracking zero-observations in m_t , and Γ a scalar to be estimated. Mertens and Ravn assume additionally independent random censoring errors. Therefore, the censoring error is captured by the expectation operator in front of D_t . To derive the reliability measure of the proxy variable, Mertens and Ravn (2013b) augment the VAR model in equation (3) with equation (9) to form a measurement error model.⁷ The corresponding reliability measure Λ is given by:

$$\Lambda = \left(\Gamma^2 \sum_{t=1}^T D_t \hat{\epsilon}_{1,t}^2 + \sum_{t=1}^T D_t (m_t - \Gamma \hat{\epsilon}_{1,t})^2 \right)^{-1} \Gamma^2 \sum_{t=1}^T D_t \hat{\epsilon}_{1,t}^2 \quad (10)$$

Λ is the fraction of the variance in the uncensored measurements which is explained by the variance of the estimated structural shocks $\hat{\epsilon}_{1,t}$. Therefore, the measure lies in an interval between zero and one. A Λ close to one indicates a high quality proxy, while a Λ close to zero indicates a low quality measure.

4. Results

In Table 1, column two and three (R&R (2004)) display the reliability measure Λ and the correlation between the identified monetary policy shocks of the proxy VAR model and the narrative time series by Romer and Romer (2004). The reliability measure Λ is estimated to be only 0.0432. The correlation between both shock series increases, but only slightly to 0.3807. Hence, employing the narrative monetary policy shock by Romer and Romer (2004) as a proxy in the VAR model (eq.3) does not align the identified shock series.

We propose two explanations for the misalignment of the two shock series. One is that the narrative time series by Romer and Romer (2004) is plagued with major measurement error. The other is potential misspecification of the VAR model. In the following, we describe how each explanation can arise and illustrate how they affect the reliability measure and the correlation between both shock series.

Measurement error in the narrative shock time series means, that the narrative account captures only a small exogenous component of the true shock. Therefore, it is a weak proxy variable for the monetary policy shock. Yet, the quality of the measurement error also depends on the estimation of the policy rule in equation (1). Sims and Zha (2006) and Hamilton (2010) suggest that one should

⁷A detailed description can be found in Appendix B.

explicitly allow for heteroskedastic errors when estimating policy rules. Furthermore, measurement error in the narrative account could be related to neglecting innovations of the policy rule, e.g., time-variation of the policy rule’s coefficients as suggested by Boivin (2006) and Coibion and Gorodnichenko (2011) or that the policy rule misses important variables as, e.g., FOMC forecasts (Ellison and Sargent, 2012). To illustrate the relation between potential measurement error and the reliability measure, we follow Coibion (2012) and employ alternative narrative shock series. In particular, Coibion (2012) re-estimates equation (1), firstly, by using a GARCH(1,1)-model to account for heteroskedastic error terms and, secondly, by allowing for time-varying coefficients. We refer to these alternative narrative shock series as R&R-GARCH and R&R-TVC respectively.⁸ Moreover, Leeper (1997) and Coibion (2012) suggest that narrative time series could still contain endogenous components. To this end, we regress the narrative account by Romer and Romer (2004) on current and lagged macroeconomic variables of the VAR model and employ the resulting error terms as an alternative proxy variable.⁹ We refer to this alternative specification as R&R-E. The first row of Table 1 displays the results. While the third alternative specification does not lead to an increase in the reliability measure, the other two specifications do. For example, the specification R&R-TVC increases the reliability measure to 0.0642 and the correlation to 0.4575. Thus, our findings confirm the findings of the literature that the original narrative account by Romer and Romer (2004) is plagued by measurement error. Reducing the measurement error increases the reliability measure Λ and reduces the discrepancy between the structural monetary policy shock and the narrative account.

Lag length	R&R (2004)		R&R-E		R&R-TVC		R&R-GARCH	
	Λ	Corr	Λ	Corr	Λ	Corr	Λ	Corr
$p = 36$.0432	.3807	.0321	.3862	.0642	.4575	.0589	.4440
$p = 12$.3967	.6208	.3095	.6373	.4799	.6752	.4762	.6737

Table 1: Reliability measure (Λ) of different narrative shock measures and for different lag length (p). The second number (Corr) indicates the correlations between the identified structural shock series and the narrative measure.

