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Reconciling narrative monetary policy disturbances with structural VAR model shocks?

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Non-technical summary

The history of monetary policy disturbances is important and widely used for policy analysis. This time series is essential for the historical decomposition of key macroeconomic 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 the time series of monetary policy shocks is widely recognized, there is strong disagreement about its composition in the empirical literature. In the present paper, we attempt to identify and to quantify this discrepancy, which will be helpful to identify monetary policy shocks better in the future.

The existent literature is divided into two prominent strands about identification of monetary policy shocks. One the one hand, structural vector autoregressive models (VAR) are used to shape the endogenous relationship between the policy rate and different economic variables, and monetary policy shocks are identified within the model. On the other hand, monetary policy shocks are identified outside an econometric model as narrative time series, e.g., by Romer and Romer (2004). We attempt to reconcile the monetary policy shock identified with a common structural VAR model and the narrative measure. To achieve this, we incorporate the narrative monetary policy shock account into the VAR model by treating it as a proxy for the structural monetary policy shock. Moreover, we quantify the extent to which the discrepancy still applies and identify two explanations for the disagreement. Alongside the potential measurement error in the narrative time series, as pointed out by the literature, we determine a potential misspecification of the VAR model as a second explanation.

Nicht-technische Zusammenfassung

Die Abweichungen der Notenbankzinsen von ihrem durch andere ökonomische Entwicklungen bestimmten Pfad über die Zeit (sog. Schocks) sind von Bedeutung für die Messung der tatsächlichen Wirkungen der Geldpolitik. So wird diese Zeitreihe häufig verwendet, um den Beitrag geldpolitischer Änderungen auf den Konjunkturzyklus zu identifizieren (sog. historische Zerlegung). Darüber hinaus dient sie der kontrafaktischen Analyse der Rolle von Geldpolitik. Trotz dieser zentralen Bedeutung für die geldpolitische Analyse besteht in der empirischen Literatur zur amerikanischen Geldpolitik eine große Uneinigkeit darüber, wie diese Zeitreihe tatsächlich aussieht. Im vorliegenden Aufsatz leisten wir einen Beitrag zum besseren Verständnis der Diskrepanzen verschiedener Ansätze in der Literatur. Dies soll einer besseren Identifikation der tatsächlichen Schocks in der Zukunft dienen.

In der vorhandenen Literatur gibt es zwei prominente Ansätze, um die geldpolitischen Schocks zu identifizieren. Zum einen kann man ein strukturelles Vector Autoregressives Modell (VAR) verwenden, um den Zusammenhang zwischen Zinsen und anderen als wichtig erachteten ökonomischen Größen abzubilden und die geldpolitischen Schocks innerhalb dieses Modelles identifizieren. Alternativ sind geldpolitische Schocks z.B. durch Romer und Romer (2004) als narrative Zeitreihe außerhalb eines VAR Modells erfasst worden. In der vorliegenden Arbeit versuchen wir, die geldpolitischen Schocks beider Verfahren in Einklang zu bringen. Dafür verwenden wir folgende Strategie: Die narrative Reihe wird innerhalb des strukturellen VAR Modells als "proxy"-Variable für die geldpolitschen Schocks verwendet. Anschließend vergleichen wir die so identifizierten geldpolitischen Schocks mit der narrativen Zeitreihe. Im Idealfall würden beide Reihen übereinstimmen. Der fortbestehende Unterschied zwischen beiden Zeitreihen lässt sich zum einen, wie bereits in der Literatur diskutiert, durch potentielle Messfehler in der narrativen Zeitserie begründen. Zum anderen könnte aber auch eine mögliche Fehlspezifizierung des VAR Modells selbst einen Erklärungsansatz bieten.

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Reconciling narrative monetary policy disturbances with structural VAR model shocks?*

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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 quantify the extent to which the disagreement still applies and identify two explanations for the disagreement. One explanation is measurement error in the narrative time series, another is a misspecification of the VAR model.

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

JEL classification: E31, E32, E52.

