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Monetary policy and information shocks in a block-recursive SVAR

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ABSTRACT

This study introduces a new estimator that combines block-recursive restrictions with higher-order moment conditions and non-Gaussian shocks. The proposed estimator improves the accuracy of the estimation, simplifies labeling, and allows for relaxing the independence and non-Gaussianity assumptions in comparison to a purely data-driven approach. We use the approach to disentangle the interaction of stock prices and interest rates into monetary policy and stock market information shocks. We find that traditional monetary policy shocks move interest rates and stock prices in opposite directions, whereas information shocks move both variables in the same direction. Moreover, we utilize high-frequency data from FOMC announcements to derive a proxy for central bank information shocks and show that these shocks are statistically relevant for the low-frequency stock market information shock.

1. Introduction

News or information shocks have been recognized as important drivers of macroeconomic variables (see, e.g. Beaudry and Portier (2006), Bjørnland and Leitemo (2009), Jarocinski and Karadi (2020), Bauer and Swanson (2020)). Stock market data is commonly used to capture these shocks, but identifying them along with monetary policy shocks in a structural vector autoregression (SVAR) remains a challenge for econometricians. Moreover, there is an ongoing debate on whether the central bank causes information shocks or merely responds to them.

In this study, we propose the block-recursive SVAR-GMM estimator, which combines traditional identification approaches based on restrictions with a more recent data-driven identification approach based on non-Gaussianity and independence. This hybrid approach relaxes non-Gaussianity and independence assumptions, simplifies labeling, and improves estimation performance compared to a purely data-driven estimator. Using this estimator, we analyze the effects of monetary policy and information shocks retrieved from stock market data. Our findings suggest that a contractionary monetary policy shock leads to a recession with lower output and prices, along with an immediate drop in stock prices. In contrast, a stock market information shock triggers an increase in output and inflation, along with an immediate increase in stock prices and interest rates.

Identification of an SVAR requires imposing an a priori structure. Traditionally, identification is based on imposing structure on the interaction of the variables (e.g., short-run restrictions in Sims (1980), long-run restrictions in Blanchard and

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Quah (1989), sign restrictions in Uhlig (2005), or proxy variables in Mertens and Ravn (2013)). More recently, data-driven approaches allow for identification without imposing interaction restrictions. Instead, these approaches impose structure on the stochastic properties of the shocks (e.g., time-varying volatility as discussed in Rigobon (2003), Lanne et al. (2010), Lütkepohl and Netšunajev (2017), Lewis (2021), and Bertsche and Braun (2022) or non-Gaussian and independent shocks as discussed in Gouriéroux et al. (2017), Lanne et al. (2017), Lanne and Luoto (2021), Keweloh (2021b), and Guay (2021)). At first glance, in the non-Gaussian SVAR the traditional identification approach based on restrictions appears unnecessarily restrictive, especially from an asymptotic point of view. However, Montiel Olea et al. (2022) stress the advantage of traditional approaches and conclude that traditional identification approaches remain relevant. Nevertheless, in many applications we can only derive some, but not sufficiently many convincing restrictions to ensure identification. With a traditional purely restriction based approach, even the most plausible restrictions are worthless if there are not sufficiently many.

The proposed block-recursive SVAR-GMM estimator enables the use of restrictions when possible while relying on data-driven estimation when necessary. Specifically, the estimator combines a block-recursive structure that partitions shocks into blocks, where shocks within a given block only affect variables in the same block or blocks ordered below, with higher-order moment conditions derived from the assumption of independent shocks within each block. Therefore, imposing a finer block-recursive structure allows to relax the independence and non-Gaussianity assumptions and it simplifies the labeling since shocks only need to be labeled within blocks. Moreover, we demonstrate that leveraging the block-recursive structure can significantly enhance the finite sample performance of data-driven SVAR estimators, particularly in small sample sizes. By utilizing information on the block-recursive structure, we can reduce small sample bias and the mean squared error of estimated simultaneous interactions in an SVAR. Additionally, we show how combining the block-recursive structure with information from higher moments can aid in testing the exogeneity of proxy variables in small samples.

The block-recursive SVAR-GMM estimator utilizes a block-recursive structure that appears in many macroeconomic applications. Examples include applications analyzing (i) the interaction of macroeconomic and financial variables, where the former respond sluggishly while the latter respond quickly (see, e.g. Kilian and Zhou (2022)), (ii) the interaction of small and large open economies, where large economies may have an immediate impact on small economics but not vice versa (see, e.g. Zha (1999)), and (iii) applications including proxy variables using the augmented proxy variable specification, where proxy variables are affected by a noise term which does not directly affect the other variables (see, e.g. Angelini and Fanelli (2019)).

We apply the block-recursive SVAR-GMM estimator to examine the impact of monetary policy and information shocks on an SVAR system similar to the one studied in Jarocinski and Karadi (2020). In contrast to their approach, our low-frequency monetary policy and stock market information shocks do not rely on sign restrictions or high-frequency data. Instead, we assume that output and inflation are rigid and are restricted such that they cannot respond to information and monetary policy shocks within the same month. However, interest rates and stock prices remain unrestricted and can simultaneously respond to all shocks. Our findings reveal that a contractionary monetary policy shock triggers a slowdown in output and prices, and a drop in stock prices, while a stock market information shock results in increased output, prices, interest rates, and stock prices. In the second step, we investigate the effect of traditional monetary policy and central bank information shocks on intraday asset prices at FOMC announcements. Our results show that traditional monetary policy shocks have a significant impact on intraday short- and long-run interest rates as well as stock prices, while central bank information shocks only affect intraday stock prices and long-run interest rates. Furthermore, we use the intraday analysis to construct a low-frequency proxy variable for central bank information shocks. Our tests suggest that the central bank information proxy obtained from the high-frequency analysis is exogenous to all low-frequency shocks except for the low-frequency stock market information shock. This finding indicates that central bank information shocks are a relevant driver of the low-frequency stock market information shock.

The remainder of this article is structured as follows. Section 2 summarizes commonly used identification schemes to analyze the interaction of monetary policy and the stock market. Section 3 derives the block-recursive SVAR-GMM estimator and contains a Monte Carlo study illustrating how exploiting the block-recursive structure increases the finite sample performance of the estimator. In Section 4, we use the proposed block-recursive SVAR-GMM estimator to analyze the interaction of the stock market and monetary policy. Section 5 concludes.

2. Monetary policy and the stock market SVAR models

In an SVAR model, a vector of time series is explained by its past values and a linear combination of structural shocks

$$y_t = \nu + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t, \tag{1}$$

$$u_t = B_0 \varepsilon_t, \tag{2}$$

with an n-dimensional vector of macroeconomic variables y_t, an n-dimensional intercept term ν, parameter matrices $A_1, \ldots, A_p$ ensuring a stable process, i.e. $det(I - A_1 c - \ldots - A_p c^p) \neq 0$ for $|c| \leqslant 1$, a non-singular matrix B_0, the n-dimensional vector of structural shocks $\varepsilon_t = [\varepsilon_{1t}, \ldots, \varepsilon_{nt}]'$ with zero mean and unit variance, and the n-dimensional vector of reduced form shocks $u_t = [u_{1t}, \dots, u_{nt}]\prime$. Here, the vector of structural shocks will contain a monetary policy and a stock market or information shock. The goal is to identify both shocks and estimate their impact on the macroeconomic variables.

The SVAR imposes only little structure a priori, however, without further assumptions the structural shocks are not identified. Assuming that the shocks ε_t are serially uncorrelated allows to consistently estimate the vector autoregressive process in Eq. (1) and obtain estimates of the reduced form shocks u_t. However, identification of the structural shocks ε_t and their simultaneous impact B_0 requires additional assumptions. To see this define the innovations

$$e(B)_t := B^{-1}u_t. \tag{3}$$

For $B = B_0$ it holds that the innovations are equal to the structural shocks. Normalizing the shocks ε_t to unit variance implies n variance conditions

$$E\left[e(B)_{it}^2\right] \overset{!}{=} E\left[\varepsilon_{it}^2\right] = 1, \text{for} \quad i = 1, \dots, n. \tag{4}$$

Moreover, assuming that the components of ε_t are mutually uncorrelated implies $\frac{n(n+1)}{2} - n$ covariance conditions

$$E[e(B)_{it}e(B)_{jt}] \overset{!}{=} E[\varepsilon_{it}\varepsilon_{jt}] = 0, \text{for}[i,j] \neq [i,i]. \tag{5}$$

However, the matrix B contains n^2 unknown parameters and hence is not identified by the $\frac{n(n+1)}{2}$ (co-) variance conditions. Therefore, further assumptions are required to identify the structural shocks and their simultaneous impact.

The most commonly used identification assumption is a recursive ordering, which imposes zero restrictions on variables so that they are only affected by shocks ordered in rows above the variable. By imposing these short-run restrictions, the matrix B has only $\frac{n(n+1)}{2}$ unknown parameters left, and therefore can be identified by the $\frac{n(n+1)}{2}$ (co-) variance conditions. However, for monetary policy and the stock market, it is not credible to impose zero restrictions on the interaction of both variables.

Due to the unavailability of credible short-run restrictions Bjørnland and Leitemo (2009) identify monetary policy and the stock market shocks based on restrictions on the long-run interaction of both variables. Long-run restrictions solve the identification problem by imposing restrictions on the cumulative long-run responses with respect to a given set of shocks. Here, the authors assume long-run neutrality of monetary policy, which means that the monetary policy shock has no long-run impact on real stock prices by construction. They find that monetary policy and the stock market interact simultaneously, with a tightening of monetary policy leading to an immediate decrease in stock prices and a positive stock market shock leading to an immediate tightening of monetary policy.

Rigobon (2003) propose an estimator, which does not require any restrictions on the short- or long-run interaction, instead, identification is based on heteroskedastic shocks. Intuitively, heteroskedastic shocks can be used to derive additional (co-) variance conditions and thereby solve the identification problem. Identification is thus based on stochastic properties of the shocks. While a volatility process can be used for identification without imposing much structure on the process, Lütkepohl and Netšunajev (2017) argue that reliable estimators based on GARCH or Markov switching processes are only available in small models and few volatility states. To address this issue, they propose an estimator that imposes a parametric smooth transition function between two states of the variance–covariance matrix of the reduced form shocks. The estimator is applied to the interaction of monetary policy and the stock market, where the authors find a small simultaneous negative response of the stock market to a tightening of monetary policy.[1] However, the authors cannot label a stock market shock and hence it remains unclear how monetary policy reacts to a stock market shock.

Another branch of the SVAR literature uses non-Gaussian and independent shocks for identification (see e.g. Herwartz and Plödt (2016), Matteson and Tsay (2017), Gouriéroux et al. (2017), Lanne et al. (2017), Lanne and Luoto (2021), Keweloh (2021b), or Guay (2021)).[2] These approaches also use stochastic properties of the shocks and do not require to impose any short- or long-run restrictions. In particular, the non-Gaussian approaches exploit information beyond the variance to identify the structural shocks and their simultaneous impact. For example, if the shocks are independent, one can derive $\frac{n(n+1)(n+2)}{6} - n$ coskewness conditions from

$$E[e(B)_{it}e(B)_{jt}e(B)_{kt}] \overset{!}{=} E\,[\varepsilon_{it}\varepsilon_{jt}\varepsilon_{kt}] = 0, \quad \text{for} \quad [i,j,k] \neq [i,i,i] \tag{6}$$

and $\frac{n(n+1)(n+2)(n+3)}{24} - n$ cokurtosis conditions from

$$E[e(B)_{it}e(B)_{jt}e(B)_{kt}e(B)_{lt}] \overset{!}{=} E\,[\varepsilon_{it}\varepsilon_{jt}\varepsilon_{kt}\varepsilon_{lt}], \quad \text{for} \quad [i,j,k,l] \neq [i,i,i,i], \tag{7}$$

where $E[\varepsilon_{it}\varepsilon_{jt}\varepsilon_{kt}\varepsilon_{lt}] = 1$ if the comoment is symmetric, i.e. $E[\varepsilon_{it}^2\varepsilon_{jt}^2]$ with $i \neq j$, and otherwise $E[\varepsilon_{it}\varepsilon_{jt}\varepsilon_{kt}\varepsilon_{lt}] = 0$, see Keweloh (2021b). Using the (co-) variance, coskewness, and cokurtosis conditions allows to identify the n^2 unknown coefficients of B if the structural shocks are sufficiently non-Gaussian, see Keweloh (2021b). Lanne et al. (2017) use a data-driven identi-

[1] Moreover, a tightening of monetary policy is also found to lead to an initial increase of inflation and output. Due to the counterintuitive response of output and inflation to the shock, the authors admit that labeling the shock as a monetary policy shock in a conventional sense may be misleading.

[2] Note that different approaches require slightly different non-Gaussianity and independence assumptions.

fication approach imposing non-Gaussian and independent shocks to estimate the interdependence of monetary policy and the stock market. The authors find that an unexpected tightening of monetary policy has an immediate negative impact on financial conditions. However, they are unable to label a stock market shock. Therefore, it again remains unclear how stock market shocks influence monetary policy. More recently, Herwartz et al. (2022) revisit the interaction of monetary policy and asset prices assuming non-Gaussian and independent shocks. They find that contractionary monetary policy shocks negatively affect stock prices and positive stock market shocks lead to higher interest rates.