The second explanation for the misalignment of both shock series is misspecification of the VAR model. Misspecification of the VAR model leads to biased estimation of the reduced form shocks. Since step two in the estimation procedure by Mertens and Ravn (2013b) is based on the reduced form innovations, it is impossible to identify the true shocks correctly. One candidate of VAR model misspecification is the number of lags included in the VAR model, because the estimated reduced form error depends on the number of lags included in the VAR model. Additionally, Coibion (2012) finds that the difference between the impulse response functions of the VAR model and impulse response functions of the narrative shock series reduces if the lag length is set to 12. We follow Coibion (2012) by estimating the proxy VAR model also with 12 lags. The second

⁸The alternative narrative shock series are available at http://www.aeaweb.org/aej/mac/data/2011-0041_data.zip.

⁹More specifically, we run the regression $\epsilon_t^{rr} = c + \sum_{l=0}^L x_{t-l} + v_t$, where x is a matrix containing the same variables as the VAR model but without the intended Fed funds rate. We follow Coibion (2012) and include six lags.

row of Table 1 shows the results. For the original narrative shocks, R&R (2004), the reliability measure increases up to 0.3967. In case of the R&R-TVC specification, the reliability measure increases up to 0.4799. Correspondingly, the correlation between the structural monetary policy shocks identified within the VAR model and the narrative shock is 0.6752. Figure 2 plots both monetary shock series. Thus, even a slight misspecification of the VAR model, e.g. due to omitted variables or lag length misspecification means that the shock series do not align and the reliability measure decreases substantially. However such a misspecification of the VAR model is potentially not the most severe one. Given that Cochrane (1998) points out that monetary policy shocks can be anticipated, the information set of the VAR model would be incomplete, and the moving-average representation of the data generating process is thus not invertible (Fernández-Villaverde et al., 2007).

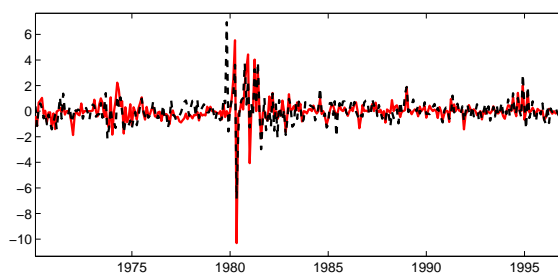


Figure 2: Monetary policy shock identified from VAR model with 12 lags using the method by Mertens and Ravn (2013b) vs. the narrative shocks estimated employing a time-varying policy rule (R&R-TVC). The correlation is 0.6752.

5. Conclusion

We find that recursively identified VAR model shocks cannot be aligned with the narrative shock series of Romer and Romer (2004) by employing the narrative account as a proxy for the structural shock series. One explanation is that the narrative account is a poor proxy variable because of measurement error. Another explanation for the nonalignment of the two shock processes is the misspecification of the VAR model. In further research, we plan to investigate, which of these two explanations accounts most for the nonalignment of the shock processes.

Appendix A. Details on the identification procedure

Recall that we partition the first row (a_1) of the impulse matrix (A), the reduced form innovations and the structural innovations in the following way:

$$\begin{aligned} a_1 &= \begin{bmatrix} a_{11} & a'_{21} \\ 1 \times 1 & n-1 \times 1 \end{bmatrix}' \\ \epsilon_t &= \begin{bmatrix} \epsilon_{1,t} & \epsilon'_{2,t} \\ 1 \times 1 & n-1 \times 1 \end{bmatrix}' \\ u_t &= \begin{bmatrix} u_{1,t} & u'_{2,t} \\ 1 \times 1 & n-1 \times 1 \end{bmatrix}' . \end{aligned}$$

The matrix A is further partitioned into: $A = \begin{bmatrix} a_{11} & a_{12} \\ 1 \times 1 & 1 \times n-1 \\ a_{21} & a_{22} \\ n-1 \times 1 & n-1 \times n-1 \end{bmatrix}$. The variance-covariance matrix of

u , Σ_u , is partitioned accordingly: $\Sigma_u = \begin{bmatrix} \Sigma_{u,11} & \Sigma_{u,12} \\ 1 \times 1 & 1 \times n-1 \\ \Sigma_{u,21} & \Sigma_{u,22} \\ n-1 \times 1 & n-1 \times n-1 \end{bmatrix}$.