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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. Additionally, the sequence of monetary policy disturbances is important for conducting counterfactuals to explore the role of monetary policy. Yet despite the importance of the time series of monetary policy shocks, there is strong disagreement about it in the empirical literature.[1]

One strand of the empirical literature estimates the monetary policy shocks using a vector autoregressive (VAR) model (e.g. Sims, 1992; Christiano, Eichenbaum, and Evans, 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] Both 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 shock identified with a common structural VAR model and the narrative measure 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 shock account into the VAR model by treating it as a proxy for the structural monetary policy shock. Hence, this method offers an identification scheme for monetary policy shocks which seems promising to reconcile both strands of the literature.

We set up a standard VAR model which includes industrial production, the intended change in the federal funds rate, the price level, commodity prices, and a monetary aggregate. Following Mertens and Ravn (2013b,a), we use the narrative measure by Romer and Romer (2004) as a proxy for the monetary policy shock. In comparison to a recursive identification scheme, we can increase the correlation between the narrative account and the identified VAR model shock. However, the discrepancy between both shock series is still large. In order to investigate potential explanations for our finding we conduct a Monte Carlo experiment. In particular, we simulate data from a New Keynesian model and investigate the ability of the VAR model to recover the true underlying monetary policy shock.[4] We suggest two explanations for the misalignment of the narrative account and the VAR model shock series. Alongside the potential measurement error in the narra-

[1]Ilzetzki 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.

[2]Similarly, 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, Sack, and Swanson, 2005) or measure market announcement movements (e.g. Cochrane and Piazzesi, 2002; Faust, Swanson, and Wright, 2004).

[3]The 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).

[4]See Canova and Pina (2005), who use a similar experiment to investigate different identification schemes for structural VAR models.

tive time series as pointed out by Mertens and Ravn (2013b,a), we determine a potential misspecification of the VAR model as a second explanation.

2 Data and the VAR model setup

2.1 Data

Throughout the paper, we use the data set of Romer and Romer (2004).[5] 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 narrative account. The construction of this time series by Romer and Romer (2004) is based on a specific monetary policy reaction function,

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

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.[6]

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:

$$y_t = \left[\begin{array}{ccccc} \Delta x_t & \Delta \pi_t & \Delta \pi_t^c & \Delta i_t & \Delta M_t \end{array} \right]' \tag{2}$$

The VAR model with n endogenous variables is given by:

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

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

[5]The data set is available at `http://www.aeaweb.org/aer/data/sept04_data_romer.zip`.

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

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:

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

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. However, as pointed out by Sims (1998), while identified VAR studies disagree among themselves and with historical events about the history of policy disturbances, they can propose a similar response of the economy to monetary policy shocks.[7]

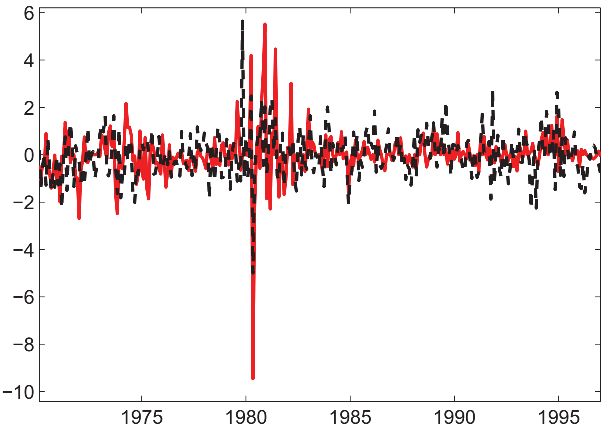


Figure 1: Shock comparison. The solid line represents the scaled narrative shock by Romer and Romer (2004), the dashed line represents the identified VAR model shock, the correlation between the two is 0.3556.

