연세대학교 상경대학

경제연구소

Economic Research Institute

Yonsei University

서울시 서대문구 연세로 50

50 Yonsei-ro, Seodaemun-gu, Seoul, Korea

TEL: (+82-2) 2123-4065 FAX: (+82-2) 364-9149

E-mail: yeri4065@yonsei.ac.kr

http://yeri.yonsei.ac.kr/new

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Hyeon-seung Huh

Yonsei University

David Kim

University of Sydney

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Hyeon-seung Huh
School of Economics
Yonsei University
Republic of Korea
hshuh@yonsei.ac.kr

David Kim
School of Economics
University of Sydney
Australia
Kim.david@sydney.edu.au

Abstract

The use of sign restrictions to identify monetary policy shocks in structural vector autoregression (SVAR) models has garnered significant attention in recent years. In this context, we revisit two influential studies—Uhlig (2005) and Arias *et al*. (2019)—which offer conflicting conclusions regarding the output effects of contractionary monetary policy shocks. Our analysis seeks to uncover the underlying causes of these discrepancies and evaluate the sensitivity of the results to alternative model specifications. Specifically, we examine four key factors: (i) the influence of rotation priors on posterior inference in sign-restricted SVAR models, (ii) the robustness of findings when employing an alternative algorithm to generate large sets of responses, (iii) the sensitivity of results to variations in identifying restrictions, and (iv) the robustness of conclusions to changes in the monetary policy equation and the inclusion of the Great Moderation.

Keywords*:* Sign restrictions, Rotation matrix, monetary policy shocks, Structural vector autoregression, Baumeister and Hamilton critique

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1. Introduction

Structural vector autoregression (SVAR) models have become the primary empirical framework for analyzing the effects of monetary policy on output. A central challenge in this literature is correctly identifying monetary policy shocks and drawing reliable structural inferences. One widely used identification approach relies on recursive assumptions based on specific informational orderings regarding the arrival of monetary shocks. A prominent example of this is Christiano *et al*. (1999), where the upper block of variables—comprising output, prices, and commodity prices—was assumed not to respond to monetary policy shocks within the same quarter (or month), while contemporaneous values of these upper-block variables were allowed to affect monetary policy decisions. A key takeaway from this identification scheme was that contractionary monetary policy shocks had significant negative effects on output (for a survey, see Leeper *et al*., 1996; Christiano *et al*., 1999; Ramey, 2016).

In recent years, there has been a growing body of research that employs sign restrictions to identify monetary policy shocks, offering an alternative to the traditional zero restrictions associated with the recursive assumption (e.g., Faust, 1998; Faust *et al*., 2004; Uhlig, 2005; Amir-Ahmadi and Uhlig, 2015; Arias *et al*., 2019). Among these studies, Uhlig (2005) and Arias *et al*. (2019) are particularly influential and have garnered considerable attention. Both studies share the same reduced-form VAR specification, which includes output, prices, commodity prices, total reserves, nonborrowed reserves, and the federal funds rate—a standard set of variables in the empirical literature. They also adopt the conventional Bayesian approach, employing a normal-inverse Wishart prior for the reduced-form VAR parameters and a Haar prior for the rotation matrix. However, despite these similarities, the two models yield opposing conclusions regarding the effects of monetary policy shocks on output.

Uhlig (2005) challenges the conventional identification scheme that imposes a zero restriction on the impact response of output to monetary policy shocks. He proposes an agnostic approach in which monetary policy shocks are identified by imposing sign restrictions on the responses of prices, commodity prices, and nonborrowed reserves, while leaving the output response unconstrained. Under this identification scheme, a monetary policy shock that raises the federal funds rate is shown to increase output, contradicting the conventional result. Similar findings are reported by Faust *et al*. (2004) and Amir-Ahmadi and Uhlig (2015), who also observe positive output effects from contractionary monetary policy. Ramey (2016), in a survey, summarizes that monetary tightening can become expansionary in the short run once the zero restriction on the output response to the monetary policy shock is relaxed.

Arias *et al*. (2019), in contrast, reaffirm the conventional finding that a contractionary monetary policy shock reduces output, even when the output response is unconstrained. They contend that since monetary policy is typically guided by a rule, most variations in monetary policy instruments stem from the systematic component of monetary policy, with the federal funds rate serving as the policy instrument, supported by empirical and anecdotal evidence.[1] To model this, they define the systematic component of monetary policy by assuming that the federal funds rate responds to output and prices with positive signs, consistent with Taylor-type rules commonly used in theoretical and empirical models. Nonborrowed reserves and total reserves do not enter the monetary policy equation. Consequently, a combination of sign and zero restrictions is imposed directly on the contemporaneous coefficients in the monetary policy equation.

We assess the robustness of the findings in Uhlig (2005) and Arias *et al*. (2019) across four key dimensions. First, both studies employ a Haar prior for the rotation matrix, a common practice in sign restriction models. Since all orthogonal matrices generated under this scheme are equally probable, the Haar prior rotation matrix is typically considered uninformative. However, because the rotation matrix does not enter the likelihood and its priors are never updated by data, the influence does not vanish asymptotically. In this regard, Baumeister and Hamilton (2015, 2018, 2020) argue that the rotation prior can be unintentionally informative about posterior inference despite having no relationship with

[1] Except for two brief periods–one in the early 1970s and another between 1979 and 1982, when the Federal Reserve explicitly targeted nonborrowed reserves–U.S. monetary policy since 1965 can be characterized by a direct and indirect regime targeting the federal funds rate, even though the federal funds rate has formally become the Federal Reserve's policy instrument since 1997 (Bernanke and Blinder, 1992; Romer and Romer, 2004; Sims and Zha, 2006).

economic interpretations or data. They provide empirical examples where the impulse response posteriors are driven by the rotation prior and caution that the density of accepted responses, along with summary measures such as the median and other percentiles, may lead to misleading conclusions. We empirically examine how the concerns raised by Baumeister and Hamilton (hereafter referred to as the "Baumeister and Hamilton critique") may affect the findings in Uhlig (2005) and Arias *et al*. (2019).

Second, we re-estimate the models of Uhlig (2005) and Arias *et al*. (2019) using an alternative algorithm that applies the same identification schemes while dispensing with the rotation matrix. This algorithm is built upon Ouliaris and Pagan (2016, 2022, hereafter referred to as 'OP'). The OP algorithm randomly draws the contemporaneous coefficients of the structural equations in the SVAR. Once values for these coefficients are generated, the SVAR becomes exactly identified and can be estimated. Impulse responses are then calculated and assessed against the sign restrictions for acceptance or rejection. This process is repeated numerous times, generating large sets of accepted responses. The OP algorithm is particularly convenient for imposing signs and zero restrictions on the SVAR structural equations (e.g., monetary policy equation). However, by design, the generated contemporaneous coefficients are assigned more probability mass close to zero (Kilian and Lütkepohl, 2017, p. 429), which may also influence the set of accepted responses, irrespective of the data. To address this issue, we leverage the idea that a uniform distribution is often used when there is little knowledge about the density. Consequently, the algorithm is modified to draw each contemporaneous coefficient from a uniform distribution that spans the entire range of possible values. While assuming a uniform distribution is arbitrary and subject to critique, it offers a fair and neutral alternative by treating all contemporaneous coefficients as equally probable, avoiding bias towards any specific values. This approach is referred to as the 'uniform OP algorithm' and can be easily extended to account for sampling uncertainty in a standard Bayesian framework.[2] We then compare how the results differ from those in Uhlig (2005) and Arias *et al*. (2019), which can be influenced by the informativeness of the rotation matrix.

[2] The original OP algorithm was developed in a non-Bayesian framework (e.g., no sampling uncertainty).

Third, we investigate why Uhlig (2005) and Arias *et al*. (2019) produce contradictory effects of monetary policy on output. Given that both studies share the same reduced-form Bayesian VAR specification, the primary cause of their differing results likely lies in the identification restrictions used. Using the uniform OP algorithm, we explore various combinations of identification restrictions to determine which ones drive the discrepancies in the results. Finally, we assess the sensitivity of the findings to two concerns that warrant special attention. The first is whether the results are sensitive to the specification of the monetary policy equation, which plays a critical role in the analysis. For comparison, we also consider a Taylor-type monetary policy equation in which the federal funds rate responds to inflation and the output gap. The second concern is how the results fare during the Great Moderation covering the mid-1980s to 2007.[3] Barakchian and Crowe (2013) and Ramey (2016) observe that the contractionary output effects of monetary policy shocks, found with most identification schemes, are not robust when the sample is limited to the Great Moderation.

The rest of the paper is structured as follows. Section 2 provides a summary of the models in Uhlig (2005) and Arias *et al*. (2019) and introduces the uniform OP algorithm. Section 3 empirically evaluates whether the findings in Uhlig and Arias *et al*. have been affected by the informativeness of the rotation matrix. Section 4 presents the results obtained using the uniform OP algorithm and compares these results with those from Uhlig and Arias *et al*. Section 5 explores the reasons why the two identification schemes yield different effects of monetary policy on output. The penultimate section examines the sensitivity of the results to alternative monetary policy equations and the Great Moderation. Section 7 concludes.