Further denote the standard deviation of ϵ_1 by $\sigma_{\epsilon,1}$. The vector a_1 is then calculated as follows:

$$a_{11}\sigma_{\epsilon,1}^{-1} = \left(I - a_{12}a_{22}^{-1}a_{21}a_{11}^{-1} \right)^{-1} \quad (\text{A.1})$$

$$a_{21}\sigma_{\epsilon,1}^{-1} = a_{21}a_{11}^{-1} \left(I - a_{12}a_{22}^{-1}a_{21}a_{11}^{-1} \right)^{-1} \quad (\text{A.2})$$

$$\sigma_{\epsilon,1}^2 = \left(I - a_{12}a_{22}^{-1}a_{21}a_{11}^{-1} \right) a_{11}a'_{11} \left(I - a_{12}a_{22}^{-1}a_{21}a_{11}^{-1} \right)' , \quad (\text{A.3})$$

where

$$\begin{aligned} a_{21}a_{11}^{-1} &= (\Sigma_{mu_1}^{-1} \Sigma_{mu_2})' \\ a_{12}a_{22}^{-1} &= (a_{12}a'_{12}(a_{21}a_{11}^{-1})' + (\Sigma_{u,21} - a_{21}a_{11}^{-1}\Sigma_{u,11}))' (a_{22}a'_{22})^{-1} \\ a_{12}a'_{12} &= (\Sigma_{u,21} - a_{21}a_{11}^{-1}\Sigma_{u,11})' Z^{-1} (\Sigma_{u,21} - a_{21}a_{11}^{-1}\Sigma_{u,11}) \\ a_{22}a'_{22} &= \Sigma_{u,22} + a_{21}a_{11}^{-1}(a_{12}a'_{12} - \Sigma_{u,11})(a_{21}a_{11}^{-1})' \\ a_{11}a'_{11} &= \Sigma_{u,11} - a_{12}a'_{12} \\ Z &= a_{21}a_{11}^{-1}\Sigma_{u,11}(a_{21}a_{11}^{-1})' - (\Sigma_{u,21}(a_{21}a_{11}^{-1})' + a_{21}a_{11}^{-1}\Sigma'_{u,21}) + \Sigma_{u,22} . \end{aligned}$$

Appendix B. Derivation of reliability measure

To derive the reliability measure, we start with the classical narrative approach,

$$y_t = B_0 + D_0d_t + B(L)y_{t-1} + C(L)m_{t-1} + error_t , \quad (\text{B.1})$$

where $C(L)$ are the exogenous shock coefficients and the remaining variables are as defined in Section 2.2. Hence, we follow Mertens and Ravn (2013b) by stacking the regressors of equation (B.1) together to obtain the following compact form

$$Y_t = B_{Y,\bar{X}}\bar{X} + Z_{1,t} , \quad (\text{B.2})$$

where

$$\bar{X} = \begin{bmatrix} 1 & d'_t & y'_{t-1} & \dots & y'_{t-p} & m'_t \end{bmatrix}' \quad (\text{B.3})$$

and

$$B_{Y,\bar{X}} = \begin{bmatrix} B_0 & D_0 & B(L) & C(L) \end{bmatrix} . \quad (\text{B.4})$$

In a second step, Mertens and Ravn (2013b) define the vector X^* :

$$X^* = \begin{bmatrix} 1 & d'_t & y'_{t-1} & \dots & y'_{t-p} & \epsilon'_{1t} \end{bmatrix}' . \quad (\text{B.5})$$

This vector is related to \bar{X} by the following equation

$$\bar{X} = B_{\bar{X},X^*} X^* + Z_{2,t}, \quad (\text{B.6})$$

where

$$B_{\bar{X},X^*} = \begin{bmatrix} I & 0 \\ 0 & \Gamma \end{bmatrix} \quad (\text{B.7})$$

and

$$Z_{2,t} = \begin{bmatrix} 0 \\ D_t v_t + (D_t - I_1) \epsilon_{1t} \end{bmatrix}. \quad (\text{B.8})$$

Inserting \bar{X} into equation (B.2) yields the following estimator B_{Y,X^*} :

$$B_{Y,X^*} = B_{Y,\bar{X}} B_{\bar{X},X^*} = B_{Y,\bar{X}} \Lambda_{\bar{X}}^{-1} \Sigma_{\bar{X}\bar{X}}^{-1} \Sigma_{\bar{X}Y}. \quad (\text{B.9})$$

$\Lambda_{\bar{X}}$ is defined as the reliability matrix:

$$\Lambda_{\bar{X}} = \begin{bmatrix} I & 0 \\ 0 & \Sigma_{mm'}^{-1} \Phi \Gamma \end{bmatrix}. \quad (\text{B.10})$$