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

[7]See Appendix C for a comparison of impulse response functions under different identification strategies.

matrix (A) in (4), the reduced form innovations, and the structural innovations as follows:

$$\begin{aligned} \underset{n\times1}{a_1} &= \begin{bmatrix} \underset{1\times1}{a_{11}} & \underset{n-1\times1}{a'_{21}} \end{bmatrix}' \\ \underset{n\times1}{\epsilon_t} &= \begin{bmatrix} \underset{1\times1}{\epsilon_{1,t}} & \underset{n-1\times1}{\epsilon'_{2,t}} \end{bmatrix}' \\ \underset{n\times1}{u_t} &= \begin{bmatrix} \underset{1\times1}{u_{1,t}} & \underset{n-1\times1}{u'_{2,t}} \end{bmatrix}' \end{aligned} \tag{5}$$

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.[8] The narrative shock series (m_t) is assumed to be a proxy variable which is correlated with $\epsilon_{1,t}$,

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

and uncorrelated with the remaining structural shocks:

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

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:

$$a_{21} = \Sigma^{-1}_{mu'_1}\Sigma_{mu'_2}a_{11} \tag{8}$$

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

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 A.

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

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

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,

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

Mertens and Ravn (2013b) augment the VAR model in equation (3) with equation (9) to form a measurement error model.[9] The corresponding reliability measure Λ is given by:

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

Λ is the fraction of the variance in the uncensored measurements which is explained by the variance of the estimated structural shocks $\hat{\epsilon}_{1t}$. 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

4.1 The estimated Proxy VAR model

Figure 2 plots the monetary policy shocks identified using the proxy VAR model and the shocks identified by Romer and Romer (2004). The correlation of the shocks identified using the proxy VAR model and the narrative time series increases, but only slightly to 0.3807. Correspondingly, the reliability measure Λ is estimated to be only 0.0851. One immediate result of this study is that employing the narrative monetary policy shock by Romer and Romer (2004) as a proxy in a VAR model does not align the identified shock series. The reason for this can be twofold. First, the narrative time series can be plagued with major measurement error. It therefore captures only a small exogenous component of the true shock and is thus a weak proxy variable for the monetary policy shock. This finding is in line with the empirical findings by Stock and Watson (2012). Moreover, it is supported by argumentation of Ellison and Sargent (2012) that the policy function by Romer and Romer (2004) is misspecified because it ignores the FOMC forecasts. Nevertheless, a second explanation for the misalignment of the VAR model shocks and the narrative account is misspecification of the VAR model. Misspecification of the VAR model can limit the possible linear combinations of the innovations in variables included in the VAR model. This can make it impossible to identify the true shocks correctly. In the following section we will discuss this issue in more detail.

4.2 Monte Carlo study

To illustrate the the connection between the misspecification of the VAR model and the reliability measure of the proxy variable, we conduct the following Monte Carlo experiment. We simulate artificial data from a DSGE model. In particular, we simulate 1000 periods and discard the first 200. The DSGE model is taken from Ireland (2004) and includes four different exogenous disturbances anlongside monetary policy.[10]

In the baseline experiment, we simulate the time series which we employ in the empirical exercise except for commodity prices. More precisely, we simulate money growth, inflation, output growth, and the change in interest rates using four exogenous shocks.

[9] A detailed description can be found in Appendix B.

[10] Among others Sargent and Surico (2011), employ this model in their analysis and estimate it using US data. The model description and its calibration are given in Appendix D.

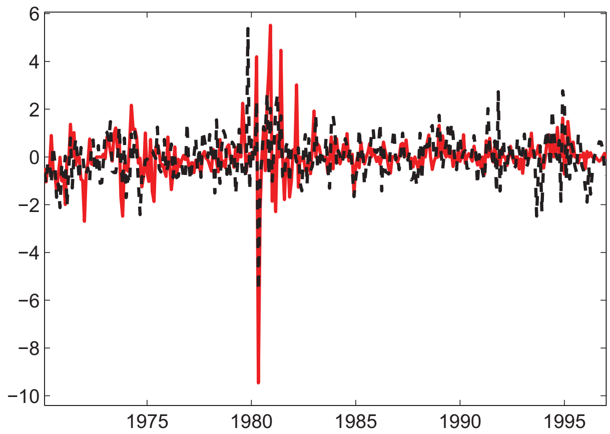


Figure 2: Monetary policy shock identified using the method by Mertens and Ravn (2013b) vs. the shocks identified by Romer and Romer (2004). The correlation is 0.3807.