2. Models and identification schemes

Following Uhlig (2005) and Arias *et al*. (2019), the model includes six endogenous variables for the U.S.: output (y_t), prices (p_t), commodity prices (cp_t), total reserves (tr_t), nonborrowed reserves (nbr_t), and the federal funds rate (r_t). Collecting the variables in a vector $z_t = (y_t,\ p_t,\ cp_t,\ tr_t,\ nbr_t,\ r_t)'$, the reduced-form vector moving average

[3] The Great Moderation refers to the period of reduced macroeconomic volatility in the U.S. from the mid-1980s to 2007. It is characterized by a multi-decade era of low inflation and steady economic growth.

representation may be expressed as

$$z_t = D(L)e_t \tag{1}$$

where $D(L) = (I + D_1L + D_2L^2 + \ldots)$, L is the lag operator, and e_t is a vector of reduced-form errors, distributed as $N(0,\ \Omega)$, so that the errors have a mean of zero and are contemporaneously correlated. An initial set of orthogonal shocks is defined as $\psi_t = Pe_t$ where $\Omega = P^{-1}P^{-T}$. In this study, the matrix P^{-1} is obtained through an eigenvalue decomposition of Ω, although it can also be derived using a Cholesky decomposition of Ω. Equation (1) is written as

$$z_t = D(L)P^{-1}Pe_t \tag{2}$$

The initial shocks are rotated using an orthogonal rotation matrix Q (i.e., $QQ' = Q'Q = I$) to form a new set of orthogonal shocks. For the purposes of this study, we focus on identifying a single shock: the monetary policy shock. Therefore, it suffices to define an orthogonal rotation vector q of dimension (6x1), where q=(q_1, q_2, q_3, q_4, q_5, q_6)'. With this, equation (2) becomes:

$$z_t = D(L)P^{-1}qq'Pe_t \tag{3}$$

After identification, the monetary policy shock is $\eta_t = q'Pe_t$, and the impulse responses to it are given by:

$$c(L) = D(L)P^{-1}q \tag{4}$$

where the impact response of dimension (6x1) is $c(0) = P^{-1}q$ ($\because$ $D(0) = I$).

2.1. Uhlig (2005) identification scheme

In Uhlig's (2005) identification scheme, the orthogonal rotation vector q is generated by drawing a random point on the unit sphere in $\mathbb{R}^6$. The simplistic way to obtain this random unit vector is to draw a (6x1) vector of independent N(0, 1) and normalize it by dividing by its norm (i.e., $\| q \|$=1).[4] Once q is generated, so are the candidate responses in equation (4),

[4] When relying solely on sign restrictions for identification, a common approach for generating the rotation matrix Q is the algorithm proposed by Rubio-Ramírez *et al*. (2010). This method involves performing a QR decomposition on an (*nxn*) matrix X, whose elements are randomly drawn from a N(0, 1) distribution. From the QR decomposition of X=QR, Q is an orthogonal matrix, and R is an upper triangular matrix. An alternative method for generating the rotation matrix Q is the algorithm proposed by Fisher and Huh (2020), which utilizes Givens rotations. For the Uhlig model, any one column of Q can be selected as a rotation vector, yielding equivalent results.

which are to be judged by the sign restrictions for acceptance or rejection. To identify a monetary policy shock, Uhlig imposes the following sign restrictions over the horizon from zero to five periods: the responses of prices, commodity prices, and nonborrowed reserves must not be positive, and the response of the federal funds rate must not be negative. As a result, only the candidate responses that satisfy these sign restrictions are retained, while others are discarded. No sign restriction is applied to the output response, which is the key variable of interest in the analysis.

2.2. Arias et al. (2019) identification scheme

Arias *et al*. (2019) propose an alternative identification scheme for monetary policy shocks, which imposes restrictions directly on a structural equation of the SVAR model rather than on the impulse responses. Without loss of generality, denote the sixth shock in the SVAR model as a monetary policy shock, and then, the sixth structural equation becomes a monetary policy equation, specifying how the federal funds rate responds systematically to economic conditions. The coefficients of the variables in the monetary policy equation can be backed out from the responses in equation (4), which is expressed as

$$a(L)z_t = \eta_t \tag{5}$$

where $a(L) = c(L)^{-1} = q'PD(L)^{-1}$. Setting $L = 0$ yields the vector of contemporaneous coefficients $a(0)$ of dimension (1x6) as

$$a(0) = q'P \tag{6}$$

Since Arias *et al*.'s identification scheme concentrates on the contemporaneous coefficients, the monetary policy equation in equations (5) and (6) can be written as

$$a_1 y_t + a_2 p_t + a_3 cp_t + a_4 tr_t + a_5 nbr_t + a_6 r_t = \eta_t \tag{7}$$

where the i^{th} element of $a(0)$ is $a_i = q'P_i$, and P_i is the i^{th} column of the matrix P. The first set of identifying restrictions enforces that the federal funds rate reacts only to output, prices, and commodity prices. This amounts to imposing that $a_4 = q'P_4 = 0$ and $a_5 = q'P_5 = 0$. Using the technique by Arias *et al*. (2018), the two zero restrictions can be imposed by finding an orthogonal vector *q* that renders $q'P_4 = q'P_5 = 0$. Once the restricted *q* is obtained, all the other coefficients a_i $(i \neq 4,5)$ in the monetary policy equation are determined. Arias *et al*. also normalize the monetary policy equation with respect to the federal funds rate with $a_6 > 0$. Hence,

$$r_t = \lambda_1 y_t + \lambda_2 p_t + \lambda_3 cp_t + \sigma\eta_t \quad (8)$$

where $\lambda_i = -a_i / a_6$ and $\sigma = 1/a_6$. Finally, the identification scheme imposes the sign restrictions that the federal funds rate reacts positively to output and prices, i.e., $\lambda_1 > 0$ and $\lambda_2 > 0$. The reaction to commodity prices is left unrestricted. If both sign restrictions are satisfied, the q vector is retained; otherwise, it is discarded. For the retained q vector, the corresponding responses to the monetary policy shock can be generated using equation (4), with the output response being unconstrained.

2.3. Uniform OP algorithm

Unlike the procedures used by Uhlig (2005) and Arias *et al*. (2019), the uniform OP algorithm does not rely on a rotation matrix to produce large sets of responses. Instead, it generates contemporaneous coefficients of the structural equations in the SVAR model by repeatedly drawing from uniform distributions. For exposition purposes, we consider a SVAR model with one lag, although the technique can be easily generalized to systems of arbitrary lag length. The SVAR(1) is

$$B_0 z_t = B_1 z_{t-1} + \xi_t \quad (9)$$

with $E(\xi_t \xi_t^{'}) = \Sigma$, a diagonal matrix. The ξ_t shocks are mutually orthogonal and referred to as structural shocks. The elements along the principal diagonal of B_0 are normalized to unity so that each element in Σ is the variance of the corresponding structural shock in ξ_t. Like Arias *et al*. (2019), denote the sixth equation as the monetary policy equation and the sixth shock as the monetary policy shock. Abstracting from lag variables, the monetary policy equation is

$$r_t = \varpi_1 y_t + \varpi_2 p_t + \varpi_3 cp_t + \varpi_4 tr_t + \varpi_5 nbr_t + \xi_{rt} \quad (10)$$

where $\varpi_i = -b_{6i}$, and b_{6i} is the (6,i) element of the B_0 matrix, while ξ_{rt} is the monetary policy shock.

For replicating Uhlig (2005), the coefficients ϖ_1, ϖ_2, ϖ_3, ϖ_4, and ϖ_5 are drawn individually from a uniform distribution covering the entire space of possible values. For replicating Arias *et al*. (2019), ϖ_4 and ϖ_5 are set to zero, reflecting the restrictions that the federal funds rate does not react to changes in reserves contemporaneously. To ensure positive coefficients for output and prices in the monetary policy equation, ϖ_1 and ϖ_2 are generated from uniform distributions with support restricted to positive values. The coefficient on commodity prices is left unrestricted, so ϖ_3 is drawn from a uniform distribution that spans the entire range of possible values. A detailed exposition of how to implement the uniform OP algorithm for the Uhlig (2005) and Arias *et al*. (2019) applications is provided in the Appendix.

3. Implications of the rotation algorithms

Our empirical analysis utilizes the dataset compiled by Arias *et al*. (2019), which is an updated version of the dataset used by Uhlig (2005).[5] This dataset includes monthly U.S. data on real GDP (y_t), the GDP deflator (p_t), a commodity price index (cp_t), total reserves (tr_t), nonborrowed reserves (nbr_t), and the federal funds rate (r_t). To construct the monthly series for real GDP and the GDP deflator, the former is interpolated using the industrial production index, and the latter is interpolated using the consumer and producer price indexes. The sample period spans from January 1965 to June 2007.[6] We also use this dataset to replicate Uhlig (2005), although his sample period ended in December 2003. As will be shown, the results do not alter when using the updated dataset from Arias *et al*. All variables are expressed in logarithms, except for the federal funds rate. In Uhlig (2005) and Arias *et al*. (2019), the reduced-form VAR model is fitted with 12 lags of the variables in levels and does not include a constant or time trend. Both studies adopt the standard Bayesian framework, which specifies a normal-inverse Wishart prior for the reduced-form VAR parameters and a Haar prior for the rotation vector. We repeat this procedure until 1,000 sets of responses are accepted.

The Uhlig (2005) and Arias *et al*. (2019) models are replicated, and Figure 1 displays the 16th, 50th (median), and 84th percentiles of the accepted responses to a monetary policy shock.

[5] The dataset can be accessed from the *Journal of Monetary Economics* website.

[6] The sample period stops in 2007 to rule out the effects of the global financial crisis and of unconventional monetary policy.

The difference in output responses to monetary policy shocks is manifested in the figure, as emphasized by both studies. In the Uhlig model, output increases in response to a monetary policy shock that raises the federal funds rate. In contrast, the Arias *et al*. model reaffirms the conventional finding that a contractionary monetary policy shock negatively affects output. Across the models, all other responses are consistent with those reported in the original papers.