Finally, event-study approaches relying on high-frequency data around monetary policy announcements can be used to identify monetary policy shocks. Jarocinski and Karadi (2020) use sign restrictions to disentangle the effects of traditional monetary policy shocks and central bank information shocks on intraday interest rates and stock market data. Specifically, they assume that traditional monetary policy shocks move intraday interest rates and stock returns in opposite directions, while central bank information shocks move both intraday variables in the same direction, allowing them to identify both shocks. By analyzing high-frequency data at FOMC announcements, they can classify the information shock driving stock returns as a central bank information shock. Furthermore, they investigate the impact of both shocks on lower frequency data and find that central bank information shocks are associated with an increase in real economic activity and a higher price level. It's worth noting that the central bank information shock that leads to an increase in intraday stock returns and interest rates is a consequence of the identifying restriction that this shock exists. Recently, Lewis (2023) and Jarocinski (2021) have identified high-frequency information shocks using asset price data without imposing sign restrictions on the interaction. Lewis (2023) combines principal component analysis and identification based on heteroskedastic shocks to estimate announcement-specific effects of different monetary policy shocks at monetary policy announcements and finds positive effects of central bank information shocks on future economic activity. Jarocinski (2021) identifies four different monetary policy shocks using asset prices at monetary policy announcements, assuming independent and heavy-tailed shocks. The results suggest that only traditional monetary policy shocks affect intraday short-term rates, while information shocks only move stock returns and long-run rates in the same direction.

3. Block-recursive SVAR estimation

The estimator proposed in this section blends the traditional restriction based approach with the more recent data-driven approach based on non-Gaussianity. Our estimator allows the researcher to rely on recursiveness restrictions if possible and to be agnostic concerning the interaction of the variables and relying on data-driven estimates when necessary. In particular, we show that identification of the block-recursive SVAR is ensured by sufficiently non-Gaussian and mutually independent shocks within blocks. By exploiting the block-recursive structure, our estimator (i) improves the finite sample performance, (ii) relaxes the non-Gaussianity and independence assumptions, and (iii) reduces the burden of labeling the shocks, in comparison to an unrestricted estimator solely based on non-Gaussian and independent shocks.

3.1. Derivation of the estimator

In the block-recursive SVAR the structural shocks are ordered in blocks of consecutive shocks and each structural shock can simultaneously affect all variables in the same block and in blocks ordered below but not variables in blocks ordered above.[3] Fig. 1 shows different block-recursive structures in an SVAR with four variables. The examples show that a block-recursive structure generalizes the unrestricted SVAR and the fully-recursive SVAR and includes both as extreme cases.

We use the following notation for the block-recursive SVAR. Suppose that the structural shocks can be ordered into blocks of consecutive shocks with $1 \leqslant m \leqslant n$. Let the indices $p_1 = 1 < p_2 < \ldots < p_m \leqslant n$ denote the beginning of a new block and for ease of notation let $p_{m+1} := n + 1$. Moreover, let $\tilde{\varepsilon}_{p_i,t} := [\varepsilon_{p_i,t}, \varepsilon_{p_i+1,t}, \ldots, \varepsilon_{p_{i+1}-1,t}]'$ and $\tilde{u}_{p_i,t} := [u_{p_i,t}, u_{p_i+1,t}, \ldots, u_{p_{i+1}-1,t}]'$ denote the vectors of consecutive structural and reduced form shocks in the i-th block and let $\#p_i$ denote the number of shocks in the i-th block. Therefore, the vector of structural shocks ε_t can be decomposed into the m blocks of consecutive shocks $\varepsilon_t = [\tilde{\varepsilon}'_{p_1,t}, \ldots, \tilde{\varepsilon}'_{p_m,t}]'$ and the reduced form shocks can be decomposed analogously into $u_t = [\tilde{u}'_{p_1,t}, \ldots, \tilde{u}'_{p_m,t}]'$. The SVAR is block-recursive, if shocks in the i-th block have no simultaneous impact on reduced form shocks in blocks j with $j < i$ such that the SVAR can be written as

$$\begin{bmatrix} \tilde{u}_{p_1,t} \\ \tilde{u}_{p_2,t} \\ \vdots \\ \tilde{u}_{p_m,t} \end{bmatrix} = \begin{bmatrix} \tilde{B}_{11,0} & 0 & \cdots & 0 \\ \tilde{B}_{21,0} & \tilde{B}_{22,0} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ \tilde{B}_{m1,0} & \cdots & \tilde{B}_{m(m-1),0} & \tilde{B}_{mm,0} \end{bmatrix} \begin{bmatrix} \tilde{\varepsilon}_{p_1,t} \\ \tilde{\varepsilon}_{p_2,t} \\ \vdots \\ \tilde{\varepsilon}_{p_m,t} \end{bmatrix}, \tag{8}$$

[3] Zha (1999) derives identifying restrictions for the block-recursive SVAR. The author restricts not only the simultaneous interaction, but also the lagged interaction. Our proposed block-recursive structure affects only the simultaneous interaction, while the lagged interaction remains unrestricted.

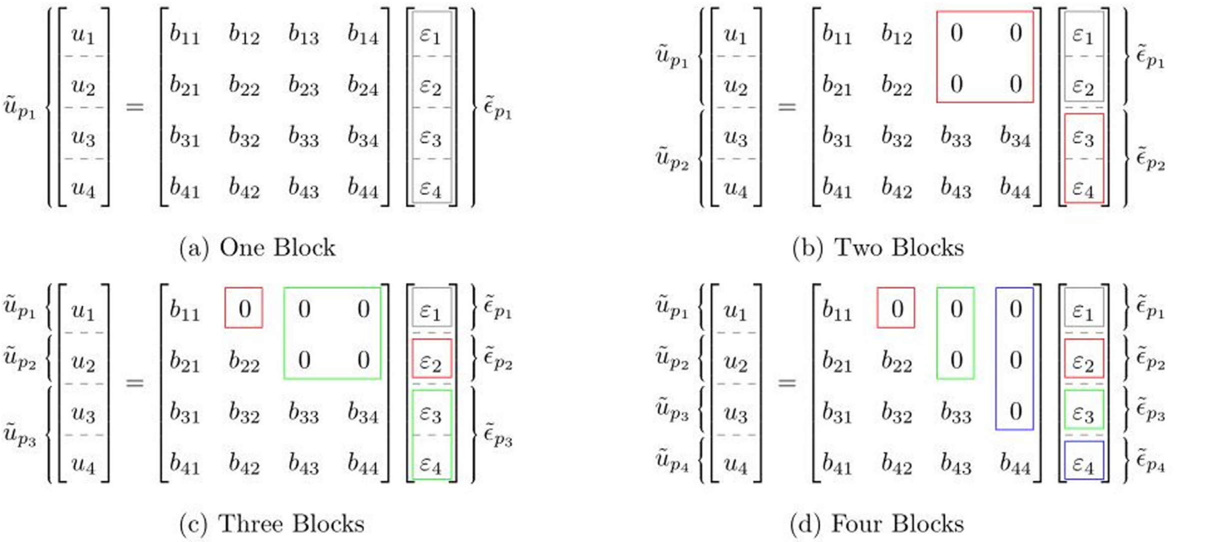

Fig. 1. Examples of different block-recursive SVAR Models. *Note:* The figure illustrates how the block structure can be defined by the structural shocks and our definition of $\tilde{\varepsilon}_{p_i}$ and $\tilde{u}_{p_i}, i = 1, \ldots, m$, where we omit the time index for simplicity.

where $\widetilde{B}_{ji,0}$ is equal to the impact of shocks in the i-th block on reduced form shocks in the j-th block. Moreover, let the set $\mathbb{B}_{brec}(p_1, \ldots, p_m)$contain all invertible B matrices which satisfy the block-recursive structure for the block indices $p_1, \ldots, p_m$.

Intuitively, identification of the block-recursive SVAR consists of two steps. First, we use the assumption of uncorrelated shocks to identify the shocks in each block up to a rotation. Second, we assume that the shocks in a given block are sufficiently non-Gaussian and independent which allows to identify the correct rotation in each block using higher-order moment conditions. For simplicity, consider an SVAR model with four variables and two blocks

$$\begin{bmatrix} u_{1,t} \\ u_{2,t} \\ u_{3,t} \\ u_{4,t} \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 \\ b_{31} & b_{32} & b_{33} & b_{34} \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ \varepsilon_{4,t} \end{bmatrix}. \tag{9}$$

The first block can be written as

$$\begin{bmatrix} u_{1,t} \\ u_{2,t} \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}, \tag{10}$$

the sub-SVAR in the first two shocks which can be estimated with sufficiently non-Gaussian and independent shocks in the first block. The second block can be written as

$$\begin{bmatrix} u_{3,t} \\ u_{4,t} \end{bmatrix} = \begin{bmatrix} b_{31} & b_{32} \\ b_{41} & b_{42} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} + \begin{bmatrix} v_{3,t} \\ v_{4,t} \end{bmatrix} \quad \text{with} \quad \begin{bmatrix} v_{3,t} \\ v_{4,t} \end{bmatrix} = \begin{bmatrix} b_{33} & b_{34} \\ b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_{3,t} \\ \varepsilon_{4,t} \end{bmatrix}. \tag{11}$$

Using the estimated structural shocks $\hat{\varepsilon}_{1,t}$ and $\hat{\varepsilon}_{2,t}$ from Eq. (10) allows to estimate the lower-left block of B_0 in Eq. (11) by OLS. The adjusted reduced form shocks $[v_{3,t}, v_{4,t}]'$ are equal to the second sub-SVAR in the two shocks of the second block which can be estimated based on sufficiently non-Gaussian and independent shocks in the second block.

More generally, assuming uncorrelated shocks in the block-recursive SVAR identifies the shocks in each block up to a rotation. Therefore, we use the standard assumption of mutually uncorrelated structural shocks.

Assumption 1. The components of ε_t are mutually uncorrelated.

The following proposition shows that any B matrix satisfying the block-recursive order which yields uncorrelated innovations with unit variance identifies the shocks in each block up to a rotation.

Proposition 1. Let $u_t = B_0 \varepsilon_t$ with $B_0 \in \mathbb{B}_{brec}(p_1, \ldots, p_m)$ and ε_t satisfies Assumption 1. Let $E[f_{\mathbf{2}}(B, u_t)] = 0$ be the corresponding vector of (co-) variance moment conditions from Eq. (4) and (5). If $B \in \mathbb{B}_{brec}(p_1, \ldots, p_m)$ satisfies

$$E[f_{\mathbf{2}}(B, u_t)] = 0, \tag{12}$$

it follows that for each block $i = 1, \dots, m$ there exists a $\#p_i$ dimensional orthogonal matrix Q_i such that $\widetilde{B}_{ji} = \widetilde{B}_{ji,0} Q_i$ for $j = i, \dots, m$ and that the innovations in the i-th block are equal to a combination of the structural shocks in the i-th block, i.e. $\tilde{e}_{it}(B) = Q_i \tilde{\varepsilon}_{it}$.

Proof. The proof can be found in the appendix.

The correct rotation of the shocks in each block can then be estimated based on independent and non-Gaussian shocks in each block.

Assumption 2. The structural shocks in each block $\tilde{\varepsilon}_{p_i t}$ for $i = 1, \dots, m$ satisfy all coskewness and cokurtosis conditions implied by mutually independent shocks in the corresponding block, i.e. if $\varepsilon_{i_1 t}$ and $\varepsilon_{i_2 t}$ are contained in the same block $\tilde{\varepsilon}_{p_i t}$, then $\varepsilon_{i_1 t}$ and $\varepsilon_{i_2 t}$ satisfy all coskewness and cokurtosis conditions implied mutually independent shocks.

Assumption 2 implies coskewness and cokurtosis conditions for shocks in the same block. In particular, let $E[f_{\mathbf{3}\&\mathbf{4}_i}(B, u_t)] = 0$ denote the vector of coskewness and cokurtosis conditions from Eq. (6) and (7) only including shocks in the i-th block. For example, in the block-recursive system in Eq. (9) the coskewness and cokurtosis conditions of the first block $E[f_{\mathbf{3}\&\mathbf{4}_1}(B, u_t)] = 0$ are equal to

$$\begin{matrix} E[e(B)_{1t}^2 e(B)_{2t}] = 0 \\ E[e(B)_{1t} e(B)_{2t}^2] = 0 \end{matrix} \quad \text{and} \quad \begin{matrix} E[e(B)_{1t}^3 e(B)_{2t}] = 0 \\ E[e(B)_{1t}^2 e(B)_{2t}^2] - 1 = 0 \\ E[e(B)_{1t} e(B)_{2t}^3] = 0 \end{matrix} \tag{13}$$

and the coskewness and cokurtosis conditions of the second block $E[f_{\mathbf{3}\&\mathbf{4}_2}(B, u_t)] = 0$ are equal to

$$\begin{bmatrix} E[e(B)_{3t}^2 e(B)_{4t}] = 0 \\ E[e(B)_{3t} e(B)_{4t}^2] = 0 \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} E[e(B)_{3t}^3 e(B)_{4t}] = 0 \\ E[e(B)_{3t}^2 e(B)_{4t}^2] - 1 = 0 \\ E[e(B)_{3t} e(B)_{4t}^3] = 0 \end{bmatrix}. \tag{14}$$

The following proposition shows that combining mutually uncorrelated shocks with mutually independent shocks within blocks identifies the block-recursive SVAR up to sign and permutations of the shocks within blocks.[4]

Proposition 2. Let $u_t = B_0 \varepsilon_t$ with $B_0 \in \mathbb{B}_{brec}(p_1, \dots, p_m)$. Moreover, let ε_t satisfy Assumption 1 and 2. If at most one component of the shocks in each block has zero skewness and zero excess kurtosis and $B \in \mathbb{B}_{brec}(p_1, \dots, p_m)$ satisfies

$$E\begin{bmatrix} f_{\mathbf{2}}(B, u_t) \\ f_{\mathbf{3}\&\mathbf{4}_1}(B, u_t) \\ \vdots \\ f_{\mathbf{3}\&\mathbf{4}_m}(B, u_t) \end{bmatrix} = 0, \tag{15}$$

it follows that for each block $i = 1, \dots, m$ there exists a $\#p_i$ dimensional sign-permutation matrix P_i such that $\widetilde{B}_{ji} = \widetilde{B}_{ji,0} P_i$ for $j = i, \dots, m$ and that the innovations in the i-th block are equal to a sign-permutation of the structural shocks in the i-th block, i.e. $\tilde{e}_{it}(B) = P_i \tilde{\varepsilon}_{it}$. Therefore, it follows that $B = B_0 P$ for a block diagonal sign-permutation matrix $P = diag(P_1, \dots, P_m)$.

Proof. Proposition 1 ensures that $\widetilde{B}_{ji} = \widetilde{B}_{ji,0} Q_i$ and $\tilde{e}_{it}(B) = Q_i \tilde{\varepsilon}_{it}$ with a $\#p_i$ dimensional orthogonal matrix Q_i for $i = 1, \dots, m$. Therefore, each block can be seen as a separate sub-SVAR with $\#p_i$ shocks. Imposing the coskewness and cokurtosis conditions $E[f_{\mathbf{3}\&\mathbf{4}_i}(B, u_t)] = 0$ identifies each sub-SVAR up to sign and permutation, compare Keweloh (2021b).

Utilizing the block-recursive structure offers several advantages over an unrestricted estimator solely based on non-Gaussianity and independence assumptions. First, by exploiting the block-recursive order, we can relax the assumptions on non-Gaussianity and independence of the shocks, compared to an unrestricted approach. shocks in different blocks do not require higher-order dependency assumptions, and Proposition 2 allows for multiple Gaussian shocks, as long as each block contains at most one. Second, a data-driven identification scheme based only on non-Gaussian and independent shocks identifies shocks up to labeling. Thus, the researcher has to decide which impulse response belongs to which shock, which can become increasingly challenging as the number of identified shocks increases. Proposition 2 identifies shocks up to permutations within blocks. Therefore, imposing a finer block-recursive structure simplifies the labeling task.

[4] In many applications, the researcher is only interested in the effect of the shocks in a specific block of interest. For this case, we derive a partial identification result under weaker assumptions in the appendix.

The block-recursive SVAR-GMM estimator is given by

$$\widehat{B} := \underset{B \in \mathbb{B}_{brec}}{\operatorname{argmin}} \begin{bmatrix} g_{\mathbf{2}}(B) \\ g_{\mathbf{3\&4}_1}(B) \\ \vdots \\ g_{\mathbf{3\&4}_m}(B) \end{bmatrix}' W \begin{bmatrix} g_{\mathbf{2}}(B) \\ g_{\mathbf{3\&4}_1}(B) \\ \vdots \\ g_{\mathbf{3\&4}_m}(B) \end{bmatrix}, \tag{16}$$

with and $g_{\mathbf{2}}(B) := 1/T\sum_{t=1}^{T} f_{\mathbf{2}}(B, u_t), g_{\mathbf{3\&4}_i}(B) := 1/T\sum_{t=1}^{T} f_{\mathbf{3\&4}_i}(B, u_t)$ for blocks $i = 1, \ldots, m$, and a suitable weighting matrix W. With the identification result from Proposition 2, consistency, asymptotic normality, and the asymptotically efficient weighting matrix of the block-recursive SVAR-GMM estimator follow from standard assumptions, see Hall (2005).

The block-recursive SVAR GMM estimator covers two extreme cases. First, when no restrictions are imposed, the estimator becomes unrestricted and all shocks are identified based on the coskewness and cokurtosis conditions implied by Assumption 2. This is similar to the SVAR-GMM estimator proposed by Keweloh (2021b). Second, if the SVAR is restricted to be fully recursive, Assumption 2 imposes no coskewness and cokurtosis conditions, and the estimator simplifies to the commonly used estimator obtained by applying the Cholesky decomposition to the variance–covariance matrix of the reduced form shocks.

3.2. Finite sample performance

In the following Monte Carlo study, we show that the performance of data-driven SVAR estimators can be substantially improved by exploiting the block-recursive structure, particularly in small samples. Specifically, we show that using available information on the block-recursive structure reduces the small sample bias and mean squared error (MSE) of the estimated simultaneous interaction in the SVAR. Moreover, we demonstrate how the combination of the block-recursive structure and information contained in higher moments can be used to test the exogeneity of proxy variables in small samples.

We simulate an SVAR with four variables and

$$\begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ u_{4t} \end{bmatrix} = \begin{bmatrix} 10 & 0 & 0 & 0 \\ 5 & 10 & 0 & 0 \\ 5 & 5 & 10 & 5 \\ 5 & 5 & 5 & 10 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix}, \tag{17}$$

where the structural shocks $\varepsilon_{it}, i = 1, \ldots, 4, t = 1, \ldots, T$, are drawn independently and identically from the two-component mixture

$$\varepsilon_{i,t} \sim 0.79\ \mathcal{N}(-0.2, 0.7^2) + 0.21\ \mathcal{N}(0.75, 1.5^2),$$

and $\mathcal{N}(\mu, \sigma^2)$ indicates a normal distribution with mean μ and standard deviation σ. The shocks have skewness 0.9 and excess kurtosis 2.4.

We estimate the system using the block-recursive SVAR-GMM estimator from Eq. (16), applying two different sets of restrictions. The first estimator involves no restrictions, meaning all shocks are contained in a single non-recursive block. The second estimator exploits the block-recursive structure by applying the following restrictions, where the last two shocks have no simultaneous impact on the first two variables:

$$B = \begin{bmatrix} . & . & 0 & 0 \\ . & . & 0 & 0 \\ . & . & . & . \\ . & . & . & . \end{bmatrix}, \tag{18}$$

We continuously update the weighting matrix and use the assumption of serially and mutually independent shocks to estimate the asymptotically optimal weighting matrix and the asymptotic variance, as proposed in Keweloh (2021a). Note that the SVAR is only identified up to sign and permutation of the shocks in each block, and we choose the sign permutation of a given estimator $\widehat{B}$ based on a Wald test with $H_0 : \widehat{B}P = B_0$ for each suitable sign permutation matrix P and the true simultaneous impact matrix B_0 from Eq. (17).

Table 1 shows the average and MSE of each estimated element, illustrating how exploiting the block-recursive structure leads to improved performance in terms of bias and MSE for all estimated elements. Particularly, the performance gain is most notable for elements in the lower-left block, which correspond to the response of variables in the second block to shocks in the first block. By exploiting the block-recursive structure, these elements can be identified without relying on higher-order moment conditions, which explains the performance boost. In the smallest sample, the MSE for these elements decreases by over 50% compared to the unrestricted estimator. For the remaining sample sizes, the MSE also decreases substantially.

Table 1
Finite sample performance - Average and MSE of all estimated elements.

T	SVAR-GMM	block-recursive SVAR-GMM
100	$\begin{bmatrix} \underset{(2.28)}{9.17} & \underset{(3.58)}{-0.08} & \underset{(3.85)}{0.01} & \underset{(3.77)}{-0.06} \\ \underset{(3.97)}{4.7} & \underset{(3.06)}{9.15} & \underset{(4.67)}{-0.02} & \underset{(4.73)}{-0.08} \\ \underset{(6.35)}{4.61} & \underset{(5.98)}{4.53} & \underset{(4.81)}{9.2} & \underset{(7.56)}{4.33} \\ \underset{(6.33)}{4.66} & \underset{(5.8)}{4.55} & \underset{(6.44)}{4.74} & \underset{(5.69)}{8.97} \end{bmatrix}$	$\begin{bmatrix} \underset{(1.33)}{9.65} & \underset{(3.72)}{-0.04} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(3.93)}{4.93} & \underset{(2.03)}{9.63} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(2.36)}{4.84} & \underset{(2.49)}{4.8} & \underset{(2.35)}{9.57} & \underset{(4.89)}{4.6} \\ \underset{(2.38)}{4.84} & \underset{(2.55)}{4.79} & \underset{(4.53)}{4.93} & \underset{(2.59)}{9.42} \end{bmatrix}$
250	$\begin{bmatrix} \underset{(0.66)}{9.66} & \underset{(1.56)}{0.01} & \underset{(1.55)}{0.03} & \underset{(1.56)}{-0.02} \\ \underset{(1.63)}{4.81} & \underset{(1.03)}{9.64} & \underset{(2.22)}{0.06} & \underset{(2.0)}{-0.04} \\ \underset{(2.72)}{4.79} & \underset{(2.72)}{4.8} & \underset{(1.73)}{9.7} & \underset{(2.78)}{4.77} \\ \underset{(2.55)}{4.84} & \underset{(2.54)}{4.82} & \underset{(2.62)}{4.9} & \underset{(1.91)}{9.62} \end{bmatrix}$	$\begin{bmatrix} \underset{(0.47)}{9.87} & \underset{(1.36)}{0.03} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(1.45)}{4.92} & \underset{(0.71)}{9.86} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.95)}{4.92} & \underset{(0.94)}{4.96} & \underset{(0.79)}{9.84} & \underset{(1.7)}{4.89} \\ \underset{(0.93)}{4.94} & \underset{(0.93)}{4.94} & \underset{(1.59)}{4.96} & \underset{(0.88)}{9.82} \end{bmatrix}$
500	$\begin{bmatrix} \underset{(0.25)}{9.86} & \underset{(0.66)}{-0.01} & \underset{(0.65)}{0.05} & \underset{(0.65)}{-0.01} \\ \underset{(0.68)}{4.94} & \underset{(0.38)}{9.85} & \underset{(0.83)}{0.01} & \underset{(0.86)}{0.01} \\ \underset{(1.12)}{4.9} & \underset{(1.03)}{4.9} & \underset{(0.65)}{9.9} & \underset{(1.12)}{4.94} \\ \underset{(1.12)}{4.94} & \underset{(1.03)}{4.89} & \underset{(1.08)}{4.96} & \underset{(0.76)}{9.85} \end{bmatrix}$	$\begin{bmatrix} \underset{(0.22)}{9.94} & \underset{(0.65)}{-0.0} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.66)}{4.98} & \underset{(0.34)}{9.93} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.45)}{4.98} & \underset{(0.46)}{4.94} & \underset{(0.32)}{9.94} & \underset{(0.63)}{4.98} \\ \underset{(0.46)}{4.99} & \underset{(0.46)}{4.95} & \underset{(0.65)}{4.97} & \underset{(0.34)}{9.92} \end{bmatrix}$
1000	$\begin{bmatrix} \underset{(0.11)}{9.95} & \underset{(0.29)}{0.01} & \underset{(0.27)}{-0.01} & \underset{(0.29)}{0.02} \\ \underset{(0.31)}{4.97} & \underset{(0.17)}{9.94} & \underset{(0.37)}{0.0} & \underset{(0.38)}{0.01} \\ \underset{(0.46)}{4.96} & \underset{(0.48)}{4.97} & \underset{(0.31)}{9.92} & \underset{(0.49)}{4.99} \\ \underset{(0.48)}{4.95} & \underset{(0.49)}{4.98} & \underset{(0.47)}{4.95} & \underset{(0.31)}{9.95} \end{bmatrix}$	$\begin{bmatrix} \underset{(0.11)}{9.98} & \underset{(0.29)}{0.01} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.3)}{4.99} & \underset{(0.16)}{9.98} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.22)}{4.98} & \underset{(0.22)}{5.0} & \underset{(0.16)}{9.94} & \underset{(0.3)}{5.0} \\ \underset{(0.21)}{4.98} & \underset{(0.22)}{5.01} & \underset{(0.3)}{4.97} & \underset{(0.16)}{9.97} \end{bmatrix}$
5000	$\begin{bmatrix} \underset{(0.02)}{9.99} & \underset{(0.05)}{0.0} & \underset{(0.05)}{0.0} & \underset{(0.05)}{0.0} \\ \underset{(0.05)}{5.0} & \underset{(0.03)}{9.99} & \underset{(0.07)}{0.0} & \underset{(0.07)}{0.0} \\ \underset{(0.09)}{4.99} & \underset{(0.08)}{5.0} & \underset{(0.06)}{9.98} & \underset{(0.09)}{5.0} \\ \underset{(0.08)}{4.99} & \underset{(0.08)}{5.0} & \underset{(0.09)}{4.99} & \underset{(0.06)}{9.99} \end{bmatrix}$	$\begin{bmatrix} \underset{(0.02)}{10.0} & \underset{(0.05)}{0.0} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.05)}{5.0} & \underset{(0.03)}{9.99} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.04)}{5.0} & \underset{(0.04)}{5.0} & \underset{(0.03)}{9.98} & \underset{(0.06)}{5.0} \\ \underset{(0.04)}{5.01} & \underset{(0.04)}{5.0} & \underset{(0.06)}{4.99} & \underset{(0.03)}{9.99} \end{bmatrix}$

Monte Carlo simulation with $M = 2000$ replications. The table shows the average, $1/M\sum_{m=1}^{M}\hat{b}_{ij}^{m}$, and the estimated mean squared error, $1/M\sum_{m=1}^{M}\left(\hat{b}_{ij}^{m} - b_{ij}\right)^2$, of each estimated element $\hat{b}_{ij}^{m}$ of b_{ij} denoting the element of B in row i and column j. The table reports results for the SVAR-GMM estimator without restrictions, and the block-recursive SVAR-GMM estimator which uses the block-recursive restrictions..

The appendix provides analogous results for the PML estimator proposed by Gouriéroux et al. (2017) and the fast GMM estimator proposed by Keweloh (2021b). Moreover, we include results for a VAR(1) model. The additional simulations lead to a similar conclusion; if well-justified restrictions are available, these restrictions should be used as they improve the performance of the data-driven estimator.

In a second simulation, we introduce a proxy variable z_t for the last structural shock with

$$z_t = 7.5\varepsilon_{4,t} + 10\eta_t, \tag{19}$$

where the proxy noise η_t is an independent and identically drawn proxy noise from the same two-component mixture as the structural shocks. The proxy augmented SVAR is given by

$$\begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ u_{4t} \\ z_t \end{bmatrix} = \begin{bmatrix} 10 & 0 & 0 & 0 & 0 \\ 5 & 10 & 0 & 0 & 0 \\ 5 & 5 & 10 & 5 & 0 \\ 5 & 5 & 5 & 10 & 0 \\ \beta_1 & \beta_2 & \beta_3 & \beta_4 & \sigma \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3,t} \\ \varepsilon_{4t} \\ \eta_t \end{bmatrix}, \tag{20}$$

with $\beta_1 = \beta_2 = \beta_3 = 0, \beta_4 = 7.5$, and $\sigma = 10$. With independent and non-Gaussian shocks, the proxy augmented SVAR is identified without any restrictions and the proxy exogeneity assumption $\beta_i = 0$ for $i = 1, \ldots, 3$ can be tested. The following simulation shows that using additional available information on the block-recursive structure leads to a performance increase of the tests in small samples.

We estimate the proxy augmented SVAR with the block-recursive SVAR-GMM estimator from Eq. (16) and two different sets of restrictions. The first estimator uses no restrictions and the second estimator uses the block-recursive restrictions

Table 2
Percentage of rejections at $\alpha = 10\%$ for Wald tests with $H_0 : \beta_i = 0$ in the proxy augmented SVAR with $M = 2000$ replications.

	SVAR-GMM				block-recursive SVAR-GMM			
	β_1	β_2	β_3	β_4	β_1	β_2	β_3	β_4
$T = 100$	21.62	22.43	22.95	94.14	9.43	10.81	14.33	100
$T = 250$	17.19	17.52	17.57	99.48	10.62	9.1	13.1	100
$T = 500$	15.62	14.9	16.14	100	9.1	8.95	12.24	100
$T = 1000$	13.48	12.86	12.1	100	8.95	9.43	11.62	100
$T = 5000$	11.81	9.86	10.62	100	9.62	10.48	9.29	100

$$B_0 = \begin{bmatrix} . & . & 0 & 0 & 0 \\ . & . & 0 & 0 & 0 \\ . & . & . & . & 0 \\ . & . & . & . & 0 \\ . & . & . & . & . \end{bmatrix}, \tag{21}$$

that is the estimator exploits that the last two shocks have no simultaneous impact on the first two variables and the proxy noise has no impact on all variables except for the proxy variable.

Table 2 reports the rejection rates at the 10% level for the Wald tests with $H_0 : \beta_i = 0$ testing the null hypothesis that the proxy is exogenous w.r.t. ε_{it} for $i = 1, \ldots, 4$. The results demonstrate the advantages of incorporating available information on the block-recursive structure of the system. In particular, the unrestricted estimator rejects the null hypothesis $H_0 : \beta_i = 0$ for $i = 1, \ldots, 3$ far too often in small samples. The rejection rates only approach the 10% level in large samples of 5000 observations. In contrast, the estimator using the block-recursive restrictions performs substantially better, with rejection rates close to the 10% level even in the smallest sample.

4. The interdependence of U.S. monetary policy and the stock market

In this section, we apply the block-recursive SVAR-GMM estimator to disentangle the effects of monetary policy and stock market information shocks in a low-frequency SVAR. Additionally, we utilize high-frequency data from FOMC announcements to identify intraday traditional monetary policy shocks and central bank information shocks, which we subsequently use to construct low-frequency monetary policy proxies to show that central bank information is a relevant driver of the low-frequency stock market information shock.

4.1. Block-recursive SVAR

We consider an SVAR similar to the system analyzed in Jarocinski and Karadi (2020). The SVAR contains monthly U.S. data from February 1984 to December 2016 with

$$\begin{bmatrix} y_t \\ \pi_t \\ s_t \\ i_t \end{bmatrix} = \alpha + \sum_{i=1}^{12} A_i \begin{bmatrix} y_{t-i} \\ p_{t-i} \\ s_{t-i} \\ i_{t-i} \end{bmatrix} + \begin{bmatrix} u_t^y \\ u_t^p \\ u_t^s \\ u_t^i \end{bmatrix} \quad \text{with} \quad \begin{bmatrix} u_t^y \\ u_t^p \\ u_t^s \\ u_t^i \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} \\ b_{51} & b_{52} & b_{53} & b_{54} \end{bmatrix} \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^\pi \\ \varepsilon_t^{info} \\ \varepsilon_t^{mp} \end{bmatrix}, \tag{22}$$

where y_t denotes real economic activity, measured by log real GDP, p_t is the log GDP deflator and measures the price level, s_t is the monthly average of the S&P 500 in log levels, and i_t is the monthly average one-year constant-maturity Treasury yield.[5] We aim to identify the effects of the monetary policy shock ε_t^{mp} and a stock market information shock ε_t^{info}. We assume that real economic activity and the price level behave sluggishly, meaning they cannot react to monetary policy and information shocks within the same month. These restrictions can be justified by price rigidities and adjustment costs as oftentimes used in standard DSGE models, see for example Smets and Wouters (2007). However, interest rates and stock prices are unrestricted and can contemporaneously respond to all shocks.

The SVAR is estimated by the block-recursive SVAR-GMM estimator with the restrictions imposed in Eq. (22). In line with our Monte Carlo simulations, we update the weighting matrix continuously and use the assumption of serially and mutually independent shocks to estimate the asymptotically optimal weighting matrix and the asymptotic variance throughout the section.

[5] We use the data set from Jarocinski and Karadi (2020) where real GDP and the GDP deflator are interpolated to monthly frequency. Moreover, Jarocinski and Karadi (2020) additionally include the excess bond premium and we report results for the specification with the excess bond premium in the online appendix.

Table 3
Non-Gaussianity of the estimated shocks.

	ε_t^y	ε_t^π	ε_t^{info}	ε_t^{mp}
Skewness	0.018	0.236	−0.892	−0.076
Kurtosis	3.479	4.92	6.566	3.366
Jarque–Bera Test (p-value)	0.158	0	0	0.284

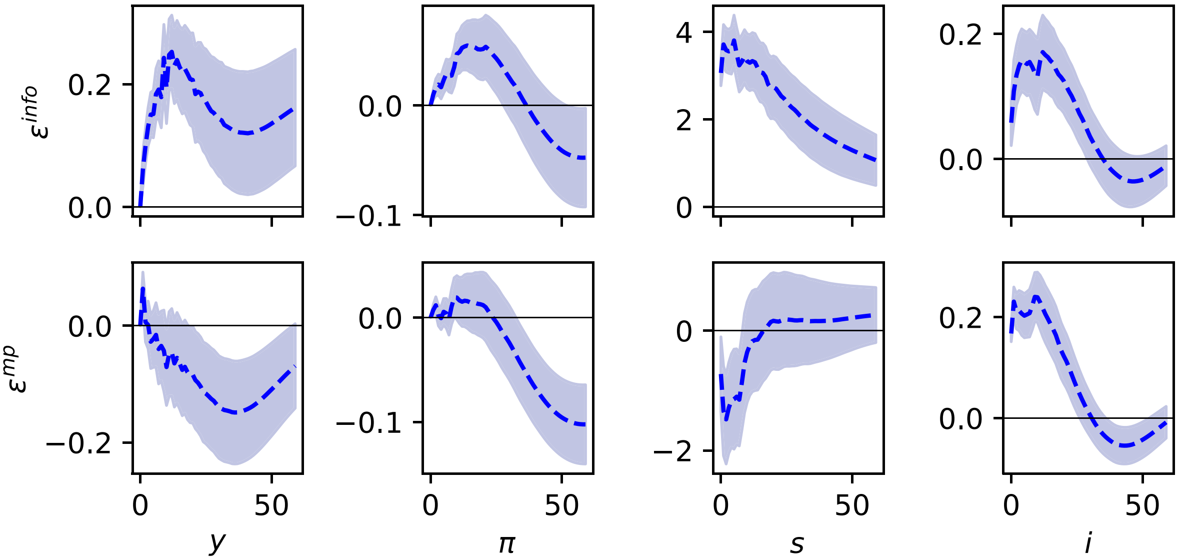

Fig. 2. Impulse responses. The figure shows the responses to one standard deviation shocks in the block-recursive SVAR. Confidence bands are symmetrical 68% bootstrap bands with 1000 replications in the bootstrap algorithm.

Table 3 presents the skewness, kurtosis, and p-value of the Jarque–Bera test for the estimated shocks. Proposition 1 guarantees that the estimated shocks in the second block are a mixture of the information and monetary policy shock, even if both shocks were Gaussian. However, Table 3 shows that the information shock is non-Gaussian, displaying a negative skewness and heavy tails. Therefore, at most one of the structural shocks in the second block can be Gaussian, and the non-Gaussianity assumption to identify the second block is satisfied. Moreover, Table 3 indicates that the first block contains an additional Gaussian shock. This implies that relying solely on a data-driven non-Gaussian estimator, without considering the block-recursive structure, could fail to ensure full identification due to the presence of two Gaussian shocks. Hence, leveraging the block-recursive structure is crucial to ensure identification of the information and monetary policy shock.

Fig. 2 shows the corresponding impulse response functions to the estimated information and monetary policy shocks.[6] Exploiting the block-recursive order makes labeling straightforward: The shock which leads to an increase in the interest rate and a decrease in output and inflation is the monetary policy shock and the remaining shock is labeled as the information shock.

The estimated response to monetary policy shocks is similar to the response in Jarocinski and Karadi (2020). Specifically, a one standard deviation monetary policy shock increases the bond yield by around two basis points and the yield reverts back to zero in about three years. The tightening of monetary policy leads to a decline of real GDP and the price level of approximately ten basis points in the medium run. Moreover, stock prices drop immediately by about one percent. Therefore, we find that a contractionary monetary policy shock induces a slowdown in output and prices. The future contraction of the economy and an efficient stock market, which immediately incorporates all available information, then explains the initial negative response of stock prices to the monetary policy shock.

Similarly to Jarocinski and Karadi (2020), we find that output, the price level, and interest rates increase in response to the information shock. However, we observe a stronger response of stock prices to the information shock. In particular, a one standard deviation information shock leads to an immediate and significant increase of stock prices by about three percent. This result suggests that stock prices can contain information about future economic activity, which explains the response of interest rates, even if the central bank is not interested in stock prices in the first place. However, we cannot determine or label the source of the stock market information shock. Specifically, the information shock may be caused by the central bank itself, i.e., a central bank information shock similar to Jarocinski and Karadi (2020), or due to other external sources, and the central bank simply reacts to the information shock.

6 The impulse responses are robust to several robustness checks reported in the appendix. These include adding the excess bond premium as an additional variable in the second block, ending the sample in 2008, and using the industrial production index and consumer price index instead of the interpolated real GDP and GDP deflator.

4.2. Intraday central bank shocks

We now use an event-study approach to analyze the intraday effects of central bank shocks, including traditional monetary policy interest rate shocks and central bank information shocks. Using the event-study approach allows us to determine the source of the information shock as a central bank information shock. We find that traditional monetary policy shocks move intraday interest rates and stock prices into opposite directions, while central bank information shocks move intraday stock prices and long-run interest rates into the same direction. Additionally, we connect the intraday event-study with the low-frequency SVAR from the previous section. Our results indicate that high-frequency central bank information shocks are exogenous with respect to all low-frequency shocks except for the stock market information shock. This suggests that the intraday analysis can identify exogenous central bank shocks and that central bank information shocks are not exogenous but relevant for the low-frequency stock market information shock.

Jarocinski and Karadi (2020) use intraday stock market and short-run interest rate data in a 30-min window around FOMC announcements to identify traditional monetary policy interest rate shocks and central bank information shocks. The shocks are identified using sign restrictions, imposing that the high-frequency stock market and interest rate movements are driven by two uncorrelated structural shocks, a traditional monetary policy shock which moves stock prices and interest rates into opposite directions and a central bank information shock which moves both variables into the same direction.

We employ a similar event-study methodology to examine the intraday effects of central bank shocks on stock prices and interest rates during FOMC announcements from 1994 to 2016. Similar to Jarocinski (2021), we add an additional long-term rate to the intraday system used by Jarocinski and Karadi (2020). Specifically, we estimate an intraday SVAR without lags in $y_t = [i_t^{(3M)}, i_t^{(2Y)}, s_t]'$, where $i_t^{(3M)}$ denotes the surprise in the three-month fed funds futures contract multiplied by 100, $i_t^{(2Y)}$ is the change in the two-year Treasury yield multiplied by 100, and s_t measures the surprise in the S&P 500 index change multiplied by 100.[7] We assume that intraday movements in y_t during FOMC announcements are driven by central bank shocks, which is the typical event-study assumption, and allows us to determine the source of a stock market information shock as a central bank information shock. Furthermore, we use the identifying assumption that there are three intraday central bank shocks that are independent and sufficiently non-Gaussian, which replaces the assumption of two uncorrelated central bank shocks identified using sign restrictions in Jarocinski and Karadi (2020).

We estimate the intraday SVAR using the unrestricted block-recursive SVAR-GMM estimator and find that all estimated shocks are non-Gaussian. The appendix provides more details on the non-Gaussianity of the estimated shocks. Table 4 displays the estimated intraday response of y_t to three structural shocks. The first shock is a traditional monetary policy shock, denoted by ϵ_t^{mp}. It causes short- and long-term interest rates to move in the same direction and stock prices to move in the opposite direction. This shock is the only one that significantly affects short-term interest rates. The second shock is a forward guidance shock, denoted by ϵ_t^{fg}. A positive forward guidance shock indicates a future tightening of monetary policy, which negatively affects stock prices and thus long-term interest rates and stock prices to move in opposite directions in response to the forward guidance shock. The third shock is a central bank information shock, denoted by ϵ_t^{CBinfo}. It causes stock prices and long-term interest rates to move in the same direction. A positive central bank information shock indicates that the central bank has revealed positive information on future economic activity, which implies that the central bank will respond with higher interest rates in the future, leading to an immediate increase in long-term rates.

Our results on the intraday effects of the traditional monetary policy shock are consistent with previous studies by Jarocinski and Karadi (2020) and Jarocinski (2021). Specifically, we find that a one standard deviation traditional monetary policy shock leads to a five basis points increase in three-month fed funds futures and a decline of approximately 21 basis points in the S&P 500 index in the 30-min window. Moreover, our forward guidance shock has a similar impact on short-term rates, long-term rates, and stock prices as the odyssean forward guidance shock in Jarocinski (2021). We find that a one standard deviation forward guidance shock leads to an increase of four basis points in the two-year rate and a decline of approximately 36 basis points in the stock index. Furthermore, in contrast to the central bank information shock in Jarocinski and Karadi (2020), but in line with the forward guidance information shock in Jarocinski (2021), we find that the central bank information shock is associated with an increase of approximately 52 basis points in the S&P 500 index, an increase of around 1 basis point in the two-year rate, but it has no significant impact on the short-term rate.

The event-study approach enables the identification of high-frequency central bank information shocks, which can be used to investigate the source of the more general stock market information shock in the low-frequency SVAR estimated in the previous section. To achieve this, we first construct a central bank information proxy, z_t^{CBinfo}, which is equal to the aggregated intraday central bank information shocks in a given month. We then estimate the low-frequency monthly SVAR model from the previous section augmented by the central bank information proxy. The simultaneous interaction of the model takes the form:

[7] The intraday data are obtained from Gürkaynak et al. (2022), and all changes are calculated from 10 minutes before to 20 minutes after the announcement.

Table 4
Response in intraday SVAR with 68% bootstrap bands.

		Shock: ϵ_t^{mp}	Shock: ϵ_t^{fg}	Shock: ϵ_t^{CBinfo}
Response:	$i_t^{(3M)}$	5.00 (4.1/5.46)	0.84 (−0.26/0.96)	−0.79 (−1.22/0.44)
Response:	$i_t^{(2Y)}$	3.75 (3.21/4.48)	4.27 (2.7/4.6)	1.06 (0.55/2.35)
Response:	s_t	−21.11 (−33.66/−16.94)	−36.65 (−40.64/−27.32)	52.19 (35.51/58.0)

The table shows the responses to one standard deviation shocks in the intraday SVAR. Confidence bands are symmetrical 68% bootstrap bands with 1000 replications in the bootstrap algorithm.

Table 5
Monthly SVAR proxy validity.

	β_1	β_2	β_3	β_4
Estimator $\hat{\beta}_i$	0.00	0.05	0.12	−0.04
Wald test statistic $H_0 : \beta_i = 0$	0.0	2.32	12.32	1.42
Wald test p-value	0.95	0.13	0.0	0.23

$$\begin{bmatrix} u_t^y \\ u_t^p \\ u_t^s \\ u_t^i \\ z_t^{CBinfo} \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} & 0 \\ b_{51} & b_{52} & b_{53} & b_{54} & 0 \\ \beta_1 & \beta_2 & \beta_3 & \beta_4 & \sigma_z \end{bmatrix} \begin{bmatrix} \varepsilon_t^y \\ \varepsilon_t^\pi \\ \varepsilon_t^{info} \\ \varepsilon_t^{mp} \\ \eta_t \end{bmatrix}. \tag{23}$$

If the intraday analysis can successfully identify exogenous central bank information shocks, then the central bank information proxy should be exogenous to all shocks in the low-frequency SVAR, except for the stock market information shock. Furthermore, if the low-frequency stock market information shock is not influenced by central bank information shocks but instead driven by other external sources, then the central bank information proxy should also be exogenous to the low-frequency stock market information shock.

Table 5 shows the estimated β coefficients that allow us to test the exogeneity of the central bank information proxy. We find that β_1, β_2, and β_4 are not significantly different from zero at the 10% level, indicating that the central bank information shocks derived from the event-study are exogenous. In addition, we find that β_3 is positive and significantly different from zero at any conventional level, suggesting that the central bank information shocks are not exogenous but are statistically relevant for the stock market information shock.

5. Conclusion

This paper proposes a hybrid approach to identify the impact of monetary policy and stock market information shocks using the block-recursive SVAR-GMM estimator. The estimator combines traditional identification methods based on restrictions with data-driven identification techniques based on non-Gaussianity and independence. The approach allows for a more accurate estimation of the SVAR, reducing small sample bias and the mean squared error of estimated simultaneous interactions. Our analysis reveals that a contractionary monetary policy shock results in a slowdown in output and prices, accompanied by a drop in stock prices. In contrast, a stock market information shock triggers an increase in output and inflation, along with an immediate increase in stock prices and interest rates. Furthermore, we use high-frequency data to show central bank information is a statistically relevant driver of the stock market information shock. Our results demonstrate the potential of a hybrid approach to identify information shocks, utilizing both traditional and data-driven identification approaches.

Data availability

Data will be made available on request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Proofs

Proof (*Proof of Proposition 1*). For ease of notation, we omit the time index t and w.l.o.g., consider an only two blocks[8]

$$\begin{bmatrix}\tilde{u}_{p_1}\\ \tilde{u}_{p_2}\end{bmatrix} = \begin{bmatrix}\widetilde{B}_{11,0} & 0\\ \widetilde{B}_{21,0} & \widetilde{B}_{22,0}\end{bmatrix}\begin{bmatrix}\tilde{\varepsilon}_{p_1}\\ \tilde{\varepsilon}_{p_2}\end{bmatrix} \quad \text{and} \quad \begin{bmatrix}\tilde{e}_{p_1}(B)\\ \tilde{e}_{p_2}(B)\end{bmatrix} = \begin{bmatrix}\widetilde{B}_{11} & 0\\ \widetilde{B}_{21} & \widetilde{B}_{22}\end{bmatrix}^{-1}\begin{bmatrix}\tilde{u}_{p_1}\\ \tilde{u}_{p_2}\end{bmatrix}.$$

where $\tilde{u}_{p_1}$ and $\tilde{u}_{p_2}$ contain the reduced form shocks of the first and second block, $\tilde{\varepsilon}_{p_1}$ and $\tilde{\varepsilon}_{p_2}$ contain the structural shocks of the first and second block, $\tilde{e}_{p_1}(B)$ and $\tilde{e}_{p_2}(B)$ contain the innovations of the first and second block corresponding to the matrix B, and $\widetilde{B}_{11,0}, \widetilde{B}_{21,0}, \widetilde{B}_{22,0}, \widetilde{B}_{11}, \widetilde{B}_{21}$, and $\widetilde{B}_{22}$are the corresponding blocks of the matrices B_0 and B.

With the block-recursive structure it holds that

$$\tilde{e}_{p_1}(B) = \widetilde{B}_{11}^{-1}\widetilde{B}_{11,0}\tilde{\varepsilon}_{p_1}, \tag{A.1}$$

meaning the innovations of the first block are equal to a linear combination of the structural shocks in the first block.

Moreover, with the block-recursive structure and the partitioned inverse it holds that

$$\tilde{e}_{p_2}(B) = -\widetilde{B}_{22}^{-1}\widetilde{B}_{21}\widetilde{B}_{11}^{-1}\widetilde{B}_{11,0}\tilde{\varepsilon}_{p_1} + \widetilde{B}_{22}^{-1}\left(\widetilde{B}_{21,0}\tilde{\varepsilon}_{p_1} + \widetilde{B}_{22,0}\tilde{\varepsilon}_{p_2}\right).$$

For any matrix B satisfying $E[f_{\mathbf{2}}(B,u_t)] = 0$ and, therefore,$0 = E\left[\tilde{e}_{p_2}(B)\tilde{e}_{p_1}(B)\prime\right]$ it holds that $0 = -\widetilde{B}_{22}^{-1}\left(\widetilde{B}_{21,0} - \widetilde{B}_{21}\widetilde{B}_{11}^{-1}\widetilde{B}_{11,0}\right)\widetilde{B}_{11,0}\prime(\widetilde{B}_{11}^{-1})\prime$and, thus,

$$\widetilde{B}_{21} = \widetilde{B}_{21,0}\widetilde{B}_{11,0}^{-1}\widetilde{B}_{11}. \tag{A.2}$$

Any B Matrix satisfying the condition $0 = E\left[\tilde{e}_{p_2}(B)\tilde{e}_{p_1}(B)\prime\right]$ thus yields innovations of the second block equal to

$$\tilde{e}_{p_2}(B) = \widetilde{B}_{22}^{-1}\widetilde{B}_{22,0}\tilde{\varepsilon}_{p_2}, \tag{A.3}$$

meaning the innovations of the second block are equal to a linear combination of the structural shocks in the second block. Eq. (A.1) implies that the innovations in the first block are equal to a combination of the structural shock in the first block. The moment condition $E[f_{\mathbf{2}}(B,u_t)] = 0$ also implies uncorrelated innovations with unit variance in the first block and therefore

$$\begin{aligned} I &= E\left[\tilde{e}_{p_1}(B)\tilde{e}_{p_1}(B)'\right] \\ &= E\left[(\widetilde{B}_{11}^{-1}\widetilde{B}_{11,0}\tilde{\varepsilon}_{p_1})(\widetilde{B}_{11}^{-1}\widetilde{B}_{11,0}\tilde{\varepsilon}_{p_1})'\right] \\ &= (\widetilde{B}_{11}^{-1}\widetilde{B}_{11,0})(\widetilde{B}_{11}^{-1}\widetilde{B}_{11,0})' \end{aligned}$$

---

[8] If the SVAR contains more than two blocks, the procedure outlined in the proof can be repeated multiple times to identify arbitrary many blocks. For example, an SVAR with three blocks

$$\begin{bmatrix}u_{p_1}\\ u_{p_2}\\ u_{p_3}\end{bmatrix} = \begin{bmatrix}B_{11,0} & 0 & 0\\ B_{21,0} & B_{22,0} & 0\\ B_{32,0} & B_{32,0} & B_{33,0}\end{bmatrix}\begin{bmatrix}\epsilon_{p_1}\\ \epsilon_{p_2}\\ \epsilon_{p_3}\end{bmatrix} \text{ can be written as } \begin{bmatrix}u_{p_1}\\ \tilde{u}_{p_2}\end{bmatrix} = \begin{bmatrix}B_{11,0} & 0\\ \widetilde{B}_{21,0} & \widetilde{B}_{22,0}\end{bmatrix}\begin{bmatrix}\epsilon_{p_1}\\ \tilde{\epsilon}_{p_2}\end{bmatrix},$$

with $\tilde{u}_{p_2} = [u_{p_2}', u_{p_3}']', \widetilde{B}_{22,0} = \begin{bmatrix}B_{22,0} & 0\\ B_{32,0} & B_{33,0}\end{bmatrix}, \widetilde{B}_{21,0} = \begin{bmatrix}B_{21,0}\\ B_{31,0}\end{bmatrix}$,and $\tilde{\epsilon}_{p_2} = [\epsilon_{p_2}', \epsilon_{p_3}']'$. Our proof then shows how to identify $B_{11,0}, \widetilde{B}_{21,0} = \begin{bmatrix}B_{21,0}\\ B_{31,0}\end{bmatrix}$, and ϵ_{p_1}. Defining

$$\begin{bmatrix}z_{p_2}\\ z_{p_3}\end{bmatrix} := \begin{bmatrix}u_{p_2}\\ u_{p_3}\end{bmatrix} - \begin{bmatrix}B_{21,0}\\ B_{31,0}\end{bmatrix}\epsilon_{p_1} \text{ then yields} \begin{bmatrix}z_{p_2}\\ z_{p_3}\end{bmatrix} = \begin{bmatrix}B_{22,0} & 0\\ B_{32,0} & B_{33,0}\end{bmatrix}\begin{bmatrix}\epsilon_{p_2}\\ \epsilon_{p_3}\end{bmatrix},$$

which is another block-recursive SVAR with two blocks.

which holds for $\widetilde{B}_{11} = \widetilde{B}_{11,0}Q_1$ with a $\#p_1$ dimensional orthogonal matrix Q_1. Therefore, it follows that $\tilde{e}_{p_1}(B) = Q_1\tilde{\varepsilon}_{p_1}$. Eq. (A.2) then implies $\widetilde{B}_{21} = \widetilde{B}_{21,0}Q_1$. Analogously, Eq. (A.3) and uncorrelated innovations with unit variance in the second block imply $\widetilde{B}_{22} = \widetilde{B}_{21,0}Q_2$ with a $\#p_2$ dimensional orthogonal matrix Q_2. Therefore, it follows that $\tilde{e}_{p_2}(B) = Q_2\tilde{\varepsilon}_{p_2}$.

Proposition 3. Let $u_t = B_0\varepsilon_t$ with $B_0 \in \mathbb{B}_{brec}(p_1, \ldots, p_m)$ and let ε_t satisfy Assumption 1. Moreover, let $\mathbb{B}_{brec}(\bar{p}_1, \ldots, \bar{p}_{\bar{m}})$ denote a potentially misspecified block-recursive structure.

Assume that there exists a block p_i in $\mathbb{B}_{brec}(p_1, \ldots, p_m)$ which contains the same shocks as block $\bar{p}_{\bar{i}}$ in $\mathbb{B}_{brec}(\bar{p}_1, \ldots, \bar{p}_{\bar{m}})$, i.e., there exits a $\bar{i}$, $1 \leqslant \bar{i} \leqslant \bar{m}$,and a i, $1 \leqslant i \leqslant m$,such that $\bar{p}_{\bar{i}} = p_i$ and $\bar{p}_{\bar{i}+1} = p_{i+1}$. Let $\widetilde{B}_{\bar{i}j,0}$ denote the impact of the shocks in block $\bar{p}_{\bar{i}}$ on variables in block $\bar{p}_j$ for $j = \bar{i}, \ldots, \bar{m}$.

Moreover, assume that the shocks in block $\bar{p}_{\bar{i}}$ are mutually independent and at most one component of the shocks in block $p_{\bar{i}}$ has zero skewness and zero excess kurtosis.

If $B \in \mathbb{B}_{brec}(\bar{p}_1, \ldots, \bar{p}_{\bar{m}})$ satisfies

$$E\begin{bmatrix} f_{\mathbf{2}}(B, u_t) \\ f_{\mathbf{3\&4}_{\bar{i}}}(B, u_t) \end{bmatrix} = 0, \tag{4}$$

it follows that $B_{\bar{i}j} = \widetilde{B}_{\bar{i}j,0}P_i$ for $j = \bar{i}, \ldots, \bar{m}$ and a sign-permutation matrices P_i, meaning that $\widetilde{B}_{\bar{i}j,0}$is identified.

Proof. To simplify the notation let

$$\begin{aligned} \bar{u}_1 &:= [u_1, \ldots, u_{p_{\bar{i}}-1}]', & \bar{e}_1(B) &:= [e_1(B), \ldots, e_{p_{\bar{i}}-1}(B)]', & \bar{\varepsilon}_1 &:= [\varepsilon_1, \ldots, \varepsilon_{p_{\bar{i}}-1}]', \\ \bar{u}_2 &:= [u_{p_{\bar{i}}}, \ldots, u_{p_{\bar{i}+1}-1}]', & \bar{e}_2(B) &:= [e_{p_{\bar{i}}}(B), \ldots, e_{p_{\bar{i}+1}-1}(B)]', & \bar{\varepsilon}_2 &:= [\varepsilon_{p_{\bar{i}}}, \ldots, \varepsilon_{p_{\bar{i}+1}-1}]', \\ \bar{u}_3 &:= [u_{p_{\bar{i}+1}}, \ldots, u_n]', & \bar{e}_3(B) &:= [e_{p_{\bar{i}+1}}(B), \ldots, e_n(B)]', & \bar{\varepsilon}_3 &:= [\varepsilon_{p_{\bar{i}+1}}, \ldots, \varepsilon_n]', \end{aligned}$$

such that $\bar{u}_1, \bar{e}_1(B)$, and $\bar{\varepsilon}_1$ contain all reduced form shocks, unmixed innovations, and structural shocks in blocks preceding the $\bar{i}$th block of $\mathbb{B}_{brec}(\bar{p}_1, \ldots, \bar{p}_{\bar{m}}), \bar{u}_2, \bar{e}_2(B)$, and $\bar{\varepsilon}_2$ contain the innovations and shocks in the $\bar{i}$th block of $\mathbb{B}_{brec}(\bar{p}_1, \ldots, \bar{p}_{\bar{m}})$, and $\bar{u}_3, \bar{e}_3(B)$, and $\bar{\varepsilon}_3$ contain the innovations and shocks following $\bar{i}$th block of $\mathbb{B}_{brec}(\bar{p}_1, \ldots, \bar{p}_{\bar{m}})$. Moreover, we denote parts of the B_0 matrix as follows

$$\begin{bmatrix} \bar{u}_1 \\ \bar{u}_2 \\ \bar{u}_3 \end{bmatrix} = \begin{bmatrix} \widetilde{B}_{11,0} & 0 & 0 \\ \widetilde{B}_{21,0} & \widetilde{B}_{22,0} & 0 \\ \widetilde{B}_{31,0} & \widetilde{B}_{32,0} & \widetilde{B}_{33,0} \end{bmatrix} \begin{bmatrix} \bar{\varepsilon}_1 \\ \bar{\varepsilon}_2 \\ \bar{\varepsilon}_3 \end{bmatrix},$$

and, for a given matrix $B \in \mathbb{B}_{brec}(\bar{p}_1, \ldots, \bar{p}_{\bar{m}})$, we denote the parts of B as $B_{11}, B_{21}, B_{31}, B_{22}, B_{32}$, and B_{33}, respectively.

Proposition 1 implies that $B_{22} = \widetilde{B}_{22,0}Q_2, B_{32} = \widetilde{B}_{32,0}Q_2$, and $\bar{e}_2(B) = Q_2\bar{\varepsilon}_2$ with a orthogonal matrix Q_2. Imposing the coskewness and cokurtosis conditions $E[f_{\mathbf{3\&4}_{\bar{i}}}(B, u_t)] = 0$ identifies the $\bar{i}$-th block up to sign and permutation, compare Keweloh (2021b). Therefore $B_{22} = \widetilde{B}_{22,0}P_2, B_{32} = \widetilde{B}_{32,0}P_2$, and $\bar{e}_2(B) = P_2\bar{\varepsilon}_2$ with a sign-permutation matrix P_2.

Appendix B. Finite sample performance

Table B.6 and B.7 report the results of the simulation in Section 3.2 using the fast SVAR-GMM estimator proposed by Keweloh (2021b) and the PML estimator proposed by Gouriéroux et al. (2017) to estimate the non-recursive block.

Fig. B.3 and B.4 show estimated impulse responses in a Monte Carlo simulation with the VAR(1)

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \\ y_{4t} \end{bmatrix} = \begin{bmatrix} 0.5 & 0 & 0 & 0 \\ 0.1 & 0.1 & 0 & 0 \\ 0.1 & 0.1 & 0.5 & 0 \\ 0.1 & 0.1 & 0.1 & 0.5 \end{bmatrix} \begin{bmatrix} y_{1(t-1)} \\ y_{2(t-1)} \\ y_{3(t-1)} \\ y_{4(t-1)} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ u_{4t} \end{bmatrix} \text{and} \begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ u_{4t} \end{bmatrix} = \begin{bmatrix} 10 & 0 & 0 & 0 \\ 5 & 10 & 0 & 0 \\ 5 & 5 & 10 & 5 \\ 5 & 5 & 5 & 10 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{bmatrix}, \tag{5}$$

where the structural shocks ε_{it}, $i = 1, \ldots, 4$, $t = 1, \ldots, T$, are drawn independently and identically from the two-component mixture $\varepsilon_{i,t} \sim 0.79\,\mathcal{N}(-0.2, 0.7^2) + 0.21\,\mathcal{N}(0.75, 1.5^2)$. In each simulation, the VAR(1) is estimated by OLS and the simultaneous interaction is estimated in a second step using the block-recursive SVAR-GMM estimator without and with the block-recursive restrictions in Section 3.2.

Table B.6
Finite sample performance - Average and MSE of all estimated elements (fast SVAR-GMM).

T	SVAR-GMMWF	block-recursive SVAR-GMMWF
100	$\begin{bmatrix} \underset{(2.7)}{9.15} & \underset{(4.8)}{-0.03} & \underset{(4.96)}{0.02} & \underset{(4.63)}{-0.05} \\ \underset{(5.48)}{4.64} & \underset{(3.73)}{9.16} & \underset{(6.01)}{-0.01} & \underset{(6.05)}{-0.01} \\ \underset{(7.62)}{4.58} & \underset{(7.84)}{4.59} & \underset{(5.95)}{9.14} & \underset{(8.33)}{4.54} \\ \underset{(7.51)}{4.64} & \underset{(7.86)}{4.57} & \underset{(7.59)}{4.59} & \underset{(6.39)}{9.11} \end{bmatrix}$	$\begin{bmatrix} \underset{(2.53)}{9.63} & \underset{(4.99)}{-0.04} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(5.86)}{4.9} & \underset{(3.77)}{9.61} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(3.09)}{4.83} & \underset{(3.11)}{4.79} & \underset{(3.21)}{9.57} & \underset{(7.21)}{4.53} \\ \underset{(3.08)}{4.83} & \underset{(3.15)}{4.78} & \underset{(5.89)}{4.97} & \underset{(4.71)}{9.34} \end{bmatrix}$
250	$\begin{bmatrix} \underset{(0.88)}{9.63} & \underset{(2.3)}{0.02} & \underset{(2.14)}{-0.01} & \underset{(2.21)}{-0.0} \\ \underset{(2.54)}{4.79} & \underset{(1.48)}{9.6} & \underset{(2.99)}{0.03} & \underset{(2.76)}{-0.02} \\ \underset{(3.75)}{4.81} & \underset{(3.79)}{4.79} & \underset{(2.39)}{9.65} & \underset{(3.7)}{4.77} \\ \underset{(3.61)}{4.82} & \underset{(3.57)}{4.81} & \underset{(3.37)}{4.88} & \underset{(2.62)}{9.6} \end{bmatrix}$	$\begin{bmatrix} \underset{(0.52)}{9.88} & \underset{(2.0)}{0.03} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(2.13)}{4.91} & \underset{(0.99)}{9.87} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(1.12)}{4.92} & \underset{(1.12)}{4.96} & \underset{(1.07)}{9.86} & \underset{(2.5)}{4.86} \\ \underset{(1.09)}{4.93} & \underset{(1.12)}{4.95} & \underset{(2.26)}{4.98} & \underset{(1.31)}{9.8} \end{bmatrix}$
500	$\begin{bmatrix} \underset{(0.33)}{9.84} & \underset{(1.02)}{-0.01} & \underset{(0.99)}{0.04} & \underset{(1.0)}{-0.03} \\ \underset{(1.1)}{4.93} & \underset{(0.52)}{9.83} & \underset{(1.2)}{-0.01} & \underset{(1.2)}{0.02} \\ \underset{(1.55)}{4.91} & \underset{(1.49)}{4.9} & \underset{(0.96)}{9.88} & \underset{(1.53)}{4.92} \\ \underset{(1.58)}{4.95} & \underset{(1.48)}{4.89} & \underset{(1.53)}{4.96} & \underset{(1.04)}{9.82} \end{bmatrix}$	$\begin{bmatrix} \underset{(0.25)}{9.95} & \underset{(0.97)}{0.0} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(1.03)}{4.98} & \underset{(0.43)}{9.94} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.55)}{4.98} & \underset{(0.53)}{4.95} & \underset{(0.42)}{9.95} & \underset{(0.97)}{4.97} \\ \underset{(0.55)}{4.99} & \underset{(0.53)}{4.96} & \underset{(0.96)}{4.98} & \underset{(0.48)}{9.91} \end{bmatrix}$
1000	$\begin{bmatrix} \underset{(0.12)}{9.95} & \underset{(0.39)}{0.01} & \underset{(0.37)}{-0.0} & \underset{(0.4)}{0.01} \\ \underset{(0.42)}{4.97} & \underset{(0.2)}{9.94} & \underset{(0.51)}{0.01} & \underset{(0.48)}{0.0} \\ \underset{(0.58)}{4.96} & \underset{(0.62)}{4.97} & \underset{(0.4)}{9.92} & \underset{(0.62)}{4.99} \\ \underset{(0.61)}{4.96} & \underset{(0.61)}{4.98} & \underset{(0.61)}{4.95} & \underset{(0.4)}{9.95} \end{bmatrix}$	$\begin{bmatrix} \underset{(0.11)}{9.99} & \underset{(0.37)}{0.01} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.4)}{4.99} & \underset{(0.2)}{9.98} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.25)}{4.98} & \underset{(0.24)}{5.0} & \underset{(0.2)}{9.94} & \underset{(0.4)}{5.0} \\ \underset{(0.24)}{4.98} & \underset{(0.24)}{5.01} & \underset{(0.4)}{4.96} & \underset{(0.2)}{9.97} \end{bmatrix}$
5000	$\begin{bmatrix} \underset{(0.02)}{9.99} & \underset{(0.07)}{0.0} & \underset{(0.07)}{0.0} & \underset{(0.06)}{0.01} \\ \underset{(0.07)}{4.99} & \underset{(0.04)}{9.99} & \underset{(0.09)}{0.01} & \underset{(0.08)}{0.0} \\ \underset{(0.11)}{4.99} & \underset{(0.1)}{5.0} & \underset{(0.07)}{9.99} & \underset{(0.11)}{5.0} \\ \underset{(0.1)}{5.0} & \underset{(0.1)}{5.0} & \underset{(0.11)}{5.0} & \underset{(0.07)}{9.99} \end{bmatrix}$	$\begin{bmatrix} \underset{(0.02)}{10.0} & \underset{(0.07)}{0.0} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.07)}{5.0} & \underset{(0.04)}{10.0} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.05)}{5.0} & \underset{(0.04)}{5.0} & \underset{(0.04)}{9.99} & \underset{(0.07)}{5.0} \\ \underset{(0.05)}{5.0} & \underset{(0.04)}{5.0} & \underset{(0.07)}{4.99} & \underset{(0.04)}{9.99} \end{bmatrix}$

Monte Carlo simulation with $M = 2000$ replications. The table shows the average, $1/M\sum_{m=1}^{M}\hat{b}_{ij}^{m}$, and the estimated mean squared error, $1/M\sum_{m=1}^{M}\left(\hat{b}_{ij}^{m} - b_{ij}\right)^2$, of each estimated element $\hat{b}_{ij}^{m}$ of b_{ij} denoting the element of B in row i and column j. The table reports results for the fast SVAR-GMM estimator proposed by Keweloh (2021b) without restrictions and with the block-recursive restrictions.

Table B.7
Finite sample performance - Average and MSE of all estimated elements (PML).

T	SVAR-PML	block-recursive SVAR-PML
100	$\begin{bmatrix} \underset{(2.49)}{9.32} & \underset{(3.53)}{-0.07} & \underset{(3.85)}{-0.06} & \underset{(3.74)}{-0.02} \\ \underset{(4.3)}{4.78} & \underset{(3.37)}{9.3} & \underset{(4.69)}{0.02} & \underset{(4.7)}{-0.03} \\ \underset{(5.85)}{4.74} & \underset{(6.78)}{4.57} & \underset{(4.71)}{9.41} & \underset{(11.74)}{3.92} \\ \underset{(5.94)}{4.74} & \underset{(6.48)}{4.58} & \underset{(6.95)}{5.19} & \underset{(10.58)}{8.72} \end{bmatrix}$	$\begin{bmatrix} \underset{(3.47)}{9.62} & \underset{(4.28)}{-0.02} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(5.67)}{4.88} & \underset{(4.33)}{9.6} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(3.27)}{4.82} & \underset{(3.03)}{4.8} & \underset{(3.62)}{9.65} & \underset{(9.86)}{4.07} \\ \underset{(3.26)}{4.82} & \underset{(3.11)}{4.78} & \underset{(5.54)}{5.3} & \underset{(8.83)}{8.99} \end{bmatrix}$
250	$\begin{bmatrix} \underset{(0.59)}{9.78} & \underset{(1.29)}{0.02} & \underset{(1.24)}{-0.03} & \underset{(1.33)}{-0.05} \\ \underset{(1.39)}{4.86} & \underset{(0.84)}{9.78} & \underset{(1.6)}{0.02} & \underset{(1.61)}{-0.04} \\ \underset{(2.09)}{4.93} & \underset{(2.05)}{4.89} & \underset{(1.46)}{9.81} & \underset{(2.98)}{4.75} \\ \underset{(2.06)}{4.95} & \underset{(1.95)}{4.9} & \underset{(2.11)}{4.99} & \underset{(2.46)}{9.67} \end{bmatrix}$	$\begin{bmatrix} \underset{(1.8)}{9.84} & \underset{(1.53)}{0.01} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(1.84)}{4.91} & \underset{(2.23)}{9.82} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(1.25)}{4.91} & \underset{(1.4)}{4.93} & \underset{(1.93)}{9.84} & \underset{(2.74)}{4.79} \\ \underset{(1.24)}{4.93} & \underset{(1.41)}{4.91} & \underset{(1.72)}{5.0} & \underset{(3.06)}{9.72} \end{bmatrix}$
500	$\begin{bmatrix} \underset{(0.24)}{9.92} & \underset{(0.52)}{-0.01} & \underset{(0.5)}{0.01} & \underset{(0.51)}{0.01} \\ \underset{(0.56)}{4.97} & \underset{(0.35)}{9.9} & \underset{(0.63)}{-0.01} & \underset{(0.67)}{0.02} \\ \underset{(0.78)}{4.96} & \underset{(0.82)}{4.94} & \underset{(0.8)}{9.92} & \underset{(0.82)}{4.98} \\ \underset{(0.8)}{4.96} & \underset{(0.81)}{4.93} & \underset{(1.04)}{4.96} & \underset{(0.63)}{9.91} \end{bmatrix}$	$\begin{bmatrix} \underset{(0.33)}{9.96} & \underset{(0.61)}{-0.01} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.67)}{5.0} & \underset{(0.46)}{9.94} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.47)}{4.99} & \underset{(0.49)}{4.95} & \underset{(0.98)}{9.93} & \underset{(0.57)}{4.99} \\ \underset{(0.47)}{5.0} & \underset{(0.49)}{4.96} & \underset{(1.16)}{4.96} & \underset{(0.43)}{9.91} \end{bmatrix}$

(*continued on next page*)

Table B.7 (*continued*)

T		
1000	$\begin{bmatrix} \underset{(0.11)}{9.97} & \underset{(0.23)}{0.01} & \underset{(0.23)}{-0.0} & \underset{(0.24)}{0.0} \\ \underset{(0.25)}{4.98} & \underset{(0.16)}{9.97} & \underset{(0.31)}{0.0} & \underset{(0.31)}{0.01} \\ \underset{(0.37)}{4.98} & \underset{(0.38)}{4.98} & \underset{(0.53)}{9.93} & \underset{(0.41)}{5.0} \\ \underset{(0.37)}{4.98} & \underset{(0.4)}{4.98} & \underset{(0.64)}{4.95} & \underset{(0.31)}{9.96} \end{bmatrix}$	$\begin{bmatrix} \underset{(0.11)}{9.99} & \underset{(0.23)}{0.01} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.25)}{4.99} & \underset{(0.16)}{9.99} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.21)}{4.99} & \underset{(0.2)}{5.0} & \underset{(0.41)}{9.94} & \underset{(0.28)}{5.0} \\ \underset{(0.2)}{4.99} & \underset{(0.21)}{5.01} & \underset{(0.5)}{4.96} & \underset{(0.2)}{9.97} \end{bmatrix}$
5000	$\begin{bmatrix} \underset{(0.02)}{10.0} & \underset{(0.05)}{0.0} & \underset{(0.05)}{0.0} & \underset{(0.04)}{0.0} \\ \underset{(0.05)}{5.0} & \underset{(0.03)}{9.99} & \underset{(0.06)}{0.01} & \underset{(0.06)}{0.0} \\ \underset{(0.07)}{5.0} & \underset{(0.07)}{5.0} & \underset{(0.05)}{9.99} & \underset{(0.07)}{5.0} \\ \underset{(0.07)}{5.0} & \underset{(0.07)}{5.0} & \underset{(0.07)}{4.99} & \underset{(0.05)}{9.99} \end{bmatrix}$	$\begin{bmatrix} \underset{(0.02)}{10.0} & \underset{(0.05)}{0.0} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.05)}{5.0} & \underset{(0.03)}{10.0} & \underset{(0.0)}{0.0} & \underset{(0.0)}{0.0} \\ \underset{(0.04)}{5.0} & \underset{(0.04)}{5.0} & \underset{(0.03)}{9.99} & \underset{(0.05)}{5.0} \\ \underset{(0.04)}{5.01} & \underset{(0.04)}{5.0} & \underset{(0.05)}{4.99} & \underset{(0.03)}{9.99} \end{bmatrix}$

Monte Carlo simulation with $M = 2000$ replications. The table shows the average, $1/M\sum_{m=1}^{M}\hat{b}_{ij}^{m}$, and the estimated mean squared error, $1/M\sum_{m=1}^{M}\left(\hat{b}_{ij}^{m} - b_{ij}\right)^2$, of each estimated element $\hat{b}_{ij}^{m}$ of b_{ij} denoting the element of B in row i and column j. The table reports results for the PML estimator proposed by Gouriéroux et al. (2017) using a t-distribution with seven degrees of freedom without restrictions and with the block-recursive restrictions.

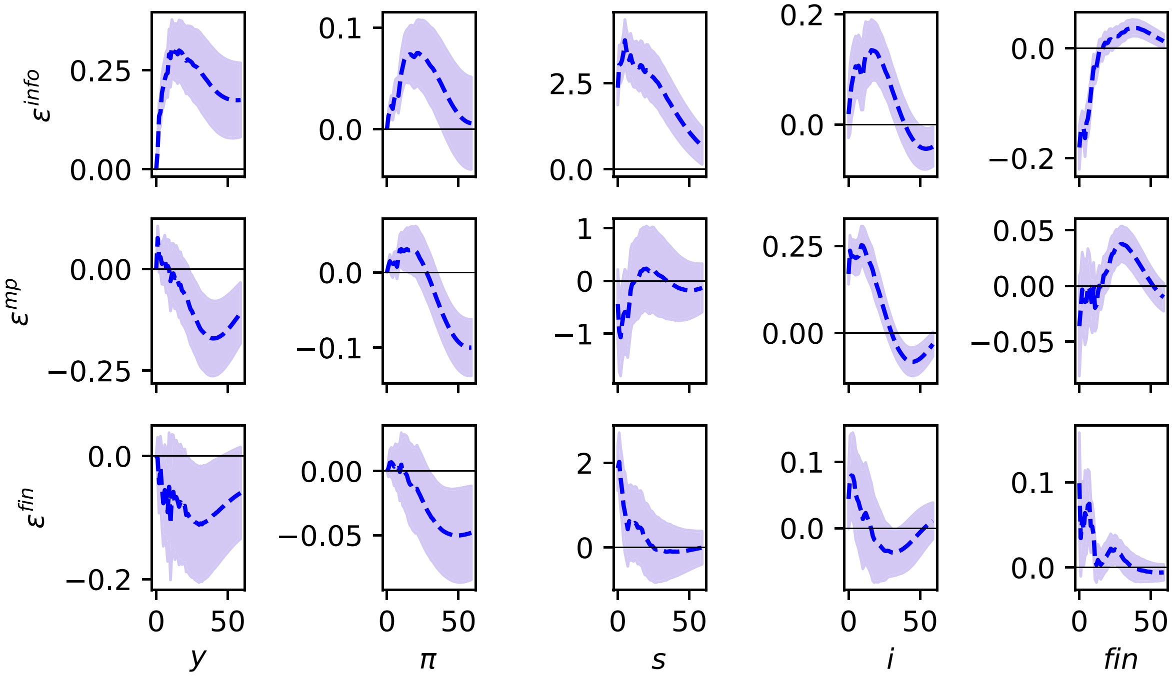

Fig. B.3. Estimated impulse responses for $T = 100$ for the VAR(1) in a Monte Carlo simulation with 2000 replications. The true impulse response is shown in red. The lower 5% and upper 95% quantiles of the estimated impulse response using the block-recursive SVAR-GMM estimator without restrictions [with the block-recursive restrictions from Section 3.2] are shown in blue [orange].

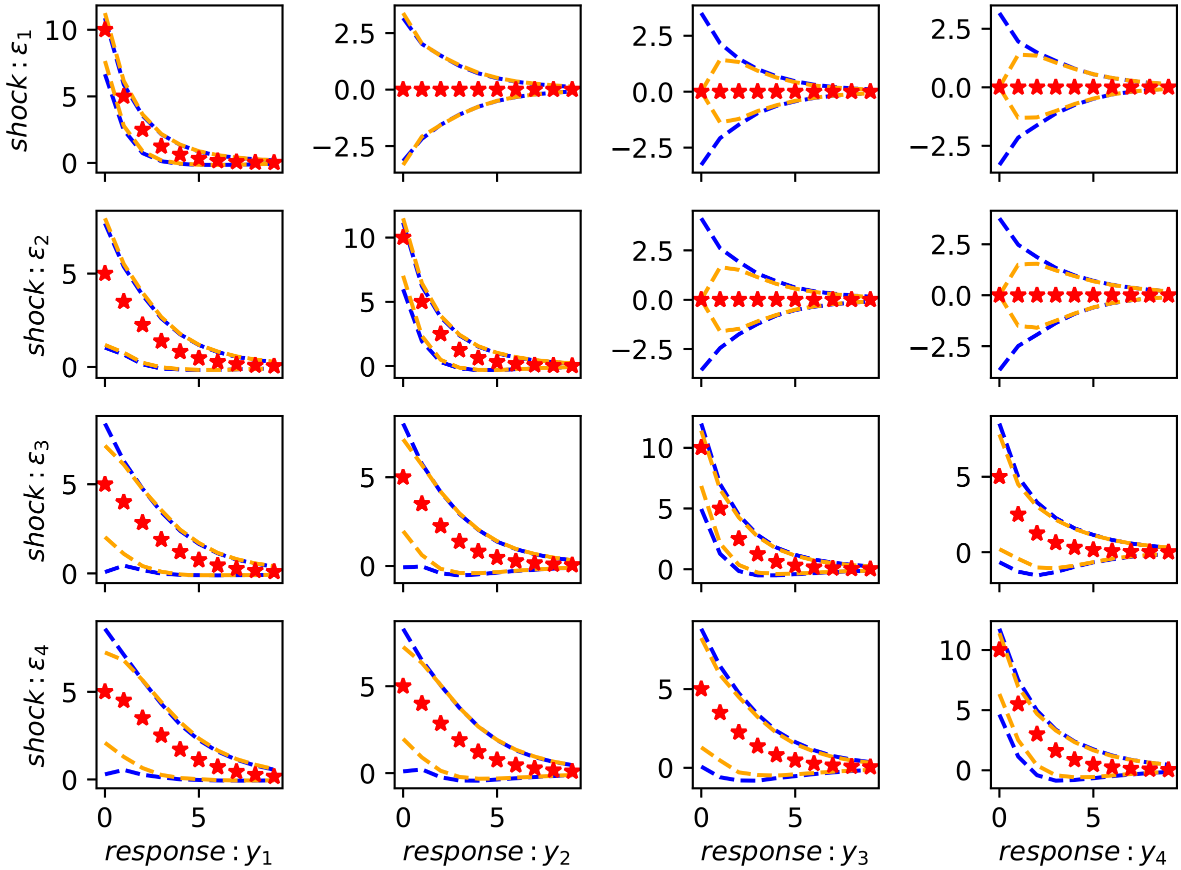

Fig. B.4. Estimated impulse responses for $T = 250$ for the VAR(1) in a Monte Carlo simulation with 2000 replications. The true impulse response is shown in red. The lower 5% and upper 95% quantiles of the estimated impulse response using the block-recursive SVAR-GMM estimator without restrictions [with the block-recursive restrictions from Section 3.2] are shown in blue [orange].

Appendix C. Application

This section contains robustness checks for the application presented in Section 4. Fig. C.5 shows the estimated impulse response function for the SVAR including the excess bond premium as an additional variable in the second block. Fig. C.6 shows the estimated impulse response function for the SVAR using the pre 2008 sub-sample. Fig. C.7 shows the estimated impulse response function for the SVAR using the industrial production index and consumer price index instead of the interpolated real GDP and GDP deflator.

Table C.8 displays the non-Gaussianity of the estimated shocks in the intraday SVAR.

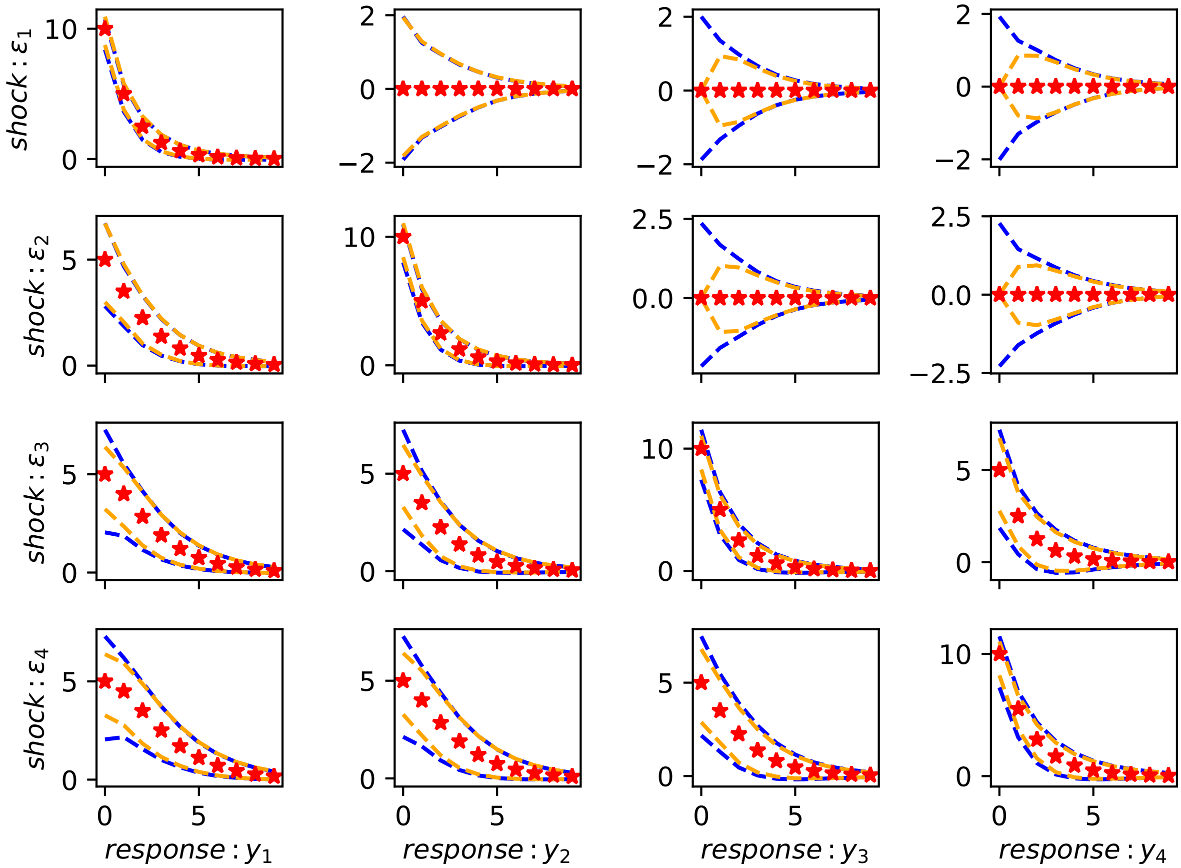

Fig. C.5. Impulse responses (including the excess bond premium). The figure shows the responses to one standard deviation shocks in the block-recursive SVAR. Confidence bands are symmetrical 68% bootstrap bands with 1000 replications in the bootstrap algorithm.

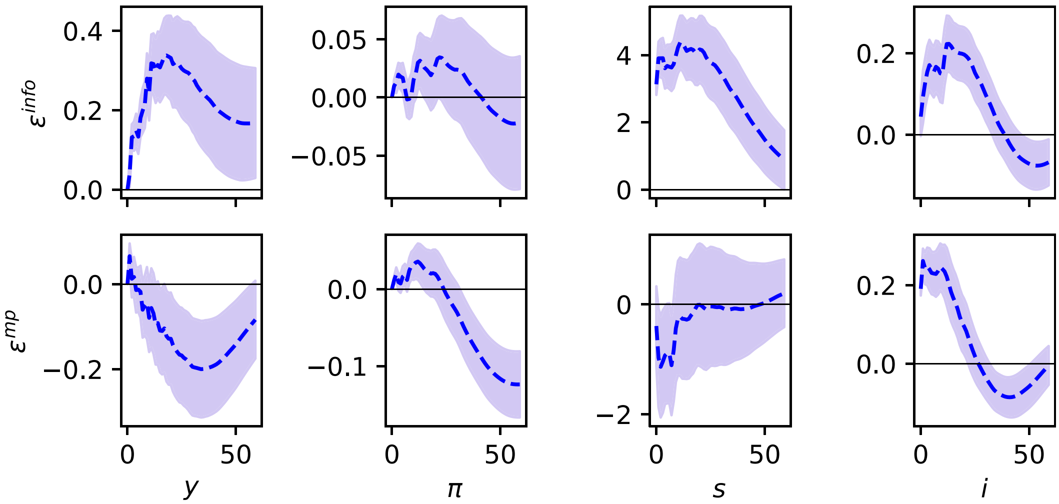

Fig. C.6. Impulse responses (pre 2008 sample). The figure shows the responses to one standard deviation shocks in the block-recursive SVAR. Confidence bands are symmetrical 68% bootstrap bands with 1000 replications in the bootstrap algorithm.

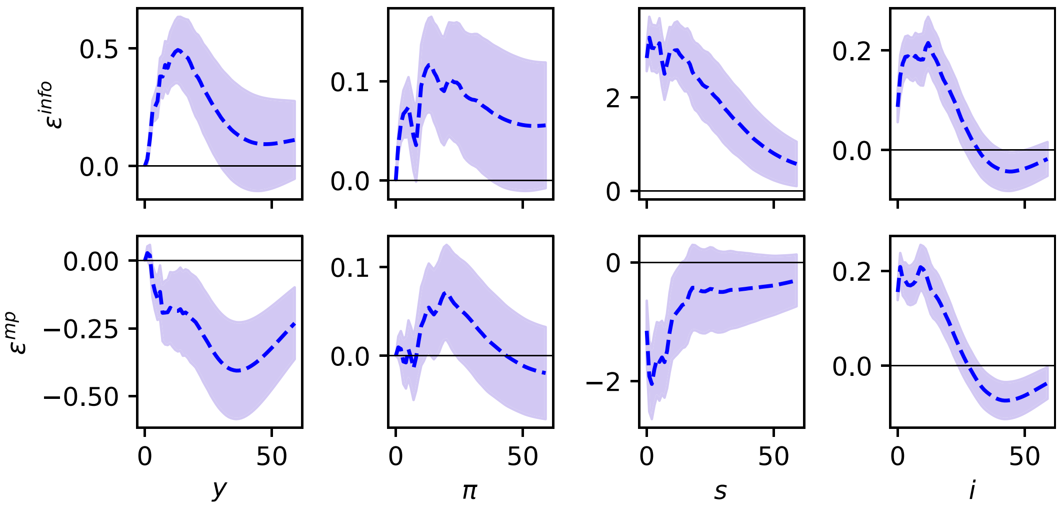

Fig. C.7. Impulse responses (with industrial production and consumer price index). The figure shows the responses to one standard deviation shocks in the block-recursive SVAR. Confidence bands are symmetrical 68% bootstrap bands with 1000 replications in the bootstrap algorithm.

Table C.8
Non-Gaussianity of the estimated intraday shocks.

	ε_t^{mp}	ε_t^{fg}	ε_t^{CBinfo}
Skewness	−2.366	0.549	0.842
Kurtosis	14.801	7.326	15.618
Jarque–Bera Test (p-value)	0	0	0

References

Angelini, G., Fanelli, L., 2019. Exogenous uncertainty and the identification of structural vector autoregressions with external instruments. J. Appl. Econ., 34, 951–971. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/jae.2736, doi: 10.1002/jae.2736, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1002/jae.2736.

Bauer, M.D., Swanson, E.T., 2020. An Alternative Explanation for the Fed Information Effect. Technical Report. National Bureau of Economic Research.

Beaudry, P., Portier, F., 2006. Stock prices, news, and economic fluctuations. Am. Econ. Rev. 96, 1293–1307. https://doi.org/10.1257/aer.96.4.1293. URL: https://www.aeaweb.org/articles?id=10.1257/aer.96.4.1293.

Bertsche, D., Braun, R., 2022. Identification of structural vector autoregressions by stochastic volatility. J. Bus. Econ. Stat. 40, 328–341. https://doi.org/10.1080/07350015.2020.1813588. arXiv:https://doi.org/10.1080/07350015.2020.1813588.

Bjørnland, H.C., Leitemo, K., 2009. Identifying the interdependence between us monetary policy and the stock market. J. Monet. Econ. 56, 275–282. https://doi.org/10.1016/j.jmoneco.2008.12.001. URL: https://www.sciencedirect.com/science/article/pii/S0304393208001748.

Blanchard, O.J., Quah, D., 1989. The dynamic effects of aggregate demand and supply disturbances. Am. Econ. Rev. 79, 655–673.

Gouriéroux, C., Monfort, A., Renne, J.P., 2017. Statistical inference for independent component analysis: Application to structural var models. J. Econ. 196, 111–126. https://doi.org/10.1016/j.jeconom.2016.09.007. URL: https://www.sciencedirect.com/science/article/pii/S0304407616301749.

Guay, A., 2021. Identification of structural vector autoregressions through higher unconditional moments. Journal of Econometrics 225, 27–46. https://doi.org/10.1016/j.jeconom.2020.10.006. themed Issue: Vector Autoregressions, URL: https://www.sciencedirect.com/science/article/pii/S0304407620303651.

Gürkaynak, R., Karasoy-Can, H.G., Lee, S.S., 2022. Stock market's assessment of monetary policy transmission: The cash flow effect. The Journal of Finance 77, 2375–2421.

Hall, A.R., 2005. Generalized Method of Moments. Oxford University Press.

Herwartz, H., Maxand, S., Rohloffa, H., 2022. The link between monetary policy, stock prices, and house prices—evidence from a statistical identification approach. International Journal of Central Banking.

Herwartz, H., Plödt, M., 2016. The macroeconomic effects of oil price shocks: Evidence from a statistical identification approach. Journal of International Money and Finance 61, 30–44. https://doi.org/10.1016/j.jimonfin.2015.11.001. URL: https://www.sciencedirect.com/science/article/pii/S0261560615001904.

Jarocinski, M., 2021. Estimating fed's unconventional policy shocks. ECB Working Paper.

Jarocinski, M., Karadi, P., 2020. Deconstructing monetary policy surprises—the role of information shocks. American Economic Journal: Macroeconomics 12, 1–43. https://doi.org/10.1257/mac.20180090. URL: https://www.aeaweb.org/articles?id=10.1257/mac.20180090.

Keweloh, S.A., 2021a. A Feasible Approach to Incorporate Information in Higher Moments in Structural Vector Autoregressions. Discussion Papers SFB 823.

Keweloh, S.A., 2021b. A generalized method of moments estimator for structural vector autoregressions based on higher moments. Journal of Business & Economic Statistics 39, 772–782. https://doi.org/10.1080/07350015.2020.1730858. arXiv:https://doi.org/10.1080/07350015.2020.1730858.

Kilian, L., Zhou, X., 2022. Oil prices, gasoline prices, and inflation expectations. Journal of Applied Econometrics 37, 867–881. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/jae.2911, doi: 10.1002/jae.2911, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1002/jae.2911.

Lanne, M., Luoto, J., 2021. Gmm estimation of non-gaussian structural vector autoregression. Journal of Business & Economic Statistics 39, 69–81. https://doi.org/10.1080/07350015.2019.1629940. arXiv:https://doi.org/10.1080/07350015.2019.1629940.

Lanne, M., Lütkepohl, H., Maciejowska, K., 2010. Structural vector autoregressions with markov switching. J. Econ. Dynam. Control 34, 121–131. https://doi.org/10.1016/j.jedc.2009.08.002. URL: https://www.sciencedirect.com/science/article/pii/S0165188909001481.

Lanne, M., Meitz, M., Saikkonen, P., 2017. Identification and estimation of non-gaussian structural vector autoregressions. Journal of Econometrics 196, 288–304. https://doi.org/10.1016/j.jeconom.2016.06.002. URL: https://www.sciencedirect.com/science/article/pii/S0304407616301828.

Lewis, D.J., 2021. Identifying shocks via time-varying volatility. The Review of Economic Studies 88, 3086–3124.

Lewis, D.J., 2023. Announcement-specific decompositions of unconventional monetary policy shocks and their effects. The Review of Economics and Statistics, 1–46.

Lütkepohl, H., Netšunajev, A., 2017. Structural vector autoregressions with smooth transition in variances. J. Econ. Dynam. Control 84, 43–57. https://doi.org/10.1016/j.jedc.2017.09.001. URL: https://www.sciencedirect.com/science/article/pii/S0165188917301811.

Matteson, D.S., Tsay, R.S., 2017. Independent component analysis via distance covariance. J. Am. Stat. Assoc. 112, 623–637. https://doi.org/10.1080/01621459.2016.1150851. arXiv:https://doi.org/10.1080/01621459.2016.1150851.

Mertens, K., Ravn, M.O., 2013. The dynamic effects of personal and corporate income tax changes in the united states. Am. Econ. Rev. 103, 1212–1247. https://doi.org/10.1257/aer.103.4.1212. URL: https://www.aeaweb.org/articles?id=10.1257/aer.103.4.1212.

Montiel Olea, J.L., Plagborg-Møller, M., Qian, E., 2022. Svar identification from higher moments: Has the simultaneous causality problem been solved? AEA Papers Proc. 112, 481–485. https://doi.org/10.1257/pandp.20221047. URL: https://www.aeaweb.org/articles?id=10.1257/pandp.20221047.

Rigobon, R., 2003. Identification through heteroskedasticity. Rev. Econ. Stat. 85, 777–792. URL http://www.jstor.org/stable/3211805.

Sims, C.A., 1980. Macroeconomics and reality. Econometrica 48, 1–48. URL http://www.jstor.org/stable/1912017.

Smets, F., Wouters, R., 2007. Shocks and frictions in us business cycles: A bayesian dsge approach. Am. Econ. Rev. 97, 586–606. https://doi.org/10.1257/aer.97.3.586. URL: https://www.aeaweb.org/articles?id=10.1257/aer.97.3.586.

Uhlig, H., 2005. What are the effects of monetary policy on output? results from an agnostic identification procedure. J. Monet. Econ. 52, 381–419. https://doi.org/10.1016/j.jmoneco.2004.05.007. URL: https://www.sciencedirect.com/science/article/pii/S0304393205000073.

Zha, T., 1999. Block recursion and structural vector autoregressions. J. Econ. 90, 291–316. https://doi.org/10.1016/S0304-4076(98)00045-1. URL: https://www.sciencedirect.com/science/article/pii/S0304407698000451.