References

- Bernanke, B.S., Mihov, I., 1998. Measuring Monetary Policy. *The Quarterly Journal of Economics* 113, 869–902.
- Boivin, J., 2006. Has U.S. Monetary Policy Changed? Evidence from Drifting Coefficients and Real-Time Data. *Journal of Money, Credit and Banking* 38, 1149–1173.
- Christiano, L.J., Eichenbaum, M., Evans, C.L., 1996. The Effects of Monetary Policy Shocks: Evidence from the Flow of Funds. *The Review of Economics and Statistics* 78, 16–34.
- Cochrane, J.H., 1998. What do the VARs mean? Measuring the output effects of monetary policy. *Journal of Monetary Economics* 41, 277–300.
- Cochrane, J.H., Piazzesi, M., 2002. The Fed and Interest Rates - A High-Frequency Identification. *American Economic Review* 92, 90–95.
- Coibion, O., 2012. Are the Effects of Monetary Policy Shocks Big or Small? *American Economic Journal: Macroeconomics* 4, 1–32.
- Coibion, O., Gorodnichenko, Y., 2011. Monetary policy, trend inflation, and the great moderation: An alternative interpretation. *American Economic Review* 101, 341–370.
- Ellison, M., Sargent, T.J., 2012. A Defense Of The Fomc. *International Economic Review* 53, 1047–1065.
- Evans, C.L., Marshall, D.A., 2009. Fundamental Economic Shocks and the Macroeconomy. *Journal of Money, Credit and Banking* 41, 1515–1555.
- Faust, J., Swanson, E.T., Wright, J.H., 2004. Identifying VARs based on high frequency futures data. *Journal of Monetary Economics* 51, 1107–1131.
- Fernández-Villaverde, J., Rubio-Ramírez, J.F., Sargent, T.J., Watson, M.W., 2007. ABCs (and Ds) of Understanding VARs. *American Economic Review* 97, 1021–1026.
- Gürkaynak, R.S., Sack, B., Swanson, E., 2005. Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements. *International Journal of Central Banking* 1, 55–93.
- Hamilton, J.D., 2003. What is an oil shock? *Journal of Econometrics* 113, 363–398.
- Hamilton, J.D., 2010. Macroeconomics and ARCH, in: Bollerslev, T., Russel, J.R., Watson, M.W. (Eds.), *Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle*. Oxford University Press, Oxford, pp. 79–96.
- Ilzetzki, E., Jin, K., 2013. The puzzling change in the transmission of u.s. macroeconomic policy shocks. Working Paper, London School of Economics.

- Kilian, L., 2008. Exogenous Oil Supply Shocks: How Big Are They and How Much Do They Matter for the U.S. Economy? *The Review of Economics and Statistics* 90, 216–240.
- Kuttner, K.N., 2001. Monetary policy surprises and interest rates: Evidence from the Fed funds futures market. *Journal of Monetary Economics* 47, 523–544.
- Leeper, E.M., 1997. Narrative and VAR approaches to monetary policy: Common identification problems. *Journal of Monetary Economics* 40, 641–657.
- Mertens, K., Ravn, M.O., 2013a. A reconciliation of SVAR and narrative estimates of tax multipliers. *Journal of Monetary Economics* doi:<http://dx.doi.org/10.1016/j.jmoneco.2013.04.004>.
- Mertens, K., Ravn, M.O., 2013b. The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States. *American Economic Review* 103, 1212–1247.
- Nevo, A., Rosen, A.M., 2012. Identification With Imperfect Instruments. *The Review of Economics and Statistics* 94, 659–671.
- Romer, C.D., Romer, D.H., 1989. Does Monetary Policy Matter? A New Test in the Spirit of Friedman and Schwartz, in: *NBER Macroeconomics Annual 1989, Volume 4*. National Bureau of Economic Research, Inc. NBER Chapters, pp. 121–184.
- Romer, C.D., Romer, D.H., 2004. A New Measure of Monetary Shocks: Derivation and Implications. *American Economic Review* 94, 1055–1084.
- Rudebusch, G.D., 1998. Do Measures of Monetary Policy in a VAR Make Sense? *International Economic Review* 39, 907–931.
- Sims, C.A., 1992. Interpreting the macroeconomic time series facts : The effects of monetary policy. *European Economic Review* 36, 975–1000.
- Sims, C.A., Zha, T., 2006. Were there regime switches in u.s. monetary policy? *American Economic Review* 96, 54–81.
- Stock, J.H., Watson, M.W., 2008. Nber summer institute what's new in econometrics: Time series lecture 7. http://www.nber.org/minicourse_2008.html.
- Stock, J.H., Watson, M.W., 2012. Disentangling the Channels of the 2007-2009 Recession. NBER Working Papers 18094. National Bureau of Economic Research, Inc.