Afterwards, we estimate a VAR model with two lags and employ the true monetary policy shock as the proxy variable. This VAR model is a good approximation of the moving-average representation of the DSGE model. We find that a good approximation of the data generating process and the true monetary policy shock as a proxy are sufficient to identify the correct underlying monetary policy shock. Correspondingly, the correlation between the identified VAR model shock and the narrative time series is 0.986, and the reliability measure is 0.971. Figure 3 plots an extract of the shock series.

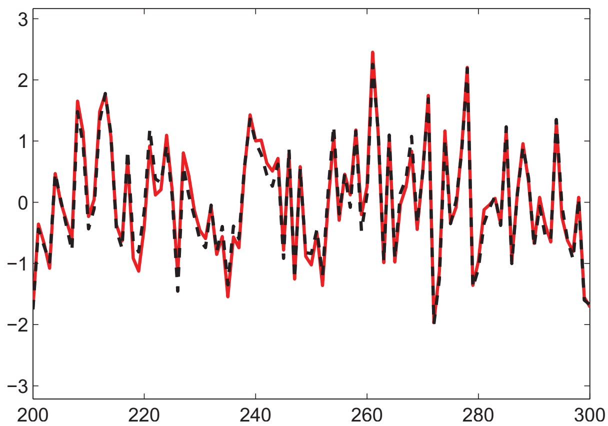


Figure 3: Monte Carlo exercise, when the true monetary policy shock is the proxy variable and the VAR model is a good approximation of the data generating process. The correlation is 0.986.

Next, we conduct an experiment in which the VAR model is misspecified. The proxy variable is again the correct monetary policy shock. The misspecification of the VAR model is due to two sources. Inflation as a state variable is not included in the VAR model. Furthermore, we add a fifth shock to the simulation of the data. Put differently, the misspecified VAR model exhibits an omitted variable problem and estimates fewer reduced form errors than there are structural shocks in the data generating process. We find that even though the proxy variable is the correct shock, the identified shock in the

VAR model is different. The correlation between the identified VAR model shock and the correct monetary policy shock is 0.8552. The reliability measure drops to 0.8127. Thus, even this slight misspecification of the VAR model means that the shock series do not align and the reliability measure decreases substantially. The misspecification of the VAR model in the Monte Carlo exercise is potentially not the most severe one. Cochrane (1998) points out that monetary policy shocks can be anticipated, the information set of the VAR model is consequently incomplete, and the moving-average representation of the data generating process is thus not invertible (Fernández-Villaverde, Rubio-Ramírez, Sargent, and Watson, 2007).

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. We demonstrate that the misspecification of the VAR model provides another explanation for the nonalignment of the two shock processes. In further research, we plan to investigate, which of the two sources provides the main explanation for the nonalignment of the shock processes.

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:

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

The matrix A is further partitioned into: $A = \begin{bmatrix} \underset{1\times 1}{a_{11}} & \underset{1\times n-1}{a_{12}} \\ \underset{n-1\times 1}{a_{21}} & \underset{n-1\times n-1}{a_{22}} \end{bmatrix}$. The variance-covariance matrix of u, Σ_u, is partitioned accordingly: $\Sigma_u = \begin{bmatrix} \underset{1\times 1}{\Sigma_{u,11}} & \underset{1\times n-1}{\Sigma_{u,12}} \\ \underset{n-1\times 1}{\Sigma_{u,21}} & \underset{n-1\times n-1}{\Sigma_{u,22}} \end{bmatrix}$.
Further denote the standard deviation of ϵ_1 by $\sigma_{\epsilon,1}$. The vector a_1 is then calculated as follows:

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

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

$$\sigma_{\epsilon,1}^{2} = \left(I - a_{12}a_{22}^{-1}a_{21}a_{11}^{-1}\right)a_{11}a'_{11}\left(I - a_{12}a_{22}^{-1}a_{21}a_{11}^{-1}\right)' , \tag{13}$$

where

$$\begin{aligned}
a_{21}a_{11}^{-1} &= (\Sigma_{mu'_1}^{-1}\Sigma_{mu'_2})' \\
a_{12}a_{22}^{-1} &= \left(a_{12}a'_{12}(a_{21}a_{11}^{-1})' + \left(\Sigma_{u,21} - a_{21}a_{11}^{-1}\Sigma_{u,11}\right)'\right)(a_{22}a_{22}'^{-1}) \\
a_{12}a'_{12} &= \left(\Sigma_{u,21} - a_{21}a_{11}^{-1}\Sigma_{u,11}\right)' Z^{-1}\left(\Sigma_{u,21} - a_{21}a_{11}^{-1}\Sigma_{u,11}\right) \\
a_{22}a'_{22} &= \Sigma_{u,22} + a_{21}a_{11}^{-1}(a_{12}a'_{12} - \Sigma_{u,11})(a_{21}a_{11}^{-1})' \\
a_{11}a'_{11} &= \Sigma_{u,11} - a_{12}a'_{12} \\
Z &= a_{21}a_{11}^{-1}\Sigma_{u,11}(a_{21}a_{11}^{-1})' - \left(\Sigma_{u,21}(a_{21}a_{11}^{-1})' + a_{21}a_{11}^{-1}\Sigma'_{u,21}\right) + \Sigma_{u,22} .
\end{aligned}$$

B Derivation of reliability measure

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

$$y_t = B_0 + D_0 d_t + B(L)y_{t-1} + C(L)m_{t-1} + error_t , \tag{14}$$

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 (14) together to obtain the following compact form

$$Y_t = B_{Y,\bar{X}}\bar{X} + Z_{1,t} , \tag{15}$$

where

$$\bar{X} = \left[\begin{array}{cccccc} 1 & d_t' & y_{t-1}' & \dots & y_{t-p}' & m_t' \end{array} \right]' \tag{16}$$

and

$$B_{Y,\bar{X}} = \left[\begin{array}{cccc} B_0 & D_0 & B(L) & C(L) \end{array} \right] \ . \tag{17}$$

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

$$X^\star = \left[\begin{array}{cccccc} 1 & d_t' & y_{t-1}' & \dots & y_{t-p}' & \epsilon_{1t}' \end{array} \right]' \ . \tag{18}$$

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

$$\bar{X} = B_{\bar{X},X^\star} X^\star + Z_{2,t} \ , \tag{19}$$

where

$$B_{\bar{X},X^\star} = \left[\begin{array}{cc} I & 0 \\ 0 & \Gamma \end{array} \right] \tag{20}$$

and

$$Z_{2,t} = \left[\begin{array}{c} 0 \\ D_t v_t + (D_t - I_1)\epsilon_{1t} \end{array} \right] \ . \tag{21}$$

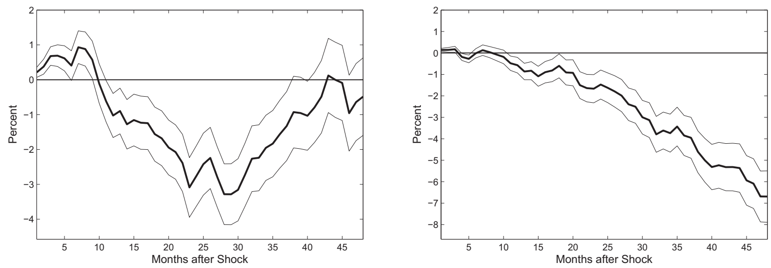
Inserting $\bar{X}$ into equation (15) yields the following estimator $B_{Y,X^\star}$:

$$B_{Y,X^\star} = B_{Y,\bar{X}} B_{\bar{X},X^\star} = B_{Y,\bar{X}} \Lambda_{\bar{X}}^{-1} \Sigma_{\bar{X}\bar{X}}^{-1} \Sigma_{\bar{X}Y} \ . \tag{22}$$

