Monetary Policy Effects With An Explicit Model Of The Fed's Information Set

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Abstract

VAR analyses on the effects of monetary policy shocks are usually based on final revised data. Instead, we explicitly model the real-time information set of the Federal Open Market Committee using Greenbook data. We jointly estimate the real-time monetary policy reaction function implied by the VAR, equations measuring the transmission of monetary policy based on final revised data and the effects of monetary policy on different vintages of Greenbook revisions. We find that monetary policy shocks have a stronger countercyclical effect when accounting for information problems than conventional final data VAR models imply. In particular, the impact of monetary policy shocks on prices is considerably underestimated when using revised data. Finally, we show that many of the empirical findings provided by the real-time monetary policy rule literature carry over to monetary policy analysis in real-time VARs.

Keywords: Real-time data, data revisions, monetary policy shocks, VARs, identification, monetary policy rules

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1 Introduction

Over the past three decades, a large body of literature has developed that employs Vector Autoregressions (VARs) to identify and trace out the transmission mechanism of monetary policy. Almost all of these studies abstract from the fact that central banks rely on imperfect measures of the contemporary economic conditions when making policy decisions. Specifically, publication lags and the data revision process drive a wedge between the real-time information set available to policy makers at the time of a policy decision and the final revised data set commonly used by econometricians when analyzing monetary policy years after interest rate decision have been made. This raises the question whether VAR-based analyses of monetary policy based on revised data are reliable or whether similar distortions arise as documented in the literature on monetary policy rules (Orphanides, 2001).

There is a broad consensus that emphasizes the importance of real-time information when estimating monetary policy rules (Orphanides, 2001, 2004; Boivin, 2006). In contrast, only few papers have investigated the consequences of using real-time data in the structural analysis of monetary policy. Explicitly modeling the data revision process underlying macroeconomic variables such as output and inflation, Croushore and Evans (2006) find no significant differences in the effects of monetary policy shocks identified in small-scale VARs with real-time and final revised data. Based on the seminal work of Orphanides (2001), we approximate the information available to the Federal Open Market Committee (FOMC) more precisely by using the Greenbook projections prepared for each scheduled meeting. This is important, given the effort that central banks such as the Federal Reserve invest into now- and forecasting based on a variety of information sources due to the publication lags in macroeconomic variables.

We jointly estimate the real-time monetary policy reaction function and the impulse responses of final revised macroeconomic variables in a single VAR model. Confronting the results with estimates from a conventional final data VAR, we are able to quantify the importance of accounting for data revisions and the real-time information set of the central bank in structural monetary policy analyses. Moreover, our VAR model allows us to relax the assumption of Croushore and Evans (2006) that data revisions are stationary and mean zero. In light of the findings of Aruoba (2008) and Jacobs and van Norden (2011), this assumption appears as being too restrictive. Further, we account for the possibility that in case of Greenbook projections the assumption that revisions are independent of monetary policy shocks might be violated. The Greenbook projections are prepared to inform the FOMC regarding the economic conditions without taking a stance on potential unsystematic policy actions. Consequently, an exogenous monetary policy shock should affect the optimal estimate of current economic conditions. While our monetary policy shock measures are orthogonal to the available information when policy is conducted, our econometric model allows us to trace out the effects of these shocks to the actual macroeconomic data as represented by the final revised variables.

Methodologically, we impose restrictions on the reduced-form VAR and on the contemporaneous interaction terms to ensure that final revised data do not enter the monetary policy reaction function, neither contemporaneously nor through lags. Consequently, new information regarding the economic state enters the policy maker's information set only through new vintages of Greenbook projections and predetermined macroeconomic variables that are observable in real time, such as commodity prices. We estimate the reduced-form VAR using Bayesian techniques for the sample period 1967Q3-2007Q2. Therewith, our setup is standard and follows Christiano et al. (1999), except for using Greenbook data.

We use two identification schemes to identify monetary policy shocks: a nonrecursive ordering and a mixture of sign and zero restrictions. The advantage of the first approach is that it builds on the standard and widely studied recursive identification strategy summarized in Christiano et al. (1999). This allows us to investigate the real-time reliability of conventional wisdom about the conduct of monetary policy and its effects on key macroeconomic variables. A drawback of this approach is that we have to make ad hoc assumptions regarding the contemporaneous interactions between revisions and previous Greenbook projections. Therefore, we additionally employ a sign identification approach to test the robustness of our results with respect to the restrictions on the revision process.

The results are as follows. We find that monetary policy shocks identified in a real-time information setting have a stronger countercyclical effect than the conventional final data VAR model implies. In particular, the posterior median response of the price level is about twice as large. We report statistically and economically significant responses of the Greenbook revisions to a monetary policy shock. Besides investigating the effects of exogenous monetary policy actions, we assess the importance of conditioning the systematic component of monetary policy on real-time available information. This is important as the estimated monetary policy reaction function directly affects the identification of monetary policy shocks. Our findings are in line with the literature on estimating single equation monetary policy rules using real-time data (Orphanides, 2001, 2004; Boivin, 2006). We find that the output growth and inflation coefficients estimates in the monetary policy reaction function are distorted when the VAR is estimated with final revised data. Further, our findings indicate a shift in the Fed's monetary policy conduct towards a lower weight on output growth and a stronger focus on inflation forecasts during the Volcker Chairmanship.