We now turn to examine the influence of the rotation vector on the responses. In doing so, we focus on the impact responses of the variables, i.e., $c(0)$ in equation (4). The main reason is that the impact responses are crucial for distinguishing the results, as responses at all horizons depend on the impact responses, according to the relationship of $c_j = D_j c(0)$ from equation (4), where c_j and D_j represent the responses to the structural shock η_t and the reduced-form errors e_t, respectively, at horizon j. Starting with the Uhlig model, Panel (A) in Figure 2 reports histograms of all accepted impact responses. The three vertical lines represent the 16% (left), 50% (center), and 84% (right) percentiles of the impact responses. Examining the entire set of accepted output responses on impact, the majority are positive, with only a small portion being negative, thus confirming Uhlig's argument.

There are two sources of randomness in the impact response $c(0) = P^{-1}q$ of equation (4): (1) sampling uncertainty in P^{-1} associated with the reduced-form VAR parameters, and (2) uncertainty originating purely from the rotation vector of q. Panel (B) shows the histograms of the elements in the rotation vector that generated the responses accepted by the sign restrictions. Elements 1, 2, 3, and 6 of the rotation vector exhibit histograms that are similar in shape to the accepted impact responses for output, prices, commodity prices, and the federal funds rate, respectively (note that the elements in the rotation vector range from -1 to 1 by definition). For these variables, the accepted impact responses reflect primarily the rotation vector, which is randomly drawn and unrelated to the data. Sampling uncertainty appears to have a minimal role in determining the accepted impact responses.

The result echoes the critique by Baumeister and Hamilton (2015, 2018, 2020) regarding the influence of the rotation prior in deriving the set of accepted responses. Since the accepted responses are influenced mainly by the randomness in the rotation vector, their density and summary statistics, such as 16%, 50%, and 84% percentiles, can lead to misleading inferences. For example, the observation that certain responses occur more frequently than others could be largely due to the rotation vector, rather than the data itself. It should also be reminded that the sign restrictions in Uhlig's framework were applied not only to the impact responses but also to subsequent responses up to five horizons. The rotation vector q was retained only when the sign restrictions on the responses $c(L)$ were satisfied over the horizons L=0, 1, 2, 3, 4, and 5. Nonetheless, the influence of the rotation vector appears to be strongly present in the impact responses.

The influence of the rotation vector can also be assessed using the approach of Baumeister and Hamilton (2018, 2020), who analyzed the relative contribution of two sources of randomness in the impact response by shutting down the first one. We conduct a similar exercise by fixing the reduced-form VAR parameters at their OLS estimates for every draw. Panel (C) reports the resulting histograms of all accepted responses on impact. Under this setup, sampling uncertainty is muted, leaving the randomness associated with the rotation vector as the sole driver of variation. It turns out that the histograms in Panel (C) closely resemble those in Panel (A), which incorporate both uncertainties.[7] This confirms that the accepted impact responses in Panel (A) are determined mainly by the randomness of the rotation vector. The similarity between Panels (A) and (C) also confirms that sampling uncertainty plays a minimal role in determining the accepted impact responses.

Figure 3 reports the results for the case of Arias *et al*. (2019) in a similar format. The histograms of all accepted impact responses in Panel (A) indicate that output predominantly decreases, aligning with the conclusions of Arias *et al*. Beyond this, the findings regarding the influence of the rotation vector are not different from those observed in the Uhlig (2005) model. Except for the federal funds rate, the histograms closely resemble the shapes of the histograms for the accepted rotation vectors in Panel (B). When sampling uncertainty is muted, as shown in Panel (C), the histograms of the accepted impact responses closely mirror those in Panel (A), which incorporates both sources of uncertainty. As such, the

[7] Although not displayed here for brevity, the histograms of the elements in the accepted rotation vector also closely resemble those in Panel (B), which account for both sources of uncertainty.

accepted impact responses in Panel (A) are influenced primarily by the randomness of the rotation vector, with sampling uncertainty playing a negligible role. These results also underscore the critique by Baumeister and Hamilton (2015, 2018, 2020).

4. Results from the uniform OP algorithm

This section evaluates the models of Uhlig (2005) and Arias *et al*. (2019) using the uniform OP algorithm introduced in Section 2.3. Figure 4 presents the estimation results based on the Uhlig (2005) identification scheme. In Panel (A), the main finding of Uhlig is recurrent: output increases in response to a monetary policy shock that raises the federal funds rate. The responses of other responses are also consistent with the results in Figure 1. However, Panel (B) reveals that the histograms of all accepted impact responses differ from those of the Uhlig result in Figure 2. The effects are particularly pronounced for the last three variables. For total and nonborrowed reserves, the histograms exhibit a markedly different shape, with extreme negative values occurring more frequently, and the 16%, 50%, and 84% percentiles of the impact responses shifting to the left. The histogram for the federal funds rate, on the other hand, is shifted to the right with a concentrated mass of positive responses.

Panel (C) illustrates the histograms of contemporaneous coefficients in the monetary policy equation implied by the model. The median coefficient for output is estimated at -0.53, with the distribution placing more weight on negative values than positive ones. The median coefficient for prices is 2.93, with most coefficients being positive. In the literature, Taylor-type monetary policy equations typically postulate or estimate a positive response of the federal funds rate to changes in prices and output. This does not endorse the negative output coefficients found under the Uhlig identification scheme, the details of which are discussed in the next section. The figure also shows that the federal funds rate generally responds positively to changes in commodity prices. For total and nonborrowed reserves, both positive and negative coefficients are observed, but the former are more frequent. The coefficient for the federal funds rate is set to one by normalization.

Figure 5 presents the estimation results from the uniform OP algorithm using the Arias *et al*. (2019) identification scheme. Panel (A) shows that the responses to a monetary policy shock align with those observed in the Arias *et al.* results from Figure 1, with the key finding of output decreasing being clearly evident. However, in Panel (B), the histograms of all accepted impact responses differ significantly in shape from those in the Arial *et al*. results shown in Figure 3. These histograms also show a more concentrated distribution across variables. Panel (C) illustrates the histograms of contemporaneous coefficients in the monetary policy equation implied by the model. The Arias *et al*. identification scheme constrained the coefficients for output and prices to be positive. For output, the 16%, 50%, and 84% percentiles of the coefficients are estimated at 0.29, 0.87, and 1.41, respectively, while for prices, they are estimated at 0.86, 2.83, and 4.45. The coefficients on total and nonborrowed reserves were constrained to zero by the identification restrictions.

5. Revisiting the identification schemes of Uhlig (2005) and Arias *et al*. (2019)

Using the uniform OP algorithm, we have also found that the Uhlig (2005) and Arias *et al*. (2019) identification schemes produce notably different results for the output response to a monetary policy shock: output increases under the former and decreases under the latter. A natural question is which identifying restrictions drive this difference. To address this question, we estimate an auxiliary model that incorporates both sets of identifying restrictions from Uhlig and Arias *et al*. Hence, the model achieves identification by simultaneously imposing Arias *et al*.'s sign and zero restrictions on the monetary policy equation and Uhlig's sign restrictions on the impulse responses. The uniform OP algorithm is well-suited to handle this task. Panel (A) of Figure 6 displays the 16^{th}, 50^{th} (median), and 84^{th} percentiles of the accepted responses to a monetary policy shock. The resulting responses closely resemble those from Uhlig rather than Arias *et al*., primarily reflecting the sign restrictions on the impulse responses. However, there is one key exception: output decreases in response to the monetary policy shock, which aligns with the findings of Arias *et al.*, but not Uhlig. Focusing on the output response, this result suggests that the Arias *et al*. identification scheme continues to produce a decrease in output even when the identifying restrictions of Uhlig are additionally imposed. Conversely, the increase in output observed with the Uhlig identification scheme reverses to a decrease when the identifying restrictions from Arias *et al*. are additionally imposed.

In this light, we examine which restrictions in the Arias *et al*. identification scheme caused the change in the output response within the Uhlig model. The experiment is conducted by sequentially adding the identifying restrictions from Arias *et al*. to the Uhlig identification scheme. The results indicate that the increase in output in response to a monetary policy shock persists when the two zero restrictions on total and nonborrowed reserves in the monetary policy equation are added (not shown). Similarly, the output increase remains when the coefficient on prices in the monetary policy equation is constrained to be positive (not shown). This outcome is unsurprising, given that Panel (C) of Figure 4 indicates that the Uhlig identification scheme yields mostly positive coefficients on prices. The output increase does not alter either when all three restrictions are applied simultaneously (not shown). Accordingly, the observed change in the output response must stem from the final restriction: that the output coefficient in the monetary policy equation is positive. As illustrated in Panel (A) of Figure 6, output decreases—rather than increases—once this restriction is added to the Uhlig identification scheme.

Thus, under the Uhlig identification scheme, the output response to a monetary policy shock hinges on how the federal funds rate reacts to changes in output. If the coefficient on output in the monetary policy equation is unrestricted, output increases in response to a monetary policy shock that raises the federal funds rate. Output decreases if the coefficient for output is restricted to be positive. As shown in Panel (C) of Figure 4, the Uhlig identification scheme more frequently produces negative output coefficients in the monetary policy equation than positive ones. A possible implication is that these negative coefficients may be linked to the observed increase in output following a monetary policy shock. To explore the empirical relevance of this, we conduct an additional experiment with two contrasting cases. In the first case, the Uhlig identification scheme is augmented with a restriction that the coefficient on output in the monetary policy equation is positive. In the second case, the coefficient on output is restricted to be negative. Panels (B) and (C) of Figure 6 display the responses to a monetary policy shock for each scenario. The responses are similar across the two specifications, except for the output response. When the coefficient on output in the monetary policy equation is restricted to be positive, output decreases in response to a monetary policy shock. In contrast, when the coefficient is restricted to be negative, output responds with a robust increase. These results indicate that negative coefficients for output in the monetary policy equation are likely to be responsible for the observed increase in output following a monetary policy shock. As discussed in the introduction, U.S. monetary policy since 1965 has largely operated under a direct and indirect federal funds rate targeting regime, with only a few brief exceptions. If this observation holds, the empirical validity of the expansionary output response to a monetary policy shock under Uhlig identification scheme depends on whether a negative coefficient for output in the monetary policy equation is a typical feature of the federal funds rate targeting regime.

6. Robustness of the results

Section 4 reported the results of applying the uniform OP algorithm to the models of Uhlig (2005) and Arias *et al*. (2019). These baseline results are now evaluated for robustness with respect to two key concerns. First, we explore an alternative specification for the monetary policy equation. Second, we examine whether the results are sensitive to the Great Moderation.

6.1. Alternative specification for the monetary policy equation

In the preceding sections, the federal funds rate responded to the levels of output and prices. However, researchers, particularly those working with DSGE models, often adopt Taylor-type monetary policy equations in which the federal funds rate responds to inflation and a measure of economic activity, such as the output gap. To check the robustness of our baseline results to this modification, we estimate an alternative reduced-form Bayesian VAR model. The monthly variables are the output gap (GAP_t), annual inflation (Π_t), annual commodity price inflation $(c\Pi_t)$, monthly changes in total reserves (Δtr_t), monthly changes in nonborrowed reserves (Δnbr_t), and the federal funds rate (r_t). The output gap is calculated as the difference between the logarithms of GDP (y_t) and potential GDP ($\overline{y}_t$), where the monthly series for potential GDP is obtained by interpolating the quarterly potential GDP measure from the Congressional Budget Office.[8] These variables are collected in a vector $z_t = (GAP_t,\ \Pi_t,\ c\Pi_t,\ \Delta tr_t,\ \Delta nbr_t,\ r_t)'$. All other model specifications follow the baseline model in Section 4, except that a constant term is now included.

As before, denote the sixth equation as the monetary policy equation and the associated sixth shock as the monetary policy shock. Abstracting from lag variables and the constant term, the monetary policy equation can be written as

$$r_t = \varpi_1 GAP_t + \varpi_2 \Pi_t + \varpi_3 c\Pi_t + \varpi_4 \Delta tr_t + \varpi_5 \Delta nbr_t + \xi_{rt} \qquad (11)$$

where ξ_{rt} represents the monetary policy shock. For the implementation of Uhlig's (2005) identifying restrictions, it is assumed that the responses of inflation, commodity price inflation, and changes in nonborrowed reserves to the monetary policy shock are not positive, while the response of the federal funds rate is not negative, over horizons zero to five. For the application of Arias *et al.*'s (2019) identifying restrictions, ϖ_4 and ϖ_5 are set to zero, reflecting the restrictions that the federal funds rate does not contemporaneously react to changes in reserves. The contemporaneous reactions of the federal funds rate to the output gap and inflation are restricted to be positive, i.e., $\varpi_1 > 0$ and $\varpi_2 > 0$. In both models, no restrictions are imposed on the output response to the monetary policy shock.

Figure 7 reports the results for the output gap (GAP), inflation (Π), and the federal funds rate (R) when the uniform OP algorithm is applied with the identifying restrictions of Uhlig (2005, left panel) and Arias *et al*. (2019, right panel).[9] In the left panel, the top row shows that the response of the output gap to a monetary policy shock is ambiguous at short horizons, as the 16–84% band of accepted responses includes the zero line. This weakens Uhlig's key implication, which posits an increase in output. The middle row reveals that the accepted output gap responses on impact are nearly equally split between positive and negative values. As discussed in Section 5, under the Uhlig identification scheme, output decreases (increases) when the coefficient on output in the monetary policy equation is positive (negative). Accordingly, the bottom row shows that the distribution of output gap coefficients in the monetary policy contains roughly equal proportions of positive and

[8] Quarterly potential GDP data are available on the Congressional Budget Office website.
[9] To conserve space, we present the results for these three variables, while the results for the other three variables are available upon request.

negative values. This contrasts with the baseline result, where negative coefficients are more frequent than positive ones. Overall, the findings indicate that the expansionary output response to a monetary policy shock, as proposed by Uhlig, may not be robust to the alternative model specification considered here. In contrast, the right panel shows that the results under Arias *et al.*'s identifying restrictions align closely with those of the baseline model. The top row shows that the output gap unambiguously decreases in response to a monetary policy shock. The middle row suggests that the majority of accepted output gap responses on impact are negative. The result that output decreases following a monetary policy shock, as identified by Arias *et al.*, remains unchanged.

6.2. Great Moderation

Barakchian and Crowe (2013) and Ramey (2016) argue that most models showing a decrease in output following a contractionary monetary policy shock report the opposite result—an increase in output—when restricting the sample to the Great Moderation period. This section investigates whether the baseline results exhibit the same sensitivity by considering two subsamples. The first subsample begins in January 1965, as in the full sample, but ends in December 1982. The second subsample covers the periods from January 1983 to June 2007, capturing the Great Moderation while excluding periods when the Federal Reserve abandoned targeting the federal funds rate (Ramey, 2016; Arias *et al*., 2019). Figure 8 displays the 16th, 50th (median), and 84th percentiles of the accepted responses for the two subsamples using the uniform OP algorithm with the identifying restrictions of Arias *et al*. (2019). In response to a monetary policy shock, output decreases in the short run across both subsamples. Monetary policy shocks remained contractionary during the Great Moderation, and consistent with the results from the full sample in Section 4, the model does not exhibit sufficient instability to undermine the main conclusion regarding the output effects of monetary policy shocks.[10]

Meanwhile, the figure shows that the impact responses of the federal funds rate during the Great Moderation are significantly smaller than those in the first subsample, which predates

[10] Although the concern raised by Barakchian and Crowe (2013) and Ramey (2016) may not be directly applicable to the results of Uhlig (2005), we also conducted the same sensitivity analysis using the uniform OP algorithm with Uhlig's identifying restrictions. For both subsamples, there is no noticeable change in the Uhlig result that output increases in response to a monetary policy shock. These results are available upon request.

the Great Moderation. This suggests that the size of the monetary policy shocks was diminished during the Great Moderation. This finding aligns with the conventional view that the Federal Reserve's conduct of monetary policy became more systematic during the Great Moderation, compared to the 1960s and 1970s. As a result, monetary policy was less erratic, leading to a reduction in the variability of monetary policy shocks. Despite the smaller monetary policy shocks, the short-run output responses remain similar to those estimated for the first subsample. Monetary policy shocks also had stronger effects on prices, with nearly all accepted responses being negative across the horizons. These findings suggest that the efficacy of monetary policy was greater during the Great Moderation, which is consistent with the views of Bernanke (2004), Bean (2009), Sims (2012), and Hakkio (2013). Bean (2009) and Bernanke (2004) further argue that improvements in monetary policy were likely a key factor contributing to the Great Moderation, a period marked by low inflation and sustained economic growth.

7. Conclusion

Understanding the impact of monetary policy shocks on output is a central question in macroeconomics. To address this issue, numerous studies have sought to correctly identify monetary policy shocks within the structural vector autoregression (SVAR) framework. However, structural inferences of monetary policy shocks in SVAR models remain contentious. Recently, an increasing number of studies have turned to 'agnostic' sign restrictions as an alternative to the traditional scheme using parametric restrictions, such as short- or (and) long-run zero restrictions, for identifying monetary policy shocks. While the sign-restricted SVAR model offers greater flexibility, it only achieves set identification, which introduces methodological challenges.

In this paper, we revisit two influential studies that utilized sign restrictions to investigate the effects of monetary policy shocks on output: Uhlig (2005) and Arias *et al*. (2019). These two models are particularly compelling because they reach opposite conclusions about the output effects of monetary policy shocks, despite sharing many similarities. In the Uhlig model, output increases in response to a monetary policy shock that raises the federal funds rate. In contrast, the Arias *et al*. model reinstates the conventional finding that contractionary monetary policy shocks reduce output. To understand the source of these differing results, we examine the issues related to the algorithms used, the identifying restrictions applied, and the sensitivity of the findings to alternative model specifications.

Our findings are summarized as follows. First, we find that both the Uhlig and Arias *et al*. models are empirically vulnerable to the critique by Bauermeister and Hamilton (2015, 2018, 2020), as the accepted responses reflect mainly the rotation vector, which is randomly drawn and unrelated to the data. As a result, the density of accepted responses, along with summary measures such as the median and other percentile responses, may lead to misleading inferences. Second, we re-estimated the Uhlig and Arias *et al*. models using the uniform OP algorithm, which does not rely on the rotation vector to generate large sets of responses. Across both models, the uniform OP algorithm produced histograms of accepted impact responses that differ from the original results. This supports the finding that the rotation vectors in the Uhlig and Arias *et al*. models may have influenced the responses. Third, the differing output effects of monetary policy shocks between the Uhlig and Arias *et al*. models can be primarily explained by the output coefficient in the monetary policy equation. Finally, Uhlig's findings on the output effects of monetary policy shocks appear somewhat fragile when an alternative monetary policy equation is applied, whereas the results of Arias *et al*. remain robust. Taking all the results into account, the findings from Arias *et al*., which show that output decreases in response to a monetary policy shock, are more empirically supported than Uhlig's finding that output increases. In line with previous studies, we also find evidence that the efficacy of monetary policy improved during the Great Moderation.

Appendix

This appendix provides a detailed exposition of how to implement the uniform OP algorithm for the applications of Uhlig (2005) and Arias *et al*. (2019). Recall the SVAR(1) in equation (9):

$$B_0 z_t = B_1 z_{t-1} + \xi_t \tag{9}$$

The corresponding reduced-form VAR(1) is given as

$$z_t = W_1 z_{t-1} + e_t \tag{A1}$$

where e_t is distributed as $N(0,\ \Omega)$ as in equation (1) of the main text. The relationships between the SVAR and VAR coefficients are $W_1 = B_0^{-1} B_1$, and $e_t = B_0^{-1}\xi_t$ with $\Omega = B_0^{-1}\Sigma B_0^{-T}$.

We allow for sampling uncertainty in the VAR(1) parameters using a standard Bayesian prior. Specifically, the prior distribution for Ω follows an inverse-Wishart, and the prior distribution for the VAR coefficients, conditional on Ω, is normal.

The steps in the uniform OP algorithm are:

Step 1

Take a draw of W_1^* and Ω^* from the normal-inverse Wishart posterior distribution of reduced-form VAR parameters, and from the VAR, form

$$e_t^* = z_t - W_1^* z_{t-1} \tag{A2}$$

We can express the SVAR in terms of the structural and reduced-form shocks by substituting for z_t in equation (9) using equation (A2) as

$$B_0 (W_1^* z_{t-1} + e_t^*) = B_1 z_{t-1} + \xi_t \tag{A3}$$

which can be reorganized as

$$B_0 e_t^* = (B_1 - B_0 W_1^*) z_{t-1} + \xi_t \tag{A4}$$

Since $B_1 = B_0 W_1^*$ from the relationship between the SVAR and VAR coefficients, equation (A4) becomes

$$B_0 e_t^* = \xi_t \tag{A5}$$

For this posterior draw, the last equation in (A5), which is an equivalent representation of the monetary policy equation, is

$$e_{rt}^* = \varpi_1 e_{yt}^* + \varpi_2 e_{pt}^* + \varpi_3 e_{cpt}^* + \varpi_4 e_{trt}^* + \varpi_5 e_{nbrt}^* + \xi_{rt} \tag{A6}$$

where $\varpi_i = -b_{6i}$ and b_{6i} is the (6,*i*) element of the B_0 matrix.

Step 2

For the replication of Uhlig (2005), the coefficients, ϖ_1, ϖ_2, ϖ_3, ϖ_4, and ϖ_5, are generated individually from a uniform distribution. Each uniform distribution requires the upper and lower bounds. To establish these bounds, we use the conventional sign restrictions protocol, which employs an orthogonal rotation matrix/vector to generate the entire space of possible values. Recall the contemporaneous coefficient vector $a(0) = q'P$ in equation (6) of the main text. Large sets of $a(0)$ can be generated by simulating $\Omega^* = P^{-1}P^{-T}$ and the orthogonal rotation vector q. This creates the broadest possible space for $a(0)$. We can then locate the maximum and minimum for each coefficient in $a(0)$ based on the generated values. These maximum and minimum coefficients are unlikely to change materially when other generation methods are used, as they represent the limits of the coefficients and do not depend much on the shape of the distribution (Ouliaris and Pagan, 2022). What can change are the densities of the coefficients, which are influenced by the informativeness of the rotation matrix, as detailed in the main text.

Let the i^{th} element of the generated $a(0)$ be $a_i = q'P_i$, $i = 1,...,6$, where P_i is the i^{th} column of the matrix P. Normalizing on the federal funds rate, i.e., $\bar{a}_i = a_i / a_6$ for $i = 1,...,6$, yields an expression equivalent to the last row of B_0 in equation (A5). Both represent the monetary policy equation, and their coefficients, $\bar{a}_i$ and b_{6i} for $i = 1,...,5$, differ depending on the generation method. However, since the maximum and minimum are unlikely to be influenced by the generation method, we assume that $\bar{a}_i$ and b_{6i} share the same maximum and minimum bounds. Then, using the relationship of $\varpi_i = -b_{6i} = -\bar{a}_i$, $i = 1,...,5$, the maximum and minimum of $-\bar{a}_i$ are taken as the upper and lower bounds, respectively, of the uniform distribution for ϖ_i in equation (A6). Once the bounds are set, ϖ_1, ϖ_2, ϖ_3, ϖ_4, and ϖ_5 are generated from the uniform distribution, respectively. For the replication of Arias *et al*. (2019), it is assumed that $\varpi_4 = \varpi_5 = 0$ in equation (A6) to reflect the two zero restrictions—that total reserves and nonborrowed reserves do not enter the monetary policy equation. The coefficient ϖ_3 is unrestricted, so the values generated above are used.

The same applies to the coefficients ϖ_1 and ϖ_2, with one major distinction: since these coefficients are assumed to be positive, their lower bounds are set at zero to ensure positivity.

Step 3

Having generated values for each coefficient ϖ_i, the monetary policy shock ξ_{rt} is obtained from equation (A6). The value of the monetary policy shock for a given set of generated coefficients and a particular draw from the posterior is denoted as $\hat{\xi}_{rt}$. We then calculate the responses of the variables to the monetary policy shock $\hat{\xi}_{rt}$ using $e_t^* = B_0^{-1}\xi_t$ in equation (A5). To illustrate this, write out each equation in $e_t^* = B_0^{-1}\xi_t$ as

$$e_{yt}^* = b_0^{16}\hat{\xi}_{rt} + \nu_{1t} \tag{A7}$$

$$e_{pt}^* = b_0^{26}\hat{\xi}_{rt} + \nu_{2t} \tag{A8}$$

$$e_{cpt}^* = b_0^{36}\hat{\xi}_{rt} + \nu_{3t} \tag{A9}$$

$$e_{trt}^* = b_0^{46}\hat{\xi}_{rt} + \nu_{4t} \tag{A10}$$

$$e_{nbrt}^* = b_0^{56}\hat{\xi}_{rt} + \nu_{5t} \tag{A11}$$

$$e_{rt}^* = b_0^{66}\hat{\xi}_{rt} + \nu_{6t} \tag{A12}$$

where the coefficients are the elements of the sixth column of B_0^{-1}. Equations (A7) to (A12) are estimated consistently by OLS since $\hat{\xi}_{rt}$ is uncorrelated with each of the ν_{it} errors. This occurs because the ν_{it} errors are linear combinations of the structural shocks excluding $\hat{\xi}_{rt}$. The estimated coefficient b_0^{i6}, $i = 1,...,6$, gives the impact response of the i^{th} variable to a unit monetary policy shock. In our application, the responses are calculated to a one standard deviation monetary policy shock. Denote the standard deviation of $\hat{\xi}_{rt}$ as $\hat{\sigma}_r$, and calculate $b_0^{i6}\hat{\sigma}_r$ yielding the impact response of the i^{th} variable to a one standard deviation monetary policy shock. The responses at all other horizons are computed recursively.[11] If the responses satisfy the sign restrictions, they are retained and discarded otherwise.

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[11] The recursion uses the estimated VAR coefficients together with the impact response coefficients as initial values (i.e., $c_j = D_j c(0)$ from equation (4) of the main text).

Step 4

Return to Step 1 and repeat the steps. The algorithm continues until the desired number of responses is accepted.

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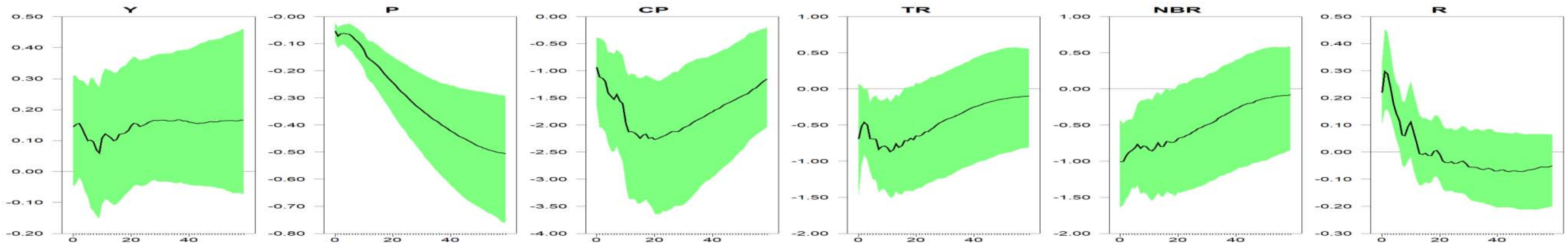
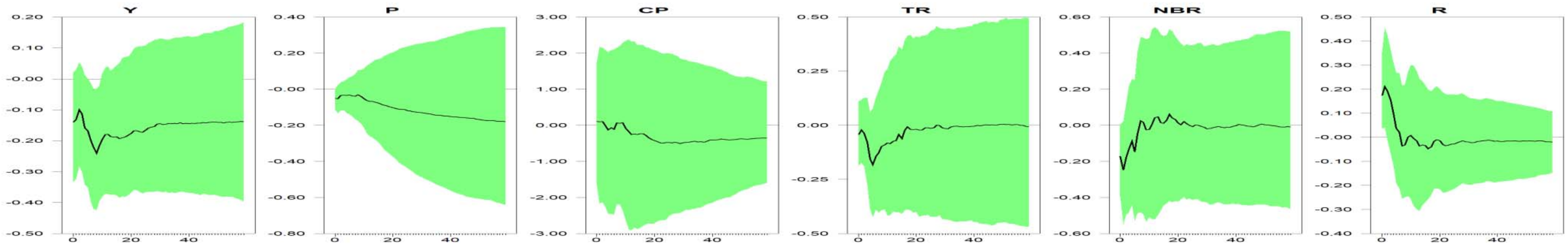
Figure 1. Responses to a monetary policy shock

(A) Uhlig (2005)



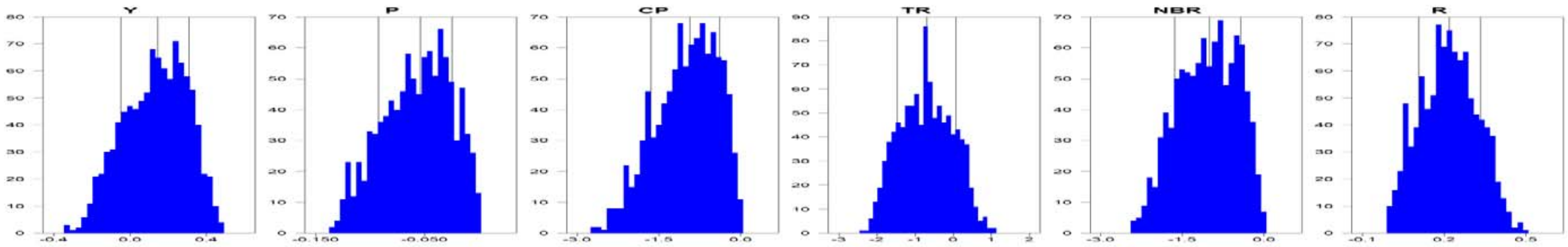
(B) Arias *et al*. (2019)



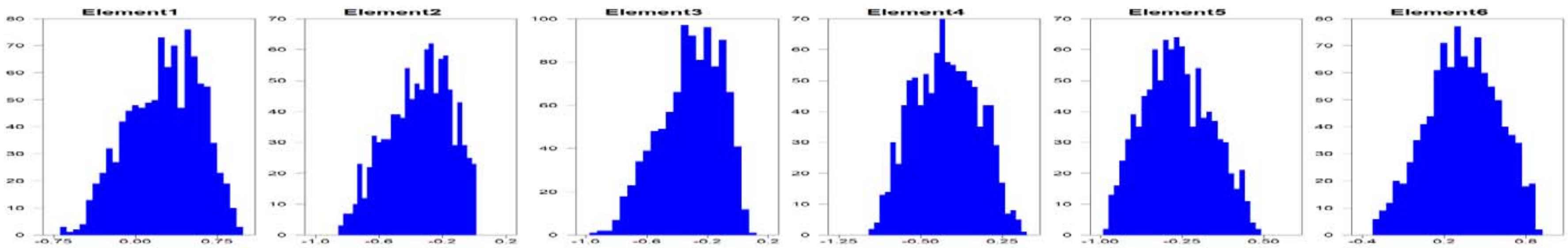
Note: The figures display the median responses (think line) and the 16%–84% band responses (shading).

Figure 2. Histograms of impact responses and elements of accepted rotation vectors in Uhlig (2005)

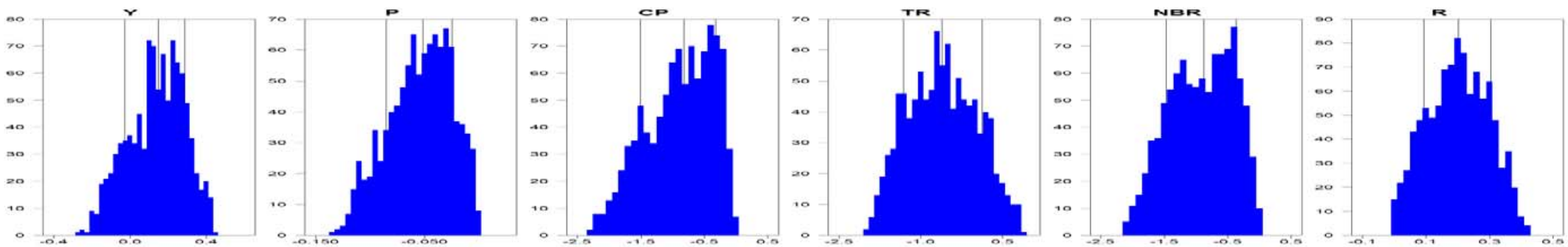
(A) Impact responses



(B) Elements of accepted rotation vectors



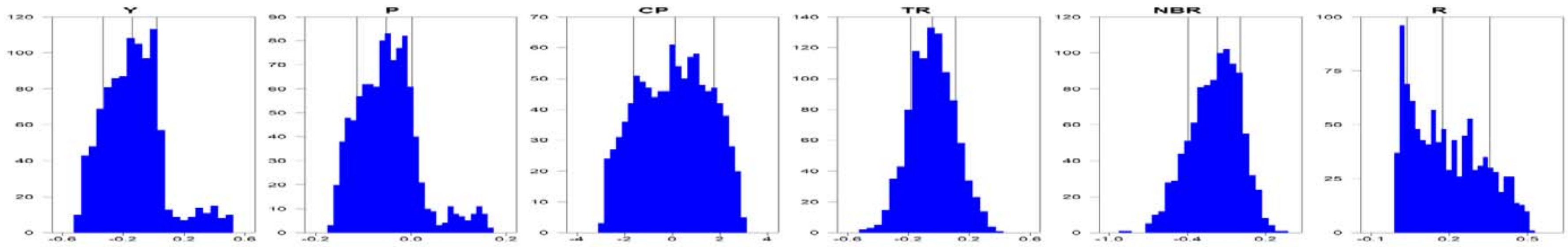
(C) Impact responses with no sampling uncertainty



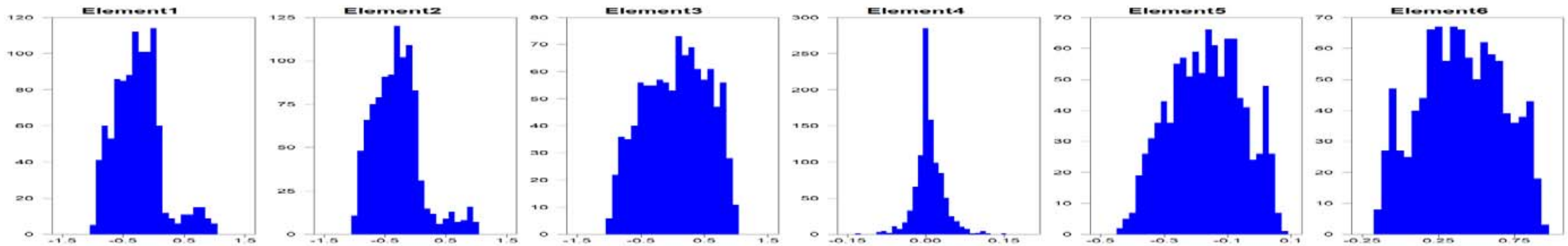
Note: In the top and bottom panels, each histogram includes three vertical lines representing the 16% (left), 50% (center), and 84% (right) percentiles, respectively.

Figure 3. Histograms of impact responses and elements of accepted rotation vectors in Arias *et al*. (2019)

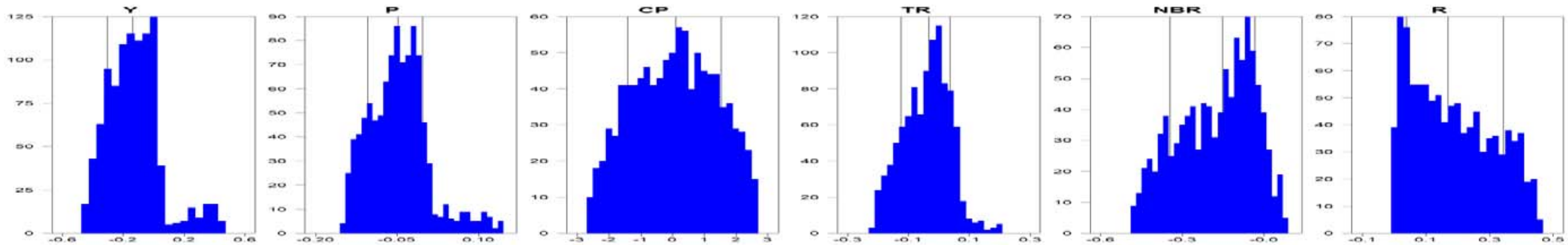
<u>(A) Impact responses</u>



<u>(B) Elements of accepted rotation vectors</u>



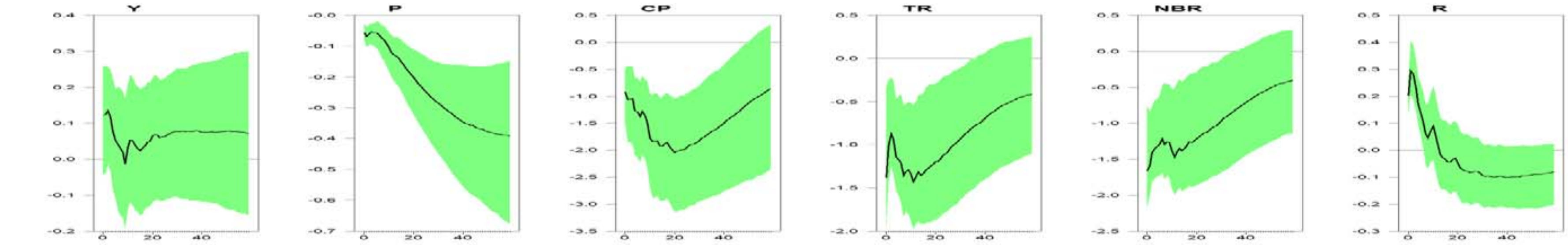
<u>(C) Impact responses with no sampling uncertainty</u>



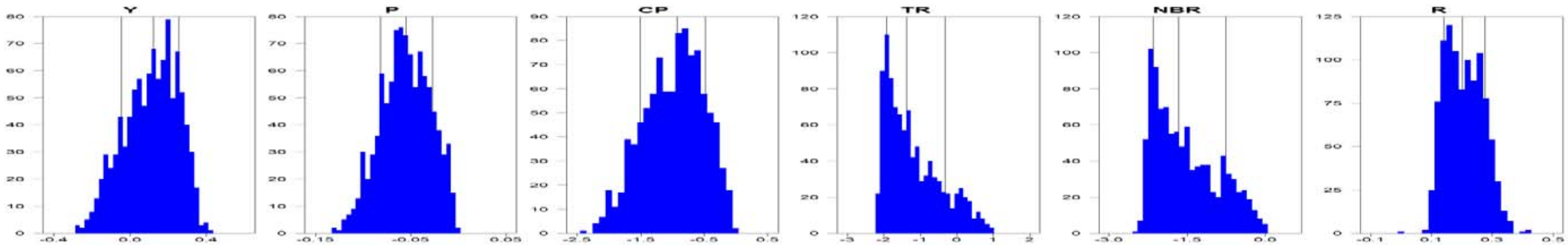
Note: In the top and bottom panels, each histogram includes three vertical lines representing the 16% (left), 50% (center), and 84% (right) percentiles, respectively.

Figure 4. Responses and histograms using the uniform OP algorithm with the restrictions from Uhlig (2005)

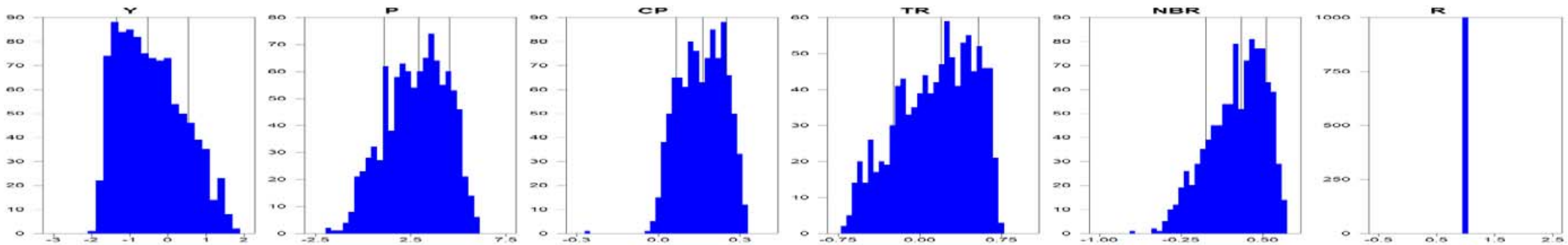
(A) Responses to a monetary policy shock



(B) Histograms of impact responses



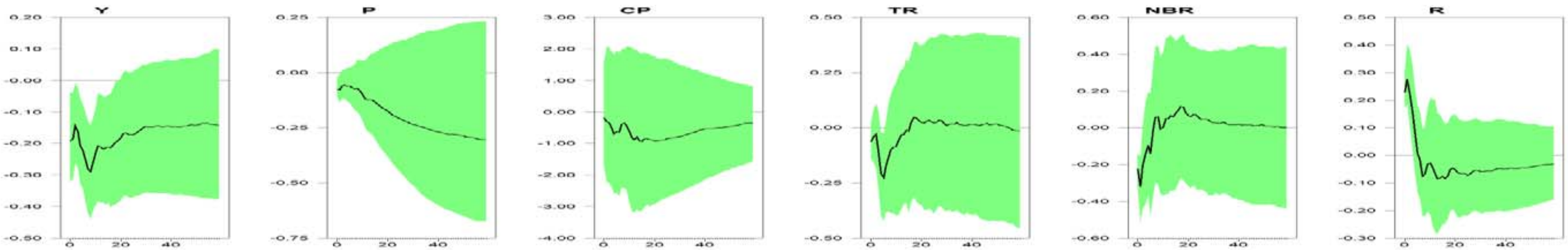
(C) Histograms of the coefficients in the monetary policy equation



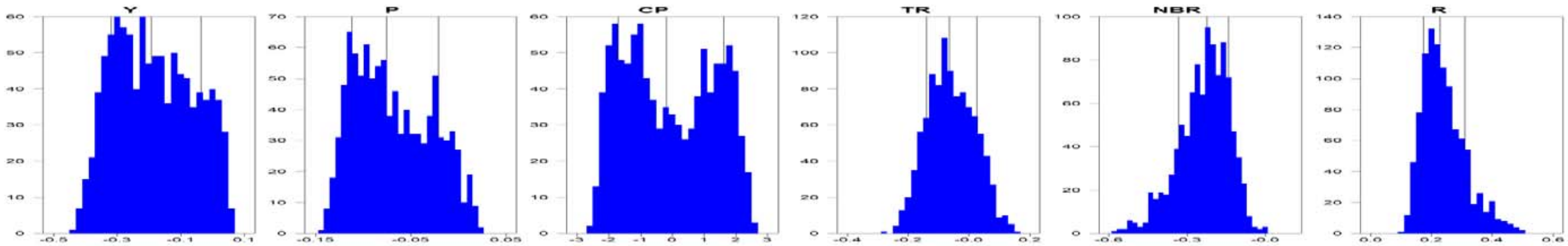
Notes: In the top panel, the figures display the median responses (think line) and the 16%–84% band responses (shading). In the middle and bottom panels, each histogram includes three vertical lines representing the 16% (left), 50% (center), and 84% (right) percentiles, respectively.

Figure 5. Responses and histograms using the uniform OP algorithm with the restrictions from Arias *et al*. (2019)

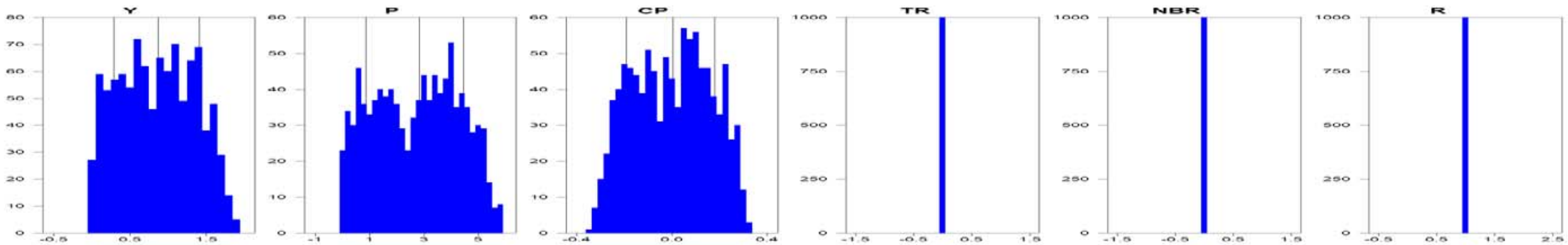
(A) Responses to a monetary policy shock



(B) Histogram of impact responses



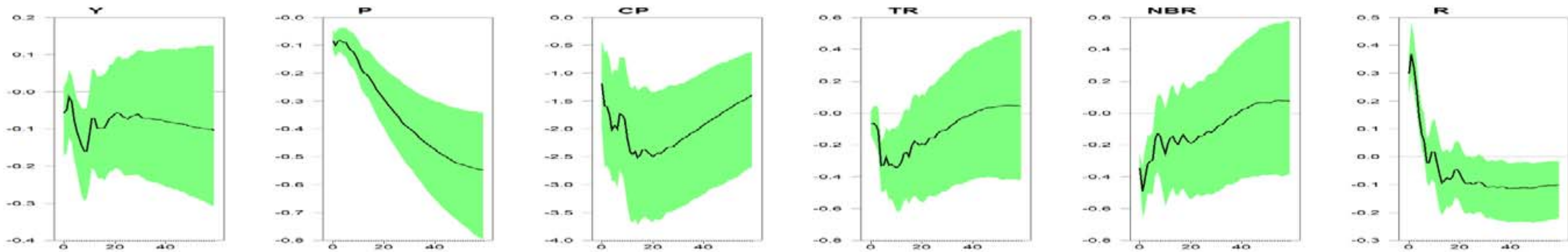
(C) Histogram of the coefficients in the monetary policy equation



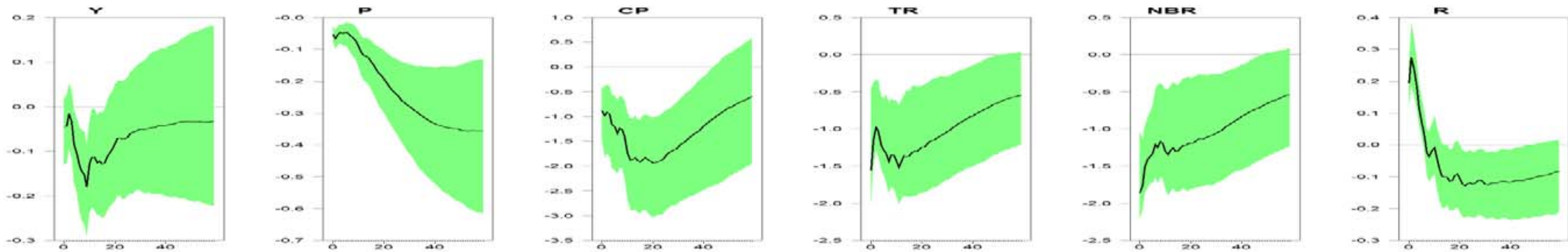
Notes: In the top panel, the figures display the median responses (think line) and the 16%–84% band responses (shading). In the middle and bottom panels, each histogram includes three vertical lines representing the 16% (left), 50% (center), and 84% (right) percentiles, respectively.

Figure 6. Responses to a monetary policy shock using the uniform OP algorithm with additional identifying restrictions

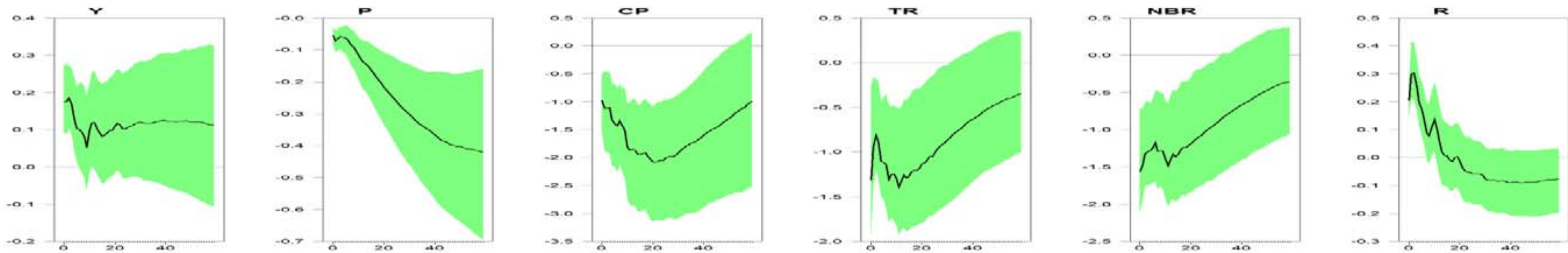
(A) Combining the restrictions from Uhlig (2005) and Arias *et al*. (2019)



(B) Restrictions of Uhlig (2005) plus the additional restriction that the coefficient of output in the monetary policy equation is positive



(C) Restrictions of Uhlig (2005) plus the additional restriction that the coefficient of output in the monetary policy equation is negative

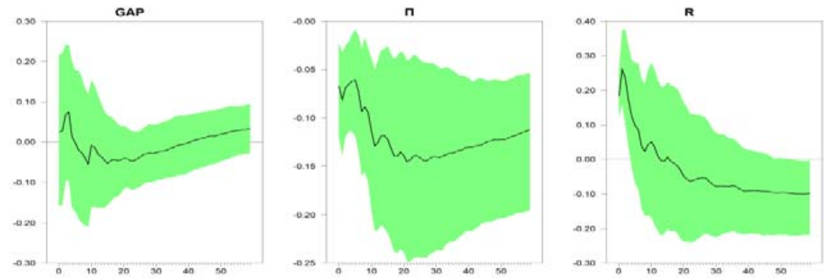


Note: The figures display the median responses (think line) and the 16%–84% band responses (shading).

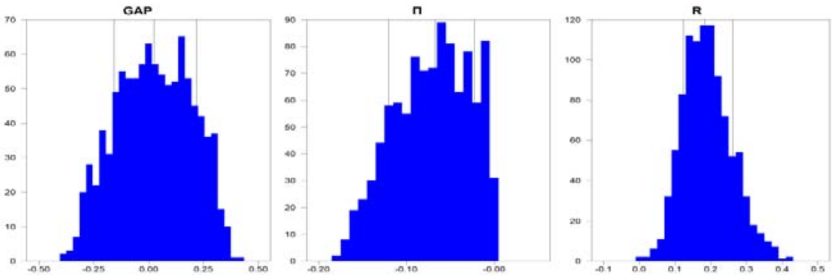
Figure 7. Uniform OP algorithm with a Taylor-type monetary policy equation

Uhlig restrictions

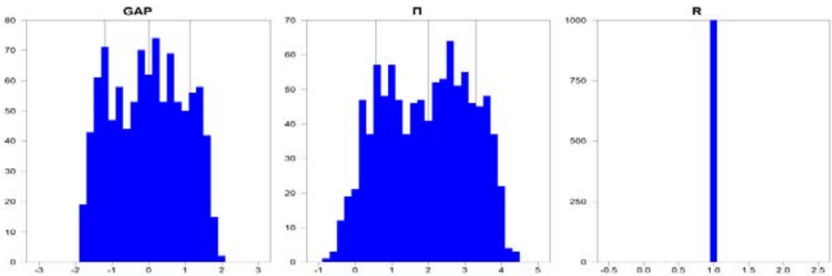
(A) Responses to a monetary policy shock



(B) Histogram of impact responses

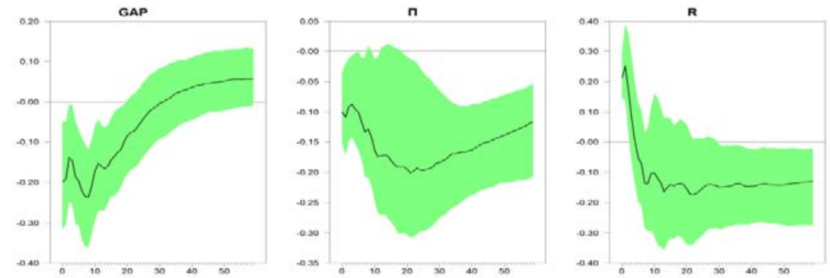


(C) Histogram of the coefficients in the monetary policy equation

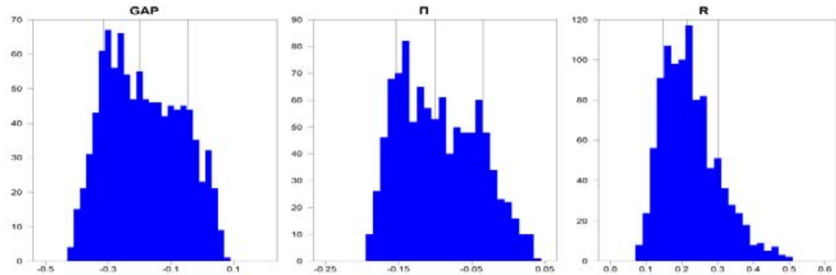


Arias *et al*. restrictions

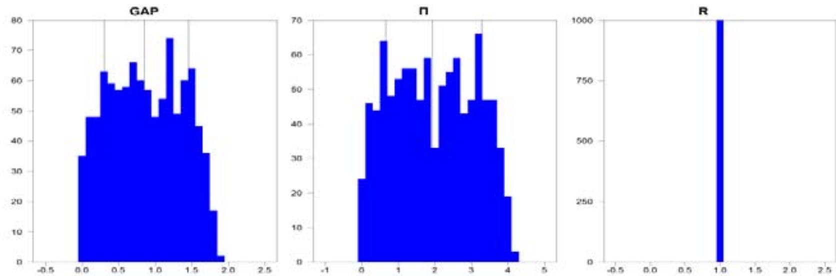
(A) Responses to a monetary policy shock



(B) Histogram of impact responses



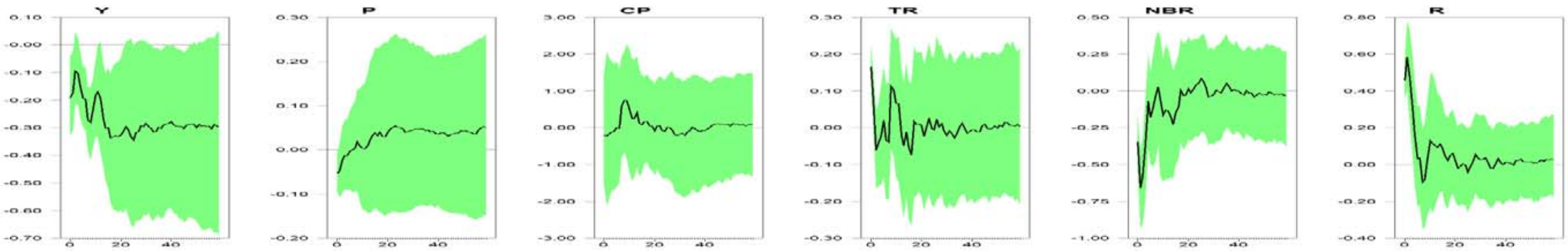
(C) Histogram of the coefficients in the monetary policy equation



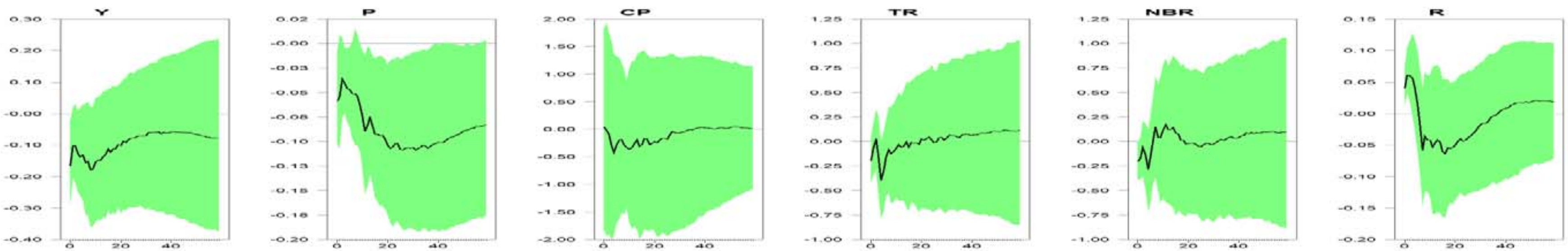
Notes: In the top panel, the figures display the median responses (think line) and the 16%–84% band responses (shading). In the middle and bottom panels, each histogram includes three vertical lines representing the 16% (left), 50% (center), and 84% (right) percentiles, respectively.

Figure 8. Sensitivity analysis of the results from the uniform OP algorithm with Arias *et al*.'s (2019) restrictions

(A) Sample period: 1965:1 to 1982:12



(B) Sample period: 1983:1 to 2007:6



Note: The figures display the median responses (think line) and the 16%–84% band responses (shading).