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

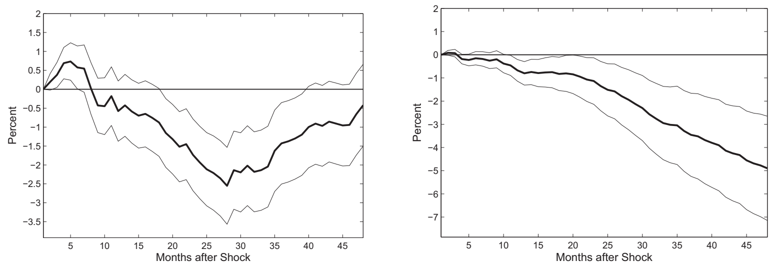
$$\Lambda_{\bar{X}} = \left[\begin{array}{cc} I & 0 \\ 0 & \Sigma_{mm'}^{-1} \Phi \Gamma \end{array} \right] \ . \tag{23}$$

C Comparison of impulse response functions



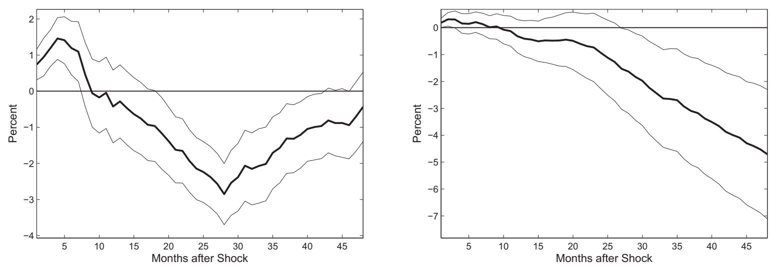
(a) Effect on output (b) Effect on prices

Figure 4: Impulse response due to a contractionary monetary policy shock using a classical narrative approach, e.g. by Romer and Romer (2004). One standard deviation uncertainty bands.



(a) Effect on output (b) Effect on prices

Figure 5: Impulse response due to a contractionary monetary policy shock using recursive identification. One standard deviation uncertainty bands.



(a) Effect on output (b) Effect on prices

Figure 6: Impulse response due to a contractionary monetary policy shock using a proxy variable. One standard deviation uncertainty bands.

D The DSGE model

$$
\begin{aligned}
\text{Philips curve:} \quad & \pi_t = \beta (1-\alpha_\pi) E_t [\pi_{t+1}] + \beta \alpha_\pi \pi_{t-1} + \kappa x_t + \frac{1}{\tau} e_t && (24) \\
\text{IS curve:} \quad & x_t = (1-\alpha_x) E_t [x_{t+1}] + \alpha_x x_{t-1} - \sigma (R_t - E_t [\pi_{t+1}]) && (25) \\
& \quad - \sigma (1-\xi)(1-\rho_a) a_t && (26) \\
\text{Nominal money demand:} \quad & \Delta m_t = \frac{1}{\gamma\sigma} \Delta x_t - \frac{1}{\gamma} \Delta R_t + \frac{1}{\gamma} (\Delta \chi_t - \delta a_t) && (27) \\
\text{Output gap:} \quad & x_t = y_t - \xi a_t && (28) \\
\text{Output growth:} \quad & \Delta y_t = y_t - y_{t-1} + z_t && (29) \\
\text{Monetary policy:} \quad & R_t = \rho_R R_{t-1} + (1-\rho_R)(\psi_\pi \pi_t + \psi_y y_t) + \epsilon_{R,t} && (30)
\end{aligned}
$$

$$
\begin{aligned}
\text{Technology shock:} \quad & z_t = \epsilon_{z,t} && (31) \\
\text{Demand shock:} \quad & a_t = \rho_a a_{t-1} + \epsilon_{a,t} && (32) \\
\text{Money demand shock:} \quad & \chi_t = \rho_\chi \chi_{t-1} + \epsilon_{\chi,t} && (33) \\
\text{Markup shock:} \quad & e_t = \rho_e e_{t-1} + \epsilon_{e,t} && (34)
\end{aligned}
$$

Economy		Shocks		Policy	
β	0.99	ρ_e	0.99	ψ_π	1.50
α_π	0.5	ρ_a	0.5	ψ_y	0.1
α_x	0.5	ρ_χ	0.7	ρ_R	0.7
κ	0.1	σ_e	0.5	σ_R	0.4
τ	6	σ_a	0.5		
σ	0.1	σ_χ	0.4		
ξ	0.15	σ_z	0.5		
γ^{-1}	0.15				

Table 1: Parameter values.

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