The paper contributes to several strands of the literature. First and foremost, our work is related to Croushore and Evans (2006) who emphasize the real-time information problem in structural monetary policy analysis. In their empirical exercise, they test the robustness of the findings provided by Christiano et al. (1996) with respect to real-time available data vintages. We add to this literature by carefully modeling the real-time information set of the policy maker and the revision process following the insights taken from the monetary policy rule literature. While they find that monetary policy shocks identified using real-time information have rather small, yet not significant, effects on the macroeconomic variables included in the VAR, we find the opposite. Especially the response of the price level is considerably larger when we condition the monetary policy reaction on real-time instead of final revised data. By adopting their assumption that future revisions are unaffected by the exogenous shocks, we find that this difference in the methodology may explain the differences in the price level response to a monetary policy shock. However, the differences in the response of real GDP growth seem to be driven by the different assumptions on the policy maker's information set.

More recently, Amir-Ahmadi et al. (2017) use a time-varying parameters VAR to study the effects of monetary policy shocks on both real-time and final revised data. They find systematic and persistent differences in the impulse response functions. While their VAR includes real-time and final revised data, they do not model the real-time information set of the central bank, but allow the interest rate to respond to real-time and final revised data.

Further, our paper is related to the real-time monetary policy rule literature (see, e.g., Orphanides, 2001, 2004; Boivin, 2006). By explicitly modeling the real-time information set, we show that many of the evidence provided in this literature carries over to a VAR framework and that this has effects on the measurement of monetary policy effects.

Finally, we also contribute to the literature on the structural identification of monetary policy shocks. We propose a framework to jointly estimate the real-time monetary policy reaction function and the effects of the so identified shocks on final revised macroeconomic variables. Thus, we test the reliability of conventional wisdom about the effects of monetary policy shocks (Leeper et al., 1996; Christiano et al., 1999; Barakchian and Crowe, 2013; Ramey, 2016). Our results emphasize the importance of accounting for the exact information set of the policy maker when deciding upon the monetary policy stance, while allowing for a flexible revision process. Regarding the latter, we show that the findings of Aruoba (2008) and Jacobs and van Norden (2011) for the revision of different data vintages from statistical agencies, carry over to different vintages of Greenbook projectons.

The structure of this paper is as follows. Section 2 discusses the real-time information problem for the identification of monetary policy shocks. Section 3 describes our reduced-form VAR model, provides details about the data, and presents our identification strategies. Section 4 presents our main results using the nonrecursive identification strategy, while Section 5 presents the results of the robustness exercise using sign restrictions. Finally, Section 6 concludes.

2 A VAR with a Real-Time Consistent Interest Rate Reaction Function

2.1 Revisiting the Standard Approach of Identifying Monetary Policy Shocks in SVARs

It is standard in the literature to model monetary policy shocks as the unsystematic component of the monetary policy stance. Denoting Ω_t as the information set of the policy maker, the monetary policy shock, ε_t^{mp}, can be expressed as the orthogonal disturbance in the monetary policy instrument, s_t, that is not explained by an assumed linear policy reaction function $f(\Omega_t)$.

$$s_t = f(\Omega_t) + \varepsilon_t^{mp}. \tag{1}$$

The common approach in the VAR literature to approximate Ω_t is to use the latest available vintage of macroeconomic variables. As discussed by Croushore and Evans (2006), this assumption is particularly unreasonable for analyzing monetary policy as many key variables considered by policy makers are both i) published after the decision is made and ii) are strongly revised in subsequent years. Assuming more information than what the central bank actually has available leads to an error-in-variables bias while estimating monetary policy shocks in the standard VAR framework.

In the following, time superscripts denote the publication date of a specific data vintage and time subscripts denote the time period of the variable. For example, y_t^t refers to the real-time observation, i.e. y in period t as observed in period t, while y_t^T refers to final revised data as available in the last period of the sample T for the observation of Y in period t. A specific data vintage published in some period t contains the whole history for a variable as observed by an econometrician in period t, i.e. $y_t^t, y_{t-1}^t, y_{t-2}^t, \ldots$. Adjacent data vintages are connected via revisions:

$$y_{t-1}^t = y_{t-1}^{t-1} + h_{t-1}^t \tag{2}$$

Data vintages two or more periods apart are connected via multiple revisions. For example:

$$y_{t-2}^t = y_{t-2}^{t-2} + h_{t-2}^{t-1} + h_{t-2}^t \tag{3}$$

For the monetary policy instrument s_t we do not use a superscript as the data is not revised.

Consider a recursive VAR consisting of a monetary policy instrument s_t and another macroeconomic variable (or a vector of variables) y_t that is ordered after the policy variable. The VAR has two lags to illustrate the role of several revisions to different data vintages in a real-time information setting. The setup can be easily generalized to a higher lag order. Then it follows for the standard specification relying on revised data that:

$$y_t^T = c_1 + a_{11}s_{t-1} + a_{12}s_{t-2} + a_{13}y_{t-1}^T + a_{14}y_{t-2}^T + \varepsilon_{t,1}, \tag{4}$$
$$s_t = c_2 + a_{21}s_{t-1} + a_{22}s_{t-2} + a_{23}y_{t-1}^T + a_{24}y_{t-2}^T + a_{25}y_t^T + \varepsilon_t^{mp}. \tag{5}$$

As discussed in Leeper et al. (1996), identifying the effects of monetary policy in a structural VAR (SVAR) implicitly requires to specify a monetary policy reaction function. However, Equation (5) does not correctly reflect the information set of the central bank at the time of decision making. Instead, the policy decision is based on the information available in real time. The monetary policy equation should be conditioned on real-time data as available to the central bank at the time of the policy decision, while using final revised data for all other equations should be fine. Hence, a VAR with the central bank's information set as of period t can be written as:

$$y_t^T = c_1 + a_{11}s_{t-1} + a_{12}s_{t-2} + a_{13}y_{t-1}^T + a_{14}y_{t-2}^T + \varepsilon_{t,1}, \tag{6}$$
$$s_t = c_2 + a_{21}s_{t-1} + a_{22}s_{t-2} + a_{23}y_{t-1}^t + a_{24}y_{t-2}^t + a_{25}y_t^t + \varepsilon_t^{mp}. \tag{7}$$

The monetary policy equation could also be extended to include a forecast y_{t+1}^t of macroeconomic variables. This equation can be estimated with OLS and would correctly identify the monetary policy shock ε_t^{mp}. A version of Equation (7) without lags of y_t^t, i.e. $a_{23} = a_{24} = 0$, would be similar to a standard real-time monetary policy rule as, for example, in Orphanides (2001). In such a version, impulse responses to ε_t^{mp} could be easily computed once additional equations for the real-time observations $y_t^t, y_{t-1}^{t-1}, \ldots, y_1^1$ are added:

$$y_t^t = c_1 + a_{11}s_{t-1} + a_{12}s_{t-2} + a_{13}y_{t-1}^{t-1} + a_{14}y_{t-2}^{t-2} + \varepsilon_{t,1}, \tag{8}$$
$$s_t = c_2 + a_{21}s_{t-1} + a_{22}s_{t-2} + a_{23}y_t^t + \varepsilon_t^{mp}, \tag{9}$$
$$y_t^T = c_3 + a_{31}s_{t-1} + a_{32}s_{t-2} + a_{33}y_{t-1}^T + a_{34}y_{t-2}^T + \varepsilon_{t,2}. \tag{10}$$

However, this VAR model would not be directly comparable to the one in Equations (4) and (5). Differences in the identified monetary policy shocks and the impulse responses could be due to excluding lagged observations of macroeconomic variables in the monetary policy equation or due to the response of the policy instrument to real-time rather than final revised data. To isolate the latter effect, Equation (6) including the lags has to be used.

In this case computing impulse responses is challenging as the equations cannot be iterated forward without modeling data revisions. To see this, we can rewrite the real-time VAR consisting of Equations (6) and (7) using real-time data and data revisions:

$$y_t^T = c_1 + a_{11}s_{t-1} + a_{12}s_{t-2} + a_{13}y_{t-1}^T + a_{14}y_{t-2}^T + \varepsilon_{t,1}, \tag{11}$$
$$s_t = c_2 + a_{21}s_{t-1} + a_{22}s_{t-2} + a_{23}y_{t-1}^{t-1} + a_{24}h_{t-1}^t + a_{25}y_{t-2}^{t-2} + a_{26}h_{t-2}^{t-1} + a_{27}h_{t-2}^t + a_{28}y_t^t + \varepsilon_t^{mp}. \tag{12}$$

While we can easily iterate the real-time data forward, as y_t^t, y_{t-1}^{t-1} and y_{t-2}^{t-2} are the contemporaneous and lagged entries of the real-time data time series, it is not clear how to model the revisions h_{t-1}^t, h_{t-2}^{t-1}, and

h^t_{t-2}.[1] The nature of the data revisions has considerable impact on the statistics of interest, e.g. impulse response functions. As discussed by Orphanides (2001), if subsequent revisions are correlated with the initial announcement, i.e. revisions represent noise, the estimation of a monetary policy reaction function using final revised data is biased. Moreover, if revisions represent news, i.e. revisions are correlated with final data, and we are predominately interested in the response of final data to the estimated monetary policy shock, a recursive identification of monetary policy shocks using final data may lead to distorted impulse response functions. In Appendix A, we discuss this issue in more detail and test the nature of the revision series used in our empirical exercise. We provide evidence that these revisions contain both a news and a noise component.

In the following, we discuss how we approximate the policy makers' real-time information set and, thus, how we can model the revision process.

2.2 Modeling the Central Bank's Information Set in Real-time

Croushore and Evans (2006) point out two issues of the conventional SVAR model approach: i) usage of final, multiple times revised data and ii) ignoring publication lags. