Discussion Papers in Economics

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ISSN: 1749-5075

Identifying Monetary Policy Shocks Through External Variable Constraints[*]

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January 2023

Abstract

This paper proposes a new strategy for the identification of monetary policy shocks in structural vector autoregressions (SVARs). It combines traditional sign restrictions with external variable constraints on high-frequency monetary surprises and central bank's macroeconomic projections. I use it to characterize the transmission of US monetary policy over the period 1965-2007. First, I find that contractionary monetary policy shocks unequivocally decrease output, sharpening the ambiguous implications of standard sign-restricted SVARs. Second, I show that the identified structural models are consistent with narrative sign restrictions and restrictions on the monetary policy equation. On the contrary, the shocks identified through these alternative methodologies turn out to be correlated with the information set of the central bank and to weakly comove with monetary surprises. Finally, I implement an algorithm for robust Bayesian inference in set-identified SVARs, providing further evidence in support of my identification strategy.

Keywords: SVARs, Monetary policy shocks, Set-identification.

JEL Codes: E52; C51

[*]I am deeply indebted to Alessio Volpicella and Anastasios Karantounias for invaluable guidance and support. I also thank Cristiano Cantore, Valentina Corradi, Paul Levine, Ricardo Nunes, Emanuele Bacchiocchi, Luca Fanelli, Lukas Hack, Matthias Meier and participants at the 2022 International Association for Applied Econometrics Annual Conference (IAAE), 2022 Australasia Meeting of the Econometric Society (ESAM) and 2022 European Meeting of the Econometric Society (ESEM), 2022 Scottish Economic Society Annual Conference, 2022 Newcastle Economics Research and Development Conference, 4th QMUL Economics and Finance Workshop for PhD & Post-doctoral Students and 10th SIdE Workshop for PhD Students in Econometrics and Empirical Economics.

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1 Introduction and Related Literature

Starting with the seminal paper of Sims (1980), a large number of studies has employed structural vector autoregressions (SVARs) to evaluate how monetary policy affects the real economy. Coherently with theoretical predictions, early SVAR literature based on short-run restrictions (e.g. Christiano et al., 1996) found that monetary tightenings have contractionary effects on output. The soundness of contemporaneous zero restrictions, however, has later been questioned by Uhlig (2005), who suggests to identify monetary policy shocks through sign restrictions on the impulse responses (henceforth *standard* or *traditional* sign restrictions). This methodology, that only achieves set-identification of the structural model, has the advantage of hinging on rather uncontroversial identifying assumptions. By adopting it, Uhlig (2005) finds that US monetary contractions do not necessarily decrease output but might even have expansionary effects.

This paper proposes to sharpen the identification obtained through sign restrictions, whose ability to identify monetary policy shocks has been recently called into question. In particular, Wolf (2020) provides an insightful interpretation of the ambiguous results achieved by Uhlig (2005). Using Smets and Wouters's (2007) model as data-generating process, he shows that sign restrictions may mistake positive demand and supply shocks for 'masquerading' contractionary monetary policy shocks, which are thus misleadingly found to increase output. Although theoretically sound, sign restrictions may therefore not be enough to identify the dynamic effects of monetary policy. To address this issue, I suggest to combine them with constraints on the relationship between monetary policy shocks and additional identifying information that is external to the VAR. Specifically, I only retain structural models which, in addition to satisfying standard sign restrictions, deliver monetary policy shocks that exhibit a certain relation with Greenbook forecasts and high-frequency monetary surprises. The latter measure the movements in the three-month-ahead federal funds rate futures over 30-minute windows around Federal Open

Market Committee (FOMC) announcements. They capture therefore the unpredictable component of monetary policy and plausible measures of monetary policy shocks should thus display a substantial positive correlation with them. Using the terminology of Wolf (2020), shocks with such a feature are likely to be 'true' monetary policy shocks rather than mere demand or supply shocks 'masquerading' as such. The Greenbook forecasts represent instead a proxy of the information set of the Federal Reserve (Fed) about the current and future state of the economy. Hence, only candidate monetary policy shocks which are not correlated with them should be retained as solutions to the identification problem. The effects of changes in monetary policy might otherwise be confounded with those triggered by the release of central bank information and with the realization of the expected future conditions to which the Fed is reacting. Importantly, once standard sign restrictions are combined with external variable constraints, contractionary monetary policy shocks are unequivocally found to decrease output. This result sheds light on the ambiguous findings obtained by Uhlig (2005) and contributes to restore the conventional wisdom about the transmission of US monetary policy in set-identified SVARs.

Similar evidence has been provided by two crucial contributions in the literature on set-identification of monetary policy shocks, as Antolín-Díaz and Rubio-Ramírez (2018) and Arias et al. (2019). The former combines traditional sign restrictions with narrative constraints around key historical episodes, while the latter imposes restrictions on the coefficients of the monetary policy equation. I find that the structural models recovered through my identification strategy meet their identifying assumptions and thus exhibit two important features. First, the identified monetary policy shocks are consistent with a narrative reading of the times and, second, the structural monetary policy equations are reconcilable with Taylor-type monetary policy rules. On the contrary, a large share of the shocks recovered by these two alternative methodologies is found to be correlated with Greenbook projections and to weakly comove with monetary surprises. Moreover, narrative sign restrictions and restrictions on the monetary policy equation are imposed through a uniform prior on the space of orthonormal matrices. As shown by Baumeister and Hamilton (2015), such a uniform prior might however be informative about objects of interest as impulse responses. It is worth emphasizing that the results obtained under my identification strategy, unlike those derived by using these competing methods, still apply when inference is performed through a prior-robust Bayesian algorithm based on numerical optimization methods (Giacomini and Kitagawa, 2021; Volpicella, 2022).

The idea of resorting to central bank's forecasts or high-frequency data to refine the identification of monetary shocks is not new. Monetary surprises are typically used as external instruments in proxy-SVARs (e.g. Gertler and Karadi, 2015), while Greenbook projections have been for instance included as endogenous variables in the VAR (Barth and Ramey, 2002). Miranda-Agrippino and Ricco (2021) have recently combined them to construct a robust instrument for the identification of monetary policy shocks. Since I employ the same information, this paper is inevitably related to theirs. However, my approach is significantly different from the one they implement. First and foremost, my identification strategy does not require any of the external variables to be an exogenous and relevant instrument. Second, the use of external variable constraints does not yield point-identification but is only aimed at sharpening set-identification.

My work also relates to Braun and Brüggerman (2022), who combine restrictions on the monetary policy equation with a constraint on the relationship between monetary policy shocks and Romer and Romer's (2004) narrative series. This paper differs from their work in several respects. First, they do not directly control for the information set of the central bank and enforce the external constraint on a narrative series rather than monetary surprises. Second, they do not impose restrictions on the impulse responses but on the monetary policy equation, as in Arias et al. (2019). Third, they only perform inference through a uniform, but informative, prior on the orthonormal matrices.

The structure of this paper is as follows. Section 2 sets the econometric framework. Section 3 presents my identification strategy and the main findings. Section 4 relates my approach to narrative sign restrictions and restrictions on the monetary policy equation. Section 5 evaluates if my identification scheme effectively controls for the central bank information channel. Section 6 introduces the prior-robust inference algorithm and the resulting impulse response functions. Section 7 draws conclusions. Finally, Appendix A and Appendix B provide robustness checks and further technical details, respectively.

2 The Econometric Framework

This section sets the econometric framework and introduces the use of sign restrictions (Uhlig, 2005) for the identification of monetary policy shocks.

2.1 The Identification Problem

A reduced-form VAR(p) model takes the form:

$$y_t = \sum_{j=1}^{p} B_j L^j y_t + e_t \tag{1}$$

where L is the lag operator and p is the lag order; y_t is a $k \times 1$ vector of endogenous variables; e_t is a $k \times 1$ vector of reduced-form residuals and B_j, for $j = 1, \ldots, p$, are matrices of estimated coefficients. Let $E(e_t e_t') = \Sigma_e$ be the variance-covariance matrix of e_t and $B = [B_1, \ldots, B_p]$. If the reduced-form parameters $\omega = (\Sigma_e, B)$ are such that the VAR(p) is stationary, the following infinite-order vector moving average (VMA) representation does exist:

$$y_t = \sum_{h=0}^{\infty} C_h e_{t-h} \tag{2}$$

where C_h is the h-th coefficient matrix of $(I_k - \sum_{j=1}^{p} B_j L^j)^{-1}$. For $h = 0, \ldots, H$, the (i, l)-element of the $k \times k$ matrix C_h is the reduced-form impulse response at time $t + h$

of the *i-th* variable in y_t to a unit innovation to the *l-th* entry of e_t.

Importantly, Σ_e is non-diagonal and the elements of e_t are thus contemporaneously correlated. Hence, the identification problem consists in finding a linear transformation of e_t of the form

$$e_t = P\varepsilon_t \tag{3}$$

such that the variance-covariance matrix Σ_ε of the resulting structural shocks ε_t is diagonal. Once the structural impact matrix P is defined, the structural impulse response functions (IRFs) can then be computed, at each horizon h, as

$$\Theta_h = C_h P \tag{4}$$

where the (i,l)-element of the $k \times k$ matrix Θ_h is the impulse response at time $t+h$ of the *i-th* variable in y_t to a unit structural shock to the *l-th* element of ε_t.

2.2 Set-Identification of SVAR Models

The crucial result behind set-identification is that there are infinitely many matrices P such that Σ_ε is diagonal. Let us define the following linear transformation of e_t,

$$e_t = S\eta_t \tag{5}$$

where S is the unique lower-triangular Cholesky factor of Σ_e. From (5), it follows that the shocks η_t are by construction mutually uncorrelated and have unit variance:

$$\Sigma_\eta = S^{-1}\Sigma_e(S^{-1})' = I \tag{6}$$

The above, however, is not the only solution to the identification problem. Consider the following orthonormal transformation of η_t,

$$\hat{\varepsilon}_t = Q'\eta_t \tag{7}$$

where Q' is a square orthonormal matrix such that $Q'Q = QQ' = I$. By exploiting the orthonormality of Q and equation (7), it follows that

$$e_t = SQQ'\eta_t = SQ\hat{\varepsilon}_t \tag{8}$$

As shown in equation (9), such an orthonormal transformation succeeds in delivering a diagonal structural variance-covariance matrix Σ_ε,

$$\Sigma_\varepsilon = Q^{-1}S^{-1}SS'(S^{-1})'(Q^{-1})' = I \tag{9}$$

There are therefore infinitely many solutions to the identification problem, one for each orthonormal transformation of S. In this framework, an identification strategy can thus be thought of as a set of identifying restrictions that restraints the admissible support for the orthonormal matrices Q.

2.3 Identification by Sign Restrictions

For a certain orthonormal matrix Q and $h = 0, \ldots, H$, the $k \times k$ matrix of structural impulse responses $\hat{\Theta}_h$ can be expressed as

$$\hat{\Theta}_h = C_h A \tag{10}$$

where, to simplify the notation, I set $A = SQ$. The (i, l)-element of $\hat{\Theta}_h$ is the structural impulse response at time $t+h$ of the *i-th* variable in y to a unit structural shock to the *l-th* element of $\hat{\varepsilon}_t$. Sign restrictions address the identification problem by constraining the sign of some of the elements of $\hat{\Theta}_h$. This approach was introduced by Uhlig (2005), who implements it on the following vector y_t of US monthly variables,

$$y_t' = \begin{bmatrix} gdp_t & pi_t & ff_t & ci_t & tr_t & nr_t \end{bmatrix} \tag{11}$$

where gdp_t and pi_t are the log of real GDP and of the GDP deflator, constructed using interpolation of the quarterly series as in Bernanke and Mihov (1998); ff_t is the federal funds rate; ci_t is the log of the commodity price index from Global Financial Data; tr_t

and nr_t are the log of total and nonborrowed reserves, respectively.

The identification of monetary policy shocks is then achieved by retaining a large number of structural impact matrices A such that the resulting shock $\hat{\varepsilon}_t^m(A)$ satisfies the sign restrictions described in Restriction SR.

Restriction SR. A monetary policy shock ε_t^m leads to a negative response of pi_t, ci_t and nr_t, and to a positive response of $f\!f_t$ at horizons $h = 0, \ldots, 5$.

3 Combining Sign Restrictions With External Variable Constraints

The soundness of the shocks recovered through Restriction SR has been recently called into question. Specifically, Wolf (2020) shows that sign restrictions are likely to mistake positive demand and supply shocks for 'masquerading' contractionary monetary policy shocks, that are thus misleadingly found to increase output.

To deal with this issue, I combine sign restrictions with external variable constraints on high-frequency monetary surprises and Greenbook forecasts. The latter express the Fed's information set about the current and future state of the economy and monetary policy shocks should therefore be not correlated with them. If not, the effects of changes in monetary policy might be confounded with those induced by the disclosure of central bank information and by the realization of the expected conditions to which the Federal Reserve is responding. On the contrary, monetary surprises measure the movements in the three-month-ahead federal funds rate futures over 30-minute windows around FOMC announcements and thus proxy the unpredictable component of monetary policy. Hence, I suggest to retain only the shocks that display a strong positive correlation with them, since, using the terminology of Wolf (2020), they are likely to be 'true' monetary policy shocks rather than mere demand or supply shocks 'masquerading' as such.

My sample starts in January 1965 and ends in November 2007. This allows to extend the time frame originally considered by Uhlig (2005) while excluding the unconventional monetary policy undertaken after the global financial crisis.[1] The reduced-form VAR specification includes 12 lags of the variables in (11) and, consistently with Uhlig (2005), does not include any deterministic term. The estimation is performed by using Bayesian methods with Jeffreys (flat) priors for Σ_e and B. This implies a normal-inverse-Wishart posterior distribution for the reduced-form parameters, from which it is straightforward to obtain independent draws (see, for instance, Del Negro and Schorfheide, 2011).

3.1 The Identification Strategy

In the first stage, I enforce Restriction SR by implementing the algorithm proposed by Rubio-Ramìrez et al. (2010), described in Appendix B.

Restriction SR. A monetary policy shock ε_t^m leads to a negative response of pi_t, ci_t and nr_t, and to a positive response of ff_t at horizons $h = 0, \ldots, 5$.

I generate 10^5 draws of A satisfying the above restriction and I store them into the set $\mathcal{P}$. For $i = 1, \ldots, 10^5$, let $\hat{\varepsilon}_t^{m,i}(A)$ be the *i-th* monetary policy shock associated with the *i-th* matrix $A \in \mathcal{P}$. The set $\mathcal{P}$ is then sharpened by only retaining the matrices $A \in \mathcal{P}$ such that $\hat{\varepsilon}_t^{m,i}(A)$ meets the external variable constraints contained in Restriction ER.

Restriction ER. Over the period from 1990:M1 to 2007:M11, a monetary policy shock ε_t^m satisfies the following external variable constraints:

$$corr(\varepsilon_t^m, FF4_t) > \tau \tag{ER1}$$

$$corr(\varepsilon_t^m, FI_t) = 0 \tag{ER2}$$

where $FF4_t$ is the change in the three-month-ahead federal funds rate futures in the 30-minute window around the FOMC announcement and FI_t is the Fed's information set in month t about current and future economic developments. The latter is proxied by Greenbook forecasts for real GDP growth and CPI inflation rate for the previous quarter

[1]The findings discussed in the next few sections are still valid over Uhlig's (2005) original sample.

and up to three quarters ahead and by the Greenbook nowcast for the quarterly unemp- ment rate.[2] The parameter τ in (ER1) determines how strong the correlation between monetary surprises $FF4_t$ and $\hat{\varepsilon}_t^m(A)$ must be for the latter to be accepted as a solution. Restriction ER ensures therefore the identification of monetary policy shocks that are substantially correlated with monetary surprises and exogenous to the information set of the policymaker.[3] In particular, I enforce constraint (ER2) by running the following regression at the monthly frequency and requiring the coefficients ϑ_0, ψ_p and λ_p, for $p = -1, \ldots, 3$, to be jointly not significant at the 5% level:

$$\hat{\varepsilon}_t^{m,i} = \alpha_m^i + \sum_{p=-1}^{3} \lambda_p^i G_{t,p}^{gdp} + \sum_{p=-1}^{3} \psi_p^i G_{t,p}^{\pi} + \vartheta_0^i G_{t,0}^u + u_{m,t}^i \tag{12}$$

$\hat{\varepsilon}_t^{m,i}$, with $i = 1, \ldots, 10^5$, is the i-th candidate shock satisfying Restriction SR; $G_{t,p}^j$, for $j = \{gdp, \pi\}$, denotes the p-quarters ahead Greenbook forecast for variable j in month t, and $G_{t,0}^u$ is the nowcast for the unemployment rate. I consider three alternative calibrations for the parameter τ in (ER1), that is set at the 75^{th}, 90^{th} or 99^{th} percentile of the set of correlation coefficients between the 10^5 shocks $\hat{\varepsilon}_t^m(A)$ obtained from $A \in \mathcal{P}$ and $FF4_t$. The structural impact matrices A generating shocks $\hat{\varepsilon}_t^m(A)$ that satisfy Restriction SR and ER are then stored, respectively, into the sets of solutions $\mathcal{P}^*_{75th}$, $\mathcal{P}^*_{90th}$ and $\mathcal{P}^*_{99th}$. It is worth mentioning that the frequency of the dependent variable in (12) is originally different from the one of the regressors: the shocks $\hat{\varepsilon}_t^{m,i}$ are monthly series while the Greenbook projections are released eight times a year. The latter are in fact prepared by the Federal Reserve Board staff prior to each FOMC meeting, typically in

[2] In this, I follow Romer and Romer (2004). The inclusion of backcast, nowcast and all the forecasts of the unemployment rate would not bring any additional information, while creating collinearity issues with the output growth series in regression (12).

[3] Restriction ER can only be imposed over the period 1990:M1-2007:M11, since the $FF4_t$ series is available from January 1990. This limitation is common to the entire literature on high-frequency identification of monetary policy shocks, as Gertler and Karadi (2015) and Miranda-Agrippino and Ricco (2021). The latter, for instance, estimate the reduced-form over the period 1979:M1-2014:M12 but only run the 2SLS regression that delivers the structural parameters from January 1990 onward.

the first and third month of each quarter. Consistently with Barth and Ramey (2002), I convert Greenbook variables to monthly frequency by using the initial forecasts of the quarter to approximate the information set of the Fed in the first two months, while the projections produced for the second meeting are used to update the series in the third month. This amounts to saying that the information set of the Fed does not change in months without FOMC meetings and probably assumes slightly less information than the Fed actually has.[4]

Finally, note that identification by external variable constraints significantly differs from that achieved in proxy-SVARs. The latter point-identify the structural model by assuming exogeneity and relevance of the external instrument. Conversely, the method I propose only delivers set-identification and, most importantly, does not assume any of the external variables to be a valid instrument. This is a major advantage since it is hard to build credibly exogenous instruments for monetary policy shocks. Several popular instruments in the empirical literature on monetary policy have been in fact found to be correlated with the information set of the Fed (as Gertler and Karadi's monetary surprises) or predictable by past information (as Romer and Romer's narrative series).

3.2 Impulse Response Functions

This subsection compares the IRFs derived by imposing standard sign restrictions with those obtained using the sets of solutions recovered through my identification strategy. In Appendix A, I show instead the IRFs obtained using only Restriction ER and in the case in which constraints (ER1) and (ER2) are alternatively released.

Figure 1 displays the IRFs under Restriction SR and those formed from $A \in \mathcal{P}^{*}_{75th}$. This set contains 5171 structural impact matrices A (out of the 10^5 matrices stored in

[4] In Appendix A, I drop this assumption by imposing (ER2) at the FOMC meeting frequency. This alternative approach delivers very similar results and has the advantage of not requiring any frequency conversion. However, it largely reduces the number of observations used to estimate regression (12).

$\mathcal{P}$) delivering monetary policy shocks uncorrelated with the Greenbook and that show a correlation with high-frequency surprises higher than 0.09 (the 75^{th} percentile of the set of correlation coefficients between $FF4_t$ and the 10^5 shocks associated with $A \in \mathcal{P}$).

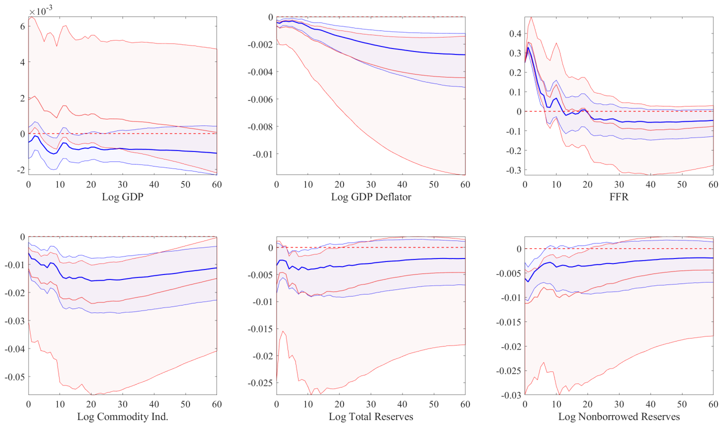

Figure 1: Responses to contractionary monetary policy shocks formed from $A \in \mathcal{P}^*_{75th}$ (in blue) and under Restriction SR (in red).

Notes: Monetary policy shocks normalized to induce a 25 basis points rise in ff_t. The solid line is the point-wise posterior median response. The shaded bands are the 68% equal-tailed point-wise posterior probability bands.

Importantly, once I discard the candidate shocks correlated with the Fed's information set or that weakly comove with $FF4_t$, expansionary effects of monetary tightenings are entirely ruled out. Figure 2 illustrates instead the IRFs obtained from $A \in \mathcal{P}^*_{90th}$. The

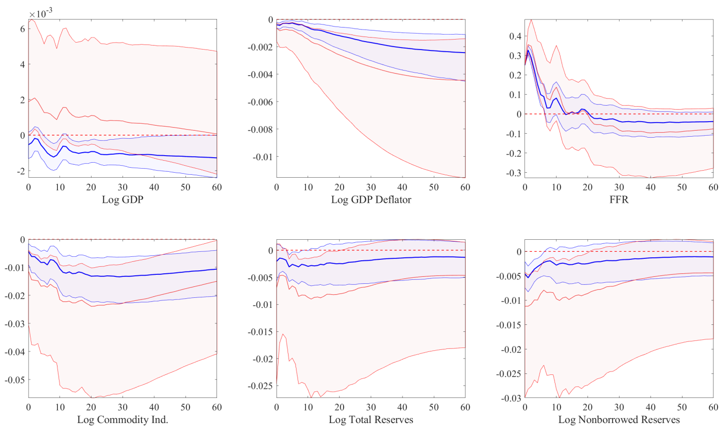

Figure 2: Responses to contractionary monetary policy shocks formed from $A \in \mathcal{P}^*_{90th}$ (in blue) and under Restriction SR (in red).

Notes: Monetary policy shocks normalized to induce a 25 basis points rise in ff_t. The solid line is the point-wise posterior median response. The shaded bands are the 68% equal-tailed point-wise posterior probability bands.

correlation between monetary policy shocks and $FF4_t$ is in this case constrained to be greater than 0.13 and the number of solutions drops to 2166. At odds with the results induced by traditional sign restrictions, US monetary contractions are found to trigger significantly negative effects on output in the short and medium-term.

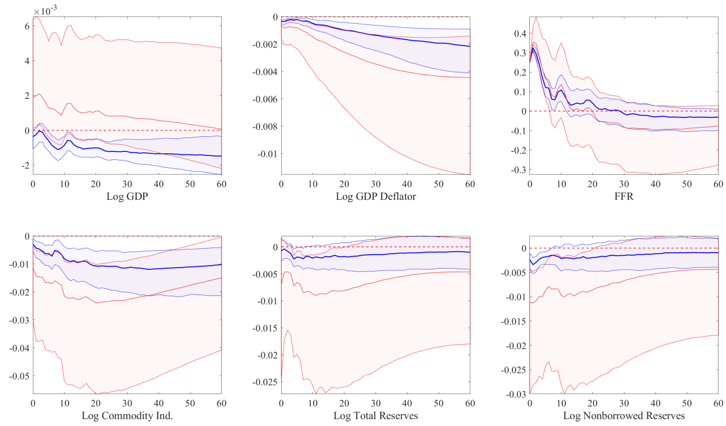

Figure 3: Responses to contractionary monetary policy shocks formed from $A \in \mathcal{P}^*_{99th}$ (in blue) and under Restriction SR (in red).

Notes: Monetary policy shocks normalized to induce a 25 basis points rise in ff_t. The solid line is the point-wise posterior median response. The shaded bands are the 68% equal-tailed point-wise posterior probability bands.

Finally, Figure 3 shows the IRFs formed from $A \in \mathcal{P}^*_{99th}$. As a result of the stricter restrictions, P^*_{99th} consists of only 227 elements. The associated monetary policy shocks are uncorrelated with Greenbook projections and exhibit a correlation with $FF4_t$ larger than 0.21. Compared to the previous cases, US monetary tightenings lower output in a shorter time and with a larger magnitude. External variable constraints appear thus to greatly mitigate the ambiguity surrounding Uhlig's (2005) findings: when Restriction SR is combined with Restriction ER, monetary contractions are unequivocally found to reduce output. Consistently with the point raised by Wolf (2020), the results obtained by Uhlig (2005) seem to be driven by a misidentification of the monetary policy shocks. As will be discussed in Section 4, 73% of the shocks identified through Restriction SR are in fact correlated with the Fed's information set, while about 24% of them negatively comove with $FF4_t$.

4 Relationship With Alternative Set-Identification Strategies

This section relates my approach to narrative sign restrictions (Antolín-Díaz and Rubio-Ramírez, 2018) and to restrictions on the monetary policy equation (Arias et al., 2019). These methods, similarly to the one I propose, build on traditional sign restrictions and are therefore based on the same model specification described in Section 3.

First, I show that the structural models recovered through my identification scheme meet their identifying assumptions. This is a key result, since it implies that Restriction SR and ER guarantee narrative consistency of monetary policy shocks and Taylor-rule consistency of monetary policy equations. On the contrary, the monetary policy shocks recovered through these alternative approaches are found to not satisfy Restriction ER. This finding seems to call into question their validity, since uncorrelation with the Fed's information set and large correlation with monetary surprises should characterize any plausible measure of monetary shock, no matter how it is recovered. For a comparison between the IRFs, the reader is instead referred to Section 6.

4.1 Identification by Narrative Sign Restrictions

Narrative sign restrictions were introduced by Antolín-Díaz and Rubio-Ramírez (2018). They combine Restriction SR with constraints on the sign of the monetary policy shocks ε_t^m and on the magnitude of their contribution to the unexpected changes in the federal funds rate ff_t during crucial episodes in the US monetary history.

In order to describe this approach, first note that the structural VMA representation can be truncated and approximated, at any t, as

$$y_t = \sum_{h=0}^{t-1} \Theta_h \varepsilon_{t-h} \tag{13}$$

where $\Theta_h = C_h P$ and $\varepsilon_t = P^{-1} e_t$. Let ff_t and ε_t^m be, respectively, the third and first entry of y_t and ε_t. The contribution of ε_t^m to the unexpected movement in $f\!f_t$, denoted by $H_{m,t}^{f\!f}$, is then given by

$$H_{m,t}^{f\!f} = \Theta_{0,31}\varepsilon_t^m \tag{14}$$

The two main identifying restrictions are imposed on the observation corresponding to October 1979, when Fed's chairman Paul Volcker started his anti-inflationary policy.

Restriction NR1. The monetary policy shock ε_t^m for the observation corresponding to October 1979 must be of positive value.

Restriction NR2. In October 1979, the absolute value of $H_{m,t}^{f\!f}$ is larger than the sum of the absolute value of the contributions of all other structural shocks.

Alternatively, they impose Restriction NR3 and NR4 on a wider set of events for which there is a reasonable agreement that an important monetary policy shock occurred.

Restriction NR3. The monetary policy shock ε_t^m must be positive for the observations corresponding to April 1974, October 1979, December 1988, and February 1994, and negative for December 1990, October 1998, April 2001, and November 2002.

Restriction NR4. For the periods specified in Restriction NR3, the absolute value of $H_{m,t}^{f\!f}$ is larger than the absolute value of the contribution of any other structural shock.

4.2 Narrative Consistency of Monetary Policy Shocks

Below, I derive the percentages of monetary policy shocks formed from $A \in \mathcal{P}_{99th}^*$ that satisfy Restriction NR1, NR2, NR3 and NR4. By doing so, I can evaluate whether my identification strategy recovers shocks that are consistent with the historical reading of the times performed by Antolín-Díaz and Rubio-Ramírez (2018).

As a benchmark, I first perform this analysis for the shocks identified through sign restrictions only. As reported in Table 1, despite almost 88% of the shocks are positive in October 1979, only a small percentage of them satisfies Restriction NR2. Moreover, their sign is reconcilable with only few of the constraints in Restriction NR3, while the vast majority of them fails in satisfying the requirements of Restriction NR4.

Restriction	1974:4	1979:10	1988:12	1990:12	1994:2	1998:10	2001:4	2002:11
NR1	-	87.9%	-	-	-	-	-	-
NR2	-	9.6%	-	-	-	-	-	-
NR3	96.3%	87.9%	36.0%	98.4%	21.0%	46.2%	42.2%	57.5%
NR4	47.3%	21.2%	14.8%	53.8%	19.3%	12.7%	9.1%	14.2%

Table 1: % of ε_t^m formed from $A \in \mathcal{P}$ satisfying Restriction NR1, NR2, NR3 and NR4

On the other hand, as displayed in Table 2, all the monetary policy shocks recovered through my method are positive on October 1979 and more than 90% of them are also found to be the overwhelming driver of unexpected movements in the federal funds rate on the same date. This result is crucial, since Antolín-Díaz and Rubio-Ramírez (2018)

Restriction	1974:4	1979:10	1988:12	1990:12	1994:2	1998:10	2001:4	2002:11
NR1	-	100.0%	-	-	-	-	-	-
NR2	-	90.3%	-	-	-	-	-	-
NR3	99.6%	100.0%	40.0%	94.3%	68.8%	100.0%	100.0%	100.0%
NR4	96.5%	97.4%	32.6%	71.8%	45.0%	99.1%	95.1%	88.6%

Table 2: % of ε_t^m formed from $A \in \mathcal{P}^*_{99th}$ satisfying Restriction NR1, NR2, NR3 and NR4

consider the Volcker reform as the clearest example of exogenous shock in the postwar period. Overall, the monetary policy shocks formed from $A \in \mathcal{P}^*_{99th}$ are also consistent with the broader set of episodes in Restriction NR3 and NR4. However, the December 1988 and February 1994 events are two exceptions that is worth investigating in more detail. A scrutiny of Greenbook forecasts and FOMC meetings minutes suggests that, rather than exogenous shocks, the federal funds rate hikes occurred on these two dates may indeed represent the endogenous response of the Fed to positive news about future economic developments. The rise in the interest rate in December 1988 is in fact paired with upward revisions in the nowcast and one-quarter ahead forecast for output growth. The minutes of the FOMC meeting that took place in February 1994 mention instead that this policy intervention was undertaken based on confidential access to 'optimistic' employment data that were not available when the Greenbook was prepared.[5]

4.3 Identification by Restrictions on the Monetary Policy Equation

The use of restrictions on the coefficients of the monetary policy equation was proposed by Arias et al. (2019). Denoting by d_{il} the (i,l)-element of the $k \times k$ matrix $D = A^{-1}$, the structural monetary policy equation can be expressed as follows,

$$ff_t = \phi_{gdp} gdp_t + \phi_{pi} pi_t + \phi_{ci} ci_t + \phi_{tr} tr_t + \phi_{nr} nr_t + \sigma \varepsilon_t^m \tag{15}$$

where $\phi_{gdp} = -\frac{d_{11}}{d_{13}}$, $\phi_{pi} = -\frac{d_{12}}{d_{13}}$, $\phi_{ci} = -\frac{d_{14}}{d_{13}}$, $\phi_{tr} = -\frac{d_{15}}{d_{13}}$, $\phi_{nr} = -\frac{d_{16}}{d_{13}}$ and $\sigma = d_{13}$.

Supported by a large literature on Taylor-type rules, they achieve set-identification by imposing the following zero and sign restrictions on the coefficients in equation (15).

Restriction TR1. The federal funds rate is the monetary policy instrument and only reacts contemporaneously to output, prices and commodity prices. Thus, $\phi_{tr}, \phi_{nr} = 0$.

Restriction TR2. The contemporaneous reaction of the federal funds rate to output and prices is positive, that is ϕ_{gdp}, $\phi_{pi} > 0$.

4.4 Taylor-Rule Consistency of Monetary Policy Equations

In this subsection, I compute the monetary policy equations associated with $A \in \mathcal{P}^*_{99th}$ and check if they satisfy Restriction TR1 and TR2. This allows to assess whether they

[5] This argument is also outlined in Antolín-Díaz and Rubio-Ramírez's (2018) Appendix C. However, given the magnitude of the increase in the federal funds rate, they nevertheless consider these two events as associated with monetary policy shocks.

are reconcilable or not with the principles underpinning Taylor-type policy rules.

As a benchmark, I first derive the posterior median estimates and the 68% probability intervals for the coefficients of equation (15) when identification is obtained through sign restrictions only. As shown in Table 3, the results are rather puzzling. In constrast with Restriction TR2, the median estimate for ϕ_{gdp} is negative. Moreover, the posterior

Coefficient	$\boldsymbol{\phi_{gdp}}$	$\boldsymbol{\phi_{pi}}$	$\boldsymbol{\phi_{ci}}$	$\boldsymbol{\phi_{tr}}$	$\boldsymbol{\phi_{nr}}$
Median	-0.38	1.90	0.11	0.09	0.04
68% Prob. Interval	[-2.42;0.82]	[-0.03;6.00]	[0.00;0.35]	[-0.44;0.64]	[-0.40;0.65]

Table 3: Coefficients in the monetary policy equations formed from $A \in \mathcal{P}$.

Notes: The entries are the posterior median estimates of the coefficients in the monetary policy equations (15) formed from $A \in \mathcal{P}$. The 68% equal-tailed posterior probability interval is reported in brackets.

estimates for ϕ_{tr} and ϕ_{nr} do not exclude large values: even though the median is close to zero, the 68% interval is quite wide and ranges up to about 0.65. The median for ϕ_{pi} is instead positive and hence consistent with Restriction TR2. However, the estimates are quite imprecise and negative values cannot be completely ruled out.

Table 4 reports the coefficients of the monetary policy equation for the case in which Restriction SR is combined with Restriction ER. As required by Restriction TR2, the

Coefficient	$\boldsymbol{\phi_{gdp}}$	$\boldsymbol{\phi_{pi}}$	$\boldsymbol{\phi_{ci}}$	$\boldsymbol{\phi_{tr}}$	$\boldsymbol{\phi_{nr}}$
Median	0.30	1.04	0.03	0.03	-0.03
68% Prob. Interval	[0.11;0.55]	[0.61;1.57]	[0.00;0.06]	[-0.07;0.11]	[-0.10;0.07]

Table 4: Coefficients in the monetary policy equations formed from $A \in \mathcal{P}^*_{99th}$.

Notes: The entries are the posterior median estimates of the coefficients in the monetary policy equations (15) formed from $A \in \mathcal{P}^*_{99th}$. The 68% equal-tailed posterior probability interval is reported in brackets.

median estimates for ϕ_{gdp} and ϕ_{pi} are positive and the 68% probability intervals entirely exclude negative values. This result is in line with the conduct of an inflation-targeting central bank that rises the interest rate to prevent an overheating economy or dampen inflationary pressures. Finally, note that ϕ_{tr} and ϕ_{nr} are narrowly concentrated around zero and are thus consistent with Restriction TR1, that assumes the federal funds rate to not respond to changes in total and nonborrowed reserves.

4.5 Alternative Set-Identification Strategies and the Fed's Information Set

Any truly exogenous measure of monetary policy shock should be uncorrelated with the Fed's information set about current and future economic conditions. Below, I identify 1000 shocks ε_t^m through narrative sign restrictions (Restriction SR, NR1 and NR2) and restrictions on the monetary policy equation (Restriction TR1 and TR2) and I project them on the Greenbook by running regression (12) over the period 1990:M1-2007:M11. I then test the null of joint nonsignificance of the estimated coefficients at the 5% level.[6] As a benchmark, I perform the same analysis on a set of 1000 shocks identified through standard sign restrictions (Restriction SR).

Table 5 reports the percentages of acceptance and rejection. More than 73% of the monetary policy shocks identified by Restriction SR are correlated with the Greenbook.

F-test result	SR	SR+NR1+NR2	TR1+TR2
Rejection	73.1%	64.0%	51.4%
Acceptance	26.9%	36.0%	48.6%

Table 5: % of acceptances and rejections of the null of joint nonsignificance of the coefficients of equation (12), 1990:M1-2007:M11.

In other words, they incorporate the endogenous response of the Fed to future economic conditions and their exogeneity is thus called into question. The additional imposition of Restriction NR1 and NR2 partly helps in alleviating this issue and, as a result, the rejection rate falls to 64%. The use of Restriction TR1 and TR2 turns out to outperform

[6] I could perform this test on a larger sample since Greenbook forecasts for CPI inflation are available from 1980. I run it from 1990 to 2007 to ensure consistency with the period on which constraint (ER2) is imposed. Increasing the sample size does not alter the results displayed in Table 5.

these two methodologies but, also in this case, the results are far from being satisfactory. About half of the shocks is in fact explained by the macroeconomic projections on which the FOMC bases its monetary policy decisions.

4.6 Alternative Set-Identification Strategies and Monetary Surprises

In this subsection, I verify whether monetary policy shocks identified by narrative sign restrictions and restrictions on the monetary policy equation display a strong positive comovement with monetary surprises. To this end, I derive the correlation coefficients ρ_m between the 1000 shocks recovered by each identification scheme and $FF4_t$. Then, I check if they are higher than 0 and 0.2, that is the minimum correlation required for A to be accepted in the set of solutions $\mathcal{P}^*_{99th}$. By defining it as a threshold, I can thus evaluate whether these methods deliver monetary policy shocks whose correlation with $FF4_t$ is comparable to that ensured by the approach I implement.

As displayed in Table 6, 24% of the shocks recovered by Restriction SR negatively comoves with $FF4_t$. Even when positive, the correlation is weak and larger than 0.2 in

ρ_m	**SR**	**SR+NR1+NR2**	**TR1+TR2**
> 0	76.2%	100.0%	99.9%
> 0.2	1.1%	8.9%	10.3%

Table 6: % of monetary policy shocks such that ρ_m is larger than 0 and 0.2, 1990:M1-2007M11

only 1% of the cases. The additional imposition of Restriction NR1 and NR2 seems to be quite effective in mitigating this issue and all the identified shocks positively comove with $FF4_t$. However, the correlation is overall low and only 8.9% of the shocks would meet the threshold implied by constraint (ER1). Similar findings hold for the monetary policy shocks retrieved through Restriction TR1 and TR2.

5 Am I Controlling for the Central Bank Information Channel?

This section assesses whether the use of Restriction SR and ER is effective in controlling for the central bank information channel. The rationale behind the analyses I perform is that 'true' contractionary monetary policy shocks should be accompanied by a drop in the stock market (Jarociński and Karadi, 2020). The comovement should be instead positive if the increase in the federal funds rate is associated with the disclosure of good news about future economic developments.

First, I compute the correlation coefficients ρ_s between monetary policy shocks and stock market surprises SPI_t^{hf}, that measure the changes in the S&P 500 over 30-minute windows around FOMC announcements. Importantly, shocks recovered by Restriction SR and ER negatively comove with SPI_t^{hf}. Despite improvements over sign restrictions, large shares of shocks recovered by narrative restrictions or restrictions on the monetary policy equation exhibit instead a positive comovement with the stock market surprises.

$\boldsymbol{\rho_s}$	**SR**	**SR+NR1+NR2**	**TR1+TR2**	**SR+ER**
< 0	45.7%	81.2%	85.6%	100.0%
> 0	54.3%	18.8%	14.4%	0%

Table 7: Percentages of shocks whose correlation with S&P 500 surprises is < 0 and > 0, 1990:M1-2007:M11.

Secondly, I use local projections to characterize the impulse responses of US stock prices to contractionary monetary policy shocks. Denoting by $\hat{\varepsilon}_t^{m,i}$ the i-th shock formed from $A \in \mathcal{P}^*_{99th}$, I estimate the following regression at the monthly frequency:

$$SPI_{t+h} = \gamma_i^{(h)} + \sum_{l=1}^{2} \alpha_{l,i}^{(h)} SPI_{t-l} + \sum_{j=0}^{5} \beta_{j,i}^{(h)} \hat{\varepsilon}_{t-j}^{m,i} + u_{t+h,i} \tag{16}$$

where $h = 0, \ldots, 48$ and $i = 1, \ldots, 227$. I denote by SPI_t the log of the US share price index produced by the OECD (computed as average of daily closing data) and I include 2 and 5 lags of SPI_t and $\hat{\varepsilon}_t^{m,i}$ as controls, respectively. The parameter of interest is $\hat{\beta}_{0,i}^{(h)}$, that measures the impulse response of SPI_t at time $t+h$ to the i-th identified shock.

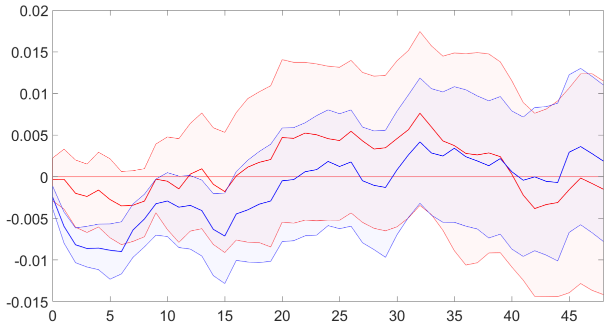

Figure 4: Response of SPI_t to contractionary monetary policy shocks formed from $A \in \mathcal{P}^*_{99th}$ (in blue) and under Restriction SR (in red)

Notes: The solid line is the median response and the shaded bands are the 68% equal-tailed probability bands. For each horizon h, they are computed point-wise by using the set of impulse responses estimated from (16).

For each horizon h, I then compute the median response and the 68% credibility interval by deriving the appropriate percentiles of the set of impulse responses $\{\hat{\beta}_{0,1}^{(h)}, \ldots, \hat{\beta}_{0,227}^{(h)}\}$. In Figure 4, I compare these results with those obtained when only sign restrictions are binding. In the latter case, the response of US stock prices is not statistically significant. On the other hand, when both Restriction SR and ER are enforced, the SPI_t turns out to considerably drop after a monetary contraction. The effect is negative on impact and reaches its minimum a few months after the shock. These findings seem to be consistent with the propagation of 'true' contractionary monetary policy shocks, rather than with the disclosure of Fed's positive information about the future economic outlook.

6 Robust Bayesian Inference

So far, in line with Antolín-Díaz and Rubio-Ramírez (2018) and Arias et al. (2019), I have imposed Restriction SR and ER through Rubio-Ramìrez et al.'s (2010) algorithm.

As detailed in Appendix B, it is based on the QR decomposition and assumes a uniform distribution of Q (the so-called Haar prior) on the space of orthonormal matrices $\mathcal{O}(k)$. However, this does not imply that the elements of Q are uniformly distributed over the identified set (Baumeister and Hamilton, 2015). The likelihood does not in fact depend on Q and this prior is thus not updated by the data. Although uniform, it may therefore be informative for objects of interest as impulse response function, even asymptotically.

In this section, I address this issue by combining numerical methods for constrained optimization with standard sampling from the posterior to calculate the infimum and supremum of the impulse responses over all admissible rotation matrices Q. Specifically, I build on Volpicella (2022) and extend his algorithm to the cases where identification is achieved by: (i) standard sign restrictions and external variable constraints (Restriction SR and ER); (ii) standard sign restrictions and narrative sign restrictions (Restriction SR, NR1 and NR2); (iii) restrictions on the monetary policy equation (Restriction TR1 and TR2). If restrictions are imposed through the uniform Haar prior, these approaches lead to similar implications about the real effects of US monetary contractions. Below, I demonstrate that my findings, unlike those obtained through alternative methodologies, are still valid when impulse responses do not depend on a specific prior for Q. For the rest of this section, let the monetary policy shock ε_t^m be the first entry of the $k \times 1$ vector ε_t and let $g'_{ih}(\phi)$ represent the i-th row of the $k \times k$ matrix $G_h = C_h S$, where C_h denotes the reduced-form impulse responses at horizon h and S is the unique lower-triangular Cholesky factor.

6.1 Algorithm 1: Sign Restrictions and External Variable Constraints

Algorithm 1 describes the procedure to obtain the prior-robust set of impulse responses of variable i to contractionary monetary policy shocks under Restriction SR and ER.[7]

[7] Computational details are provided in Appendix B.

Algorithm 1

1. Draw $\omega = (\Sigma_e, B)$ from the posterior distribution of the reduced-form VAR.

2. Given ω, check the non-emptiness of the set of solutions by verifying whether there exists an orthonormal matrix $\bar{Q}$ such that the restrictions imposed in Step 3 are satisfied. The detection of non-emptiness is executed by considering a maximum of 3000 candidate $\bar{Q}$, generated through the QR decomposition. If none of them satisfies the identifying restrictions, go back to Step 1.

3. By using $\bar{Q}$ as starting value, check if the following optimization problems have solutions Q^* at any horizon h:

$$\min_{Q} \text{ and } \max_{Q} \; g'_{ih}(\phi) q_1 \qquad \text{subject to:}$$
$$\begin{aligned}
&(i)\ S_1(\phi) q_1 \geq 0 \\
&(ii)\ corr(\hat{\varepsilon}^m_t(A), FF4_t) > \tau \\
&(iii)\ corr(\hat{\varepsilon}^m_t(A), FI_t) = 0 \\
&(iv)\ Q'Q = I
\end{aligned}$$

   where $S_1(\phi) q_1 \geq 0$ denotes the sign restrictions in Restriction SR.

4. If Step 3 is satisfied, store the impulse response functions derived using the solutions Q^* in the sets $\hat{\Omega}^{min}_{i,h}$ and $\hat{\Omega}^{max}_{i,h}$. Otherwise, go back to Step 1.

5. Repeat Steps 1-4 M times.

Below, I implement Algorithm 1 by drawing from the posterior of the reduced-form VAR detailed in Section 3. I narrow my focus on the output response and set $M = 1000$. To ensure comparability, the parameter τ is calibrated at the 99^{th} percentile of the set of correlation coefficients between $FF4_t$ and the monetary policy shocks obtained from $A \in \mathcal{P}$. In Figure 5, I compare the 68% equal-tailed credibility region obtained under a uniform prior for Q and robust Bayesian inference. Unlike Section 3, monetary shocks are in this case not normalized to generate a 25 basis points increase in ff_t. The resulting intervals may in fact be unbounded when the structural parameter $\hat{\Theta}_{0,31} = g_{30}' q_1^*$ is not bounded away from zero for all ω and Q^*. The findings achieved under my identification strategy, importantly, are still valid when inference is performed through Algorithm 1: despite the blue bands on the right panel are wider than those on the left one, monetary

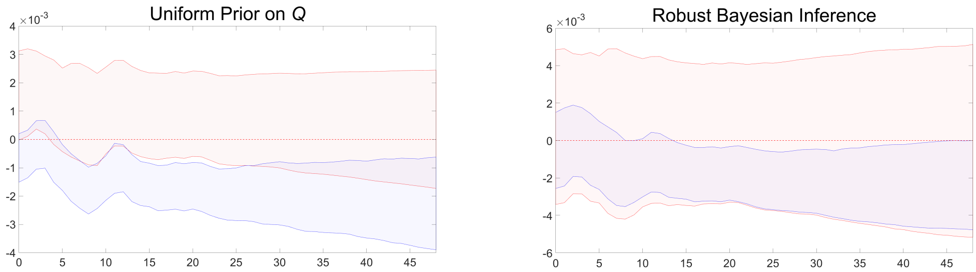

Figure 5: 68% equal-tailed credibility interval for output response using Restriction SR and ER (in blue) and using Restriction SR (in red).

contractions are in fact still found to induce a significant drop in output. When the uniform prior on Q is released, standard sign restrictions deliver instead impulse responses with even more contradictory implications and are thus completely uninformative about the transmission of US monetary policy.

6.2 Algorithm 2: Sign Restrictions and Narrative Sign Restrictions

Algorithm 2 describes the procedure to obtain the prior-robust set of impulse responses of variable i to contractionary monetary policy shocks under Restriction SR, NR1, NR2.

Algorithm 2

In Algorithm 1, replace Step 3 with the following.

3. By using $\bar{Q}$ as starting value, check if the following optimization problems have solutions Q^* at any horizon h:

$$\min_{Q} \text{ and } \max_{Q} \; g'_{ih}(\phi)q_1 \qquad \text{subject to:}$$

$$(i)\; S_1(\phi)q_1 \geq 0$$

$$(ii)\; \varepsilon^{m}_{t}(A) > 0 \quad \text{for } t\text{=1979:10}$$

$$(iii)\; H^{ff}_{1,t}(A) > \textstyle\sum_{j=2}^{k} H^{ff}_{j,t}(A) \quad \text{for } t\text{=1979:10}$$

$$(iv)\; Q'Q = I$$

where $S_1(\phi)q_1$ denotes the sign restrictions described in Restriction SR and $H^{ff}_{i,t}$, for $j = 1, \ldots, k$, denotes the contribution of shock j in explaining the historical decomposition of ff_t for observation t.

Below, I use Algorithm 2 by drawing from the posterior distribution of the reduced-form VAR described in Section 3. Figure 6 plots, in red, the resulting 68% robust equal-tailed credibility region for output response as well as the interval implied by a uniform prior for Q. To facilitate comparison with my approach, I contrast them with the bands obtained through Restriction SR and ER. The effects of contractionary monetary policy shocks on output are significantly negative when inference is performed by following the

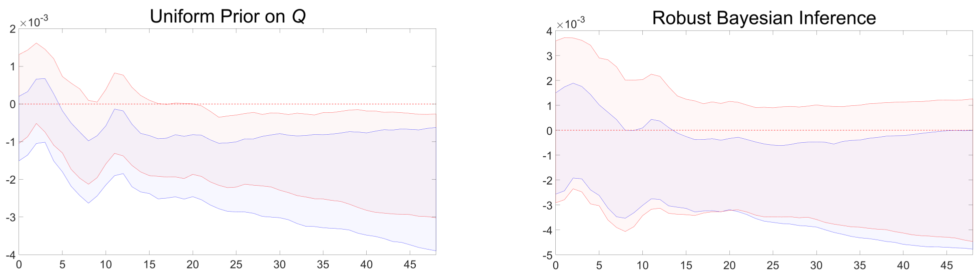

Figure 6: 68% equal-tailed credibility interval for output response using Restriction SR and ER (in blue) and using Restriction SR, NR1 and NR2 (in red).

standard procedure. Compared to those derived by my identification scheme, the effects are smaller and statistically significant with a greater delay. Furthermore, they seem to vanish when the uniform prior on Q is replaced by Algorithm 2. The robust credibility interval, in fact, includes zero at any horizon.

6.3 Algorithm 3: Restrictions on the Monetary Policy Equations

Algorithm 3 describes the procedure to obtain the prior-robust set of impulse responses of variable i to contractionary monetary policy shocks under Restriction TR1 and TR2.

Algorithm 3

In Algorithm 1, replace Step 3 with the following.

3. By using $\bar{Q}$ as starting value, check if the following optimization problems have solutions Q^* at any horizon h:

$$\min_Q \text{ and } \max_Q \; g'_{ih}(\phi)q_1 \qquad \text{subject to:}$$

$$(i)\ \phi_{gdp}(A) > 0,\ \phi_{\pi}(A) < 0,\ \phi_{tr}(A) = \phi_{nr}(A) = 0$$
$$(ii)\ Q'Q = I$$

where ϕ_j, with $j = \{gdp, \pi, tr, nr\}$, denotes the coefficients of equation (15).

After sampling from the posterior distribution of the reduced-form VAR introduced in Section 3, I derive the 68% equal-tailed credibility region for output response through Algorithm 3 and contrast it with the one obtained under a uniform prior for Q. Figure 7

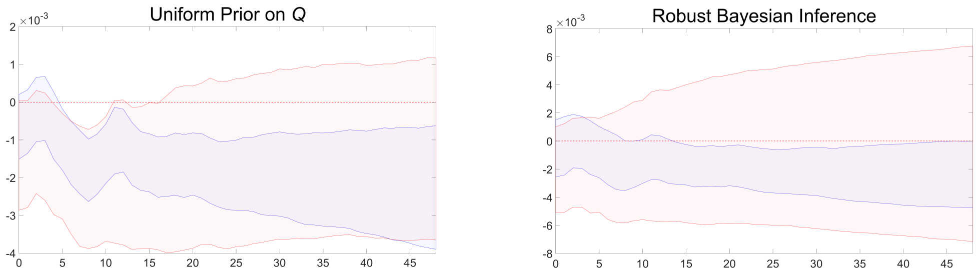

Figure 7: 68% equal-tailed credibility interval for output response using Restriction SR and ER and (in blue) and using Restriction TR1 and TR2 (in red).

plots them, in red, and runs a comparison with those derived using Restriction SR and ER. Under standard inference, contractionary monetary policy shocks turn out to have significant negative effects on output. If compared with the results achieved through my identification strategy, they are however quite short-lived and peak about eight months after the shock. Furthermore, differently from what happens by using the methodology I propose, the impact of monetary contractions is far more ambiguous when the uniform prior on Q is replaced by the robust Bayesian inference algorithm.

7 Conclusion

In this paper, I refine the identification achieved through sign restrictions (Uhlig, 2005) by combining them with external variable constraints on central bank's macroeconomic forecasts and high-frequency monetary surprises.

I employ this approach to evaluate the transmission of US monetary policy over the period 1965:M1-2007:M11. The use of external variable constraints markedly mitigates the ambiguity surrounding Uhlig's (2005) findings. In line with theoretical predictions, contractionary monetary policy shocks are uncontroversially found to decrease output. Importantly, these effects are still valid when inference is ran by using a robust Bayesian algorithm and are larger than those derived through narrative sign restrictions (Antolín-Díaz and Rubio-Ramírez, 2018) and restrictions on the monetary policy equation (Arias et al., 2019). Moreover, the shocks recovered by these two identification strategies turn out to be correlated with the Fed's information set and to poorly comove with monetary surprises. On the other hand, the use of external variable constraints delivers monetary policy shocks and monetary policy equations that are consistent with, respectively, an historical readings of the time and Taylor-type rules.

References

Antolín-Díaz, J. and Rubio-Ramírez, J. F. (2018). Narrative Sign Restrictions for SVARs. *American Economic Review*, 108(10):2802–2829.

Arias, J. E., Caldara, D., and Rubio-Ramìrez, J. F. (2019). The Systematic Component of Monetary Policy in SVARs: An Agnostic Identification Procedure. *Journal of Monetary Economics*, 2019(101):1–13.

Barth, M. J. and Ramey, V. A. (2002). The Cost Channel of Monetary Transmission. *NBER Macroeconomics Annual 2001*, 16:199–256.

Baumeister, C. and Hamilton, J. D. (2015). Sign Restrictions, Structural Vector Autoregressions, and Useful Prior Information. *Econometrica*, 83(5):1963–1999.

Bernanke, B. S. and Mihov, I. (1998). Measuring Monetary Policy. *Quarterly Journal of Economics*, 113(3):869–902.

Braun, R. and Brüggerman, R. (2022). Identification of SVAR Models by Combining Sign Restrictions With External Instruments. *Journal of Business & Economic Statistics*.

Christiano, L. J., Eichenbaum, M., and Evans, C. (1996). The Effects of Monetary Policy Shocks: Evidence from the Flow of Funds. *The Review of Economics and Statistics*, 78(1):16–34.

Del Negro, M. and Schorfheide, F. (2011). Bayesian Macroeconometrics. Prepared for *The Oxford Handbook of Bayesian Econometrics* by John Geweke, Gary Koop and Herman Van Dijk, *Oxford University Press*:293–389.

Gertler, M. and Karadi, P. (2015). Monetary Policy Surprises, Credit Costs, and Economic Activity. *American Economic Journal: Macroeconomics*, 7:44–76.

Giacomini, R. and Kitagawa, T. (2021). Robust Bayesian Inference for Set-Identified Models. *Econometrica*, 89(4):1519–1556.

Gilchrist, S. and Zakrajšek, E. (2012). Credit Spreads and Business Cycle Fluctuations.

American Economic Review, 102(4):1692–1720.

Jarociński, M. and Karadi, P. (2020). Deconstructing Monetary Policy Surprises: The Role of Information Shocks. *American Economic Journal: Macroeconomics*, 12:1–43.

Miranda-Agrippino, S. and Ricco, G. (2021). The Transmission of Monetary Policy Shocks. *American Economic Journal: Macroeconomics*, 13:74–107.

Romer, C. D. and Romer, D. H. (2004). A New Measure of Monetary Shocks: Derivation and Implications. *American Economic Review*, 94(4):1055–1084.

Rubio-Ramìrez, J. F., Waggoner, D. F., and Zha, T. (2010). Structural Vector Autoregressions: Theory of Identification and Algorithms for Inference. *The Review of Economic Studies*, 77(2):665–696.

Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica*, 48(1):1–48.

Smets, F. and Wouters, R. (2007). Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach. *American Economic Review*, 97(3):586–606.

Uhlig, H. (2005). What Are the Effects of Monetary Policy on Output? Results from an Agnostic Identification Procedure. *Journal of Monetary Economics*, 52(2):382–419.

Volpicella, A. (2022). SVARs Identification Through Bounds on the Forecast Error Variance. *Journal of Business & Economic Statistics*, 40(3):1291–1301.

Wolf, C. K. (2020). SVAR (Mis)identification and the Real Effects of Monetary Policy Shocks. *American Economic Journal: Macro*, 12(4):1–32.

A Robustness Checks

A.1 Imposing the Greenbook Constraint at the FOMC Meeting Frequency

As discussed in Section 3, enforcing constraint (ER2) at the monthly frequency requires inevitable assumptions about the timing with which the Fed updates its information set. In this section, I show the results obtained when constraint (ER2) is instead imposed at the FOMC meeting frequency. This approach does not involve any frequency conversion but considerably reduces the number of observations used to estimate regression (12).

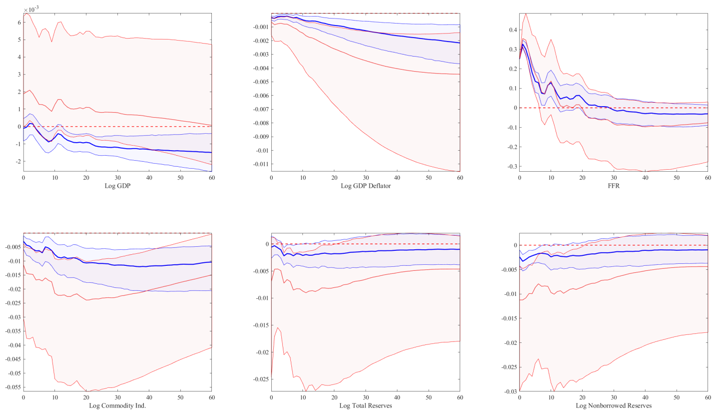

Figure A.1: Response to contractionary monetary policy shocks formed from $A \in \mathcal{P}^{*,mf}_{99th}$ (in blue) and under Restriction SR (in red)

Notes: Monetary policy shocks normalized to induce a 25 basis points rise in ff_t. The solid line is the point-wise posterior median response. The shaded bands are the 68% equal-tailed point-wise posterior probability bands.

Figure A.1 compares the IRFs derived under Restriction SR and those formed from the set of solutions $P^{*,mf}_{99th}$, that collects the 429 matrices A satisfying Restriction SR and ER when constraint (ER2) is imposed at the FOMC meeting frequency. Crucially, the output response is almost unchanged compared to that in Figure 3. Table A.1 shows instead the percentages of shocks formed from $A \in P^{*,mf}_{99th}$ that satisfy the restrictions imposed by Antolín-Díaz and Rubio-Ramírez (2018). Again, results are consistent with those in Section 3, thus showing that monetary shocks are reconcilable with a narrative reading of the times regardless of the frequency with which constraint (ER2) is enforced.

Restriction	1974:4	1979:10	1988:12	1990:12	1994:2	1998:10	2001:4	2002:11
NR1	-	100.0%	-	-	-	-	-	-
NR2	-	90.0%	-	-	-	-	-	-
NR3	99.5%	100.0%	47.5%	96.5%	57.3%	100.0%	99.8%	99.3%
NR4	94.6%	96.7%	37.7%	78.5%	44.8%	94.6%	89.7%	87.7%

Table A.1: % of ε_t^m formed from $A \in \mathcal{P}_{99th}^{*,mf}$ satisfying Restriction NR1, NR2, NR3 and NR4

As shown in Table A.2, a similar conclusion holds for the Taylor-rule consistency of the monetary policy equations. The coefficients obtained from $A \in \mathcal{P}_{99th}^{*,mf}$ are in fact overall reconcilable with Restriction TR1 and TR2.

Coefficient	ϕ_{gdp}	ϕ_{pi}	ϕ_{ci}	ϕ_{tr}	ϕ_{nr}
Median	0.21	1.06	0.03	0.03	-0.02
68% Prob. Interval	[-0.02;0.46]	[0.65;1.59]	[0.01;0.06]	[-0.07;0.12]	[-0.10;0.06]

Table A.2: Coefficients in the monetary policy equations formed from $A \in \mathcal{P}_{99th}^{*,mf}$.

Notes: The entries in the table are the posterior median estimates of the coefficients in the monetary equations (15) formed from $A \in \mathcal{P}_{99th}^{*,mf}$. The 68% equal-tailed posterior probability interval is reported in brackets.

A.2 IRFs Using Only Restriction ER

This section shows the IRFs obtained when Restriction SR is dropped and identification is achieved through Restriction ER only.

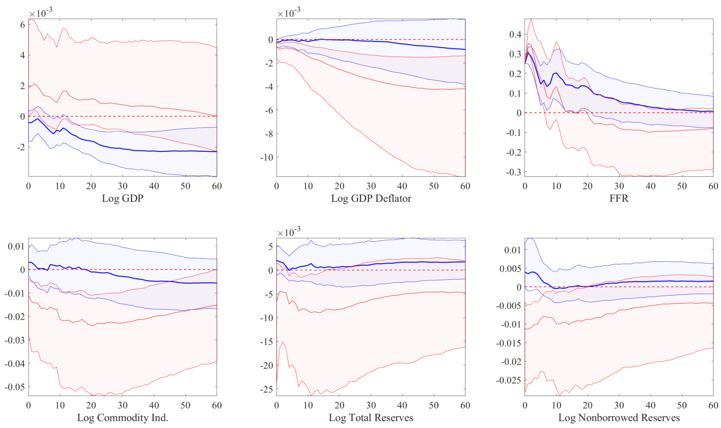

Figure A.2: Response to contractionary monetary policy shocks formed from $A \in \bar{\mathcal{P}}^{*}_{99th}$ (in blue) and under Restriction SR (in red).

Notes: Monetary policy shocks normalized to induce a 25 basis points rise in $f\!f_t$. The solid line is the point-wise posterior median response. The shaded bands are the 68% equal-tailed point-wise posterior probability bands.

As in Section 3, I generate 10^5 structural impact matrices A that are stored into the set of solutions $\bar{\mathcal{P}}$. In this case, importantly, they are not required to meet Restriction SR but only to guarantee that the resulting monetary policy shock $\hat{\varepsilon}^m_t(A)$ has a positive impact effect on $f\!f_t$. In the following step, I only retain the matrices $A \in \bar{\mathcal{P}}$ such that $\hat{\varepsilon}^m_t(A)$ meet Restriction ER. For the sake of comparability, I set the parameter τ equal to the 99^{th} percentile value of the set of correlation coefficients between $FF4_t$ and the shocks $\hat{\varepsilon}^m_t(A)$ formed from $A \in \bar{\mathcal{P}}$ (that implies $\tau = 0.23$). The matrices A that deliver monetary policy shocks $\hat{\varepsilon}^m_t(A)$ satisfying Restriction ER are finally collected into the set $\bar{\mathcal{P}}^{*}_{99th}$. The resulting IRFs are displayed in Figure A.2, where I compare them with the ones obtained under Restriction SR. Consistently with the results in Section 3, output is found to negatively react in response to contractionary monetary policy shocks. This confirms that external variable constraints drive most of the identification.

A.3 IRFs Using Minimal External Variable Constraints

This section shows the IRFs obtained by keeping Restriction SR binding and by alternatively imposing constraints (ER1) and (ER2).

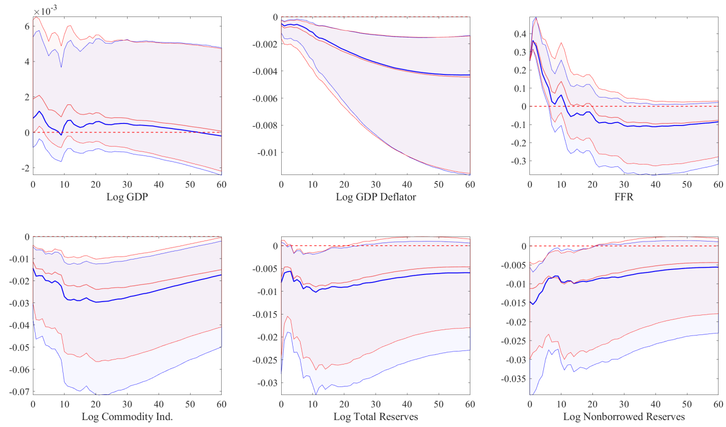

Figure A.3: Responses to contractionary monetary policy shocks formed from $A \in \mathcal{P}_f^*$ (in blue) and under Restriction SR (in red).

Notes: Monetary policy shocks normalized to induce a 25 basis points rise in ff_t. The solid line is the point-wise posterior median response. The shaded bands are the 68% equal-tailed point-wise posterior probability bands.

Figure A.3 plots the IRFs derived if only constraint (ER2) is added to Restriction SR. The resulting set of solutions is denoted by $\mathcal{P}_f^*$ and counts 27508 elements. Despite

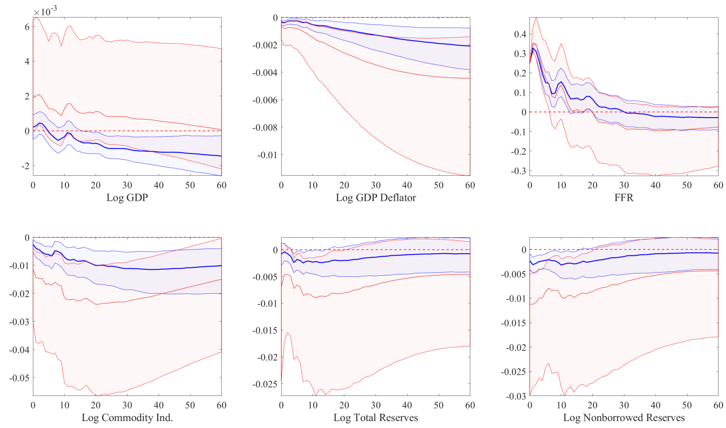

Figure A.4: Responses to contractionary monetary policy shocks formed from $A \in \mathcal{P}_m^*$ (in blue) and under Restriction SR (in red).

Notes: Monetary policy shocks normalized to induce a 25 basis points rise in ff_t. The solid line is the point-wise posterior median response. The shaded bands are the 68% equal-tailed point-wise posterior probability bands.

it shifts towards negative values, the set of output responses is similar to that obtained under only Restriction SR. Figure A.4 plots instead the IRFs obtained if only constraint (ER1) (with the parameter τ set at the 99^{th} percentile) is added to Restriction SR. The effects on output of the contractionary shocks formed from the resulting set of solutions $\mathcal{P}_m^*$ are negative in the medium and long-run but more ambiguous in the shorter-term.

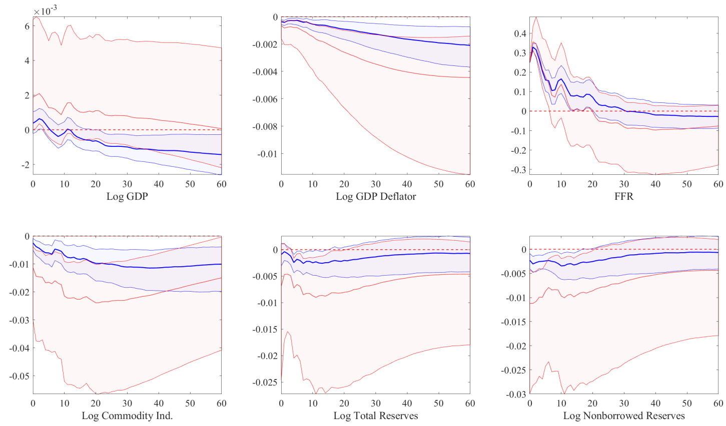

Figure A.5: Responses to contractionary monetary policy shocks formed from $A \in \mathcal{P}_m^{*,info}$ (in blue) and under Restriction SR (in red).

Notes: Monetary policy shocks normalized to induce a 25 basis points rise in ff_t. The solid line is the point-wise posterior median response. The shaded bands are the 68% equal-tailed point-wise posterior probability bands.

Although not statistically significant, the contemporaneous response is in fact positive on impact. This finding might lend itself to the following interpretation. If constraint (ER2) is not binding, the identified set also contains shocks which are correlated with the Fed's information set. The rise in output is thus consistent with a scenario in which the Fed discloses good news about future economic conditions and, given its reaction function, tightens monetary policy to partly offset the expansionary effects of the news and prevent an inflationary pressures. This argument emerges more clearly from Figure A.5, that shows the IRFs formed from the set $\mathcal{P}_m^{*,info}$. The latter contains 773 matrices A generating monetary policy shocks that satisfy constraint (ER1) (with τ set at the 99^{th} percentile) but are correlated with the Greenbook. The output response is positive and, even though only weakly, statistically significant in the first few months after the shock. Hence, constraints (ER1) and (ER2) are both necessary to obtain conventional effects of contractionary monetary policy shocks. Specifically, the exclusion of shocks correlated with the Fed's information set is crucial to rule out structural models whose short-run implications are compatible with the information channel of monetary policy.

A.4 Imposing Restriction SR and ER on a Different Model Specification

In this section, I check whether imposing Restriction SR and ER on a different system of variables delivers similar results. Specifically, I consider the same model specification as Miranda-Agrippino and Ricco (2021), that covers the period 1979:M1-2014:M12 and includes a constant as well as 12 lags of the following vector of US monthly series,

$$y_t' = \begin{bmatrix} ip_t & pi_t & f\!f_t & ci_t & u_t & ebp_t \end{bmatrix} \tag{A.1}$$

where ip_t is the log of industrial production, pi_t is the log of the consumer price index, $f\!f_t$ is the federal funds rate, ci_t is the log of a commodity price index, u_t denotes the unemployment rate and ebp_t is Gilchrist and Zakrajšek's (2012) excess bond premium. I impose the following restrictions and adopt the same procedure detailed in Section 3.

Restriction SR. A monetary policy shock ε_t^m leads to a negative response of pi_t and ci_t and to a positive response of $f\!f_t$ at horizons $h = 0, \dots, 5$.

Restriction ER. Over the period from 1990:M1 to 2007:M11, a monetary policy shock ε_t^m satisfies the following external variable constraints:

$$corr(\varepsilon_t^m, FF4_t) > \tau \tag{ER1}$$

$$corr(\varepsilon_t^m, FI_t) = 0 \tag{ER2}$$

Specifically, I focus on the case where τ is set equal to the 99^{th} percentile value of the set of correlation coefficients between $FF4_t$ and the shocks $\hat{\varepsilon}_t^m(A)$ formed from $A \in \mathcal{P}$. Out of the 10^5 elements in $\mathcal{P}$, the set of solutions $\mathcal{P}^*_{99th}$ retains 566 matrices A which deliver monetary policy shocks that are uncorrelated with the Greenbook and display a correlation with monetary surprises larger than 0.20 (the value of the 99^{th} percentile). As displayed in Figure A.6, coherently with the findings presented in Section 3, contractionary monetary policy shocks turn out to trigger negative real effects: the unemploy-

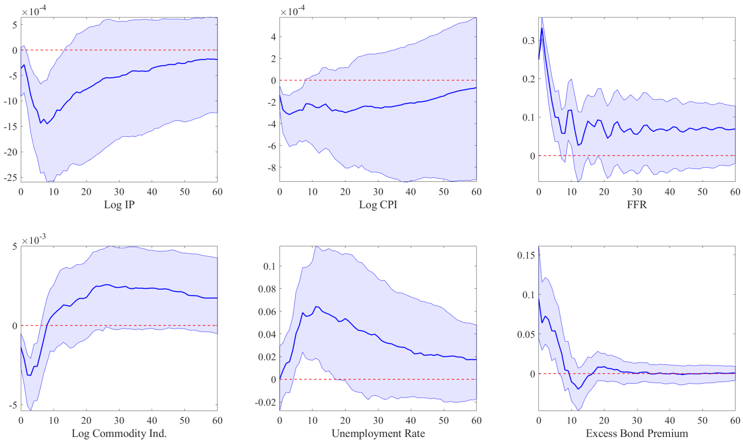

Figure A.6: Response to contractionary monetary policy shocks formed from $A \in \mathcal{P}^{*}_{99th}$ using Miranda-Agrippino and Ricco's (2021) model

Notes: Monetary policy shocks normalized to induce a 25 basis points rise in ff_t. The solid line is the point-wise posterior median response. The shaded bands are the 68% equal-tailed point-wise posterior probability bands.

ment rate is found to increase after a monetary tightening, while industrial production experiences a sharp decline.

B Technical Appendix

B.1 Rubio-Ramìrez et al.'s (2010) Algorithm

In Section 3, I impose sign restrictions through Rubio-Ramìrez et al.'s (2010) algorithm, based on the QR decomposition. For a certain draw of $\omega = (\Sigma_e, B)$ from the posterior distribution of the reduced-form VAR, I iterate the following procedure.

1. Draw from a $\mathcal{N}(0_{k\times 1}, I_k)$ and run a QR decomposition of the matrix, that delivers a $k \times k$ matrix R with positive diagonal entries and a $k \times k$ orthonormal matrix Q.
2. Let S denote the lower-triangular Cholesky factor of Σ_e. I compute the candidate impulse responses $\hat{\Theta}_h = C_h A$, where C_h are the reduced-form impulse responses, for $h = 0, \ldots, H$. If $\hat{\Theta}_h$ satisfy the sign restrictions, I store them. If not, I discard them and go back to the first step.
3. I repeat step 1 and 2 until $M = 10^5$ responses are obtained.

Once I obtain 10^5 draws, I compute the point-wise posterior median and 68% equal-tailed posterior probability bands at each horizon h.

B.2 Computational Details

The optimization problems in Section 6 are solved by using the Sequential Quadratic Programming (SQP) algorithm in MATLAB's Optimization Toolbox. Specifically, the `fmincon` solver is implemented by specifying the following optimization options.

Option	Description	Calibration
`OptimalityTolerance`	Termination tolerance on the first-order optimality measure	1e-6
`ConstraintTolerance`	Tolerance on the constraint violation	1e-6
`MaxFunctionEvaluations`	Maximum number of function evaluations allowed	3000
`MaxIterations`	Maximum number of iterations allowed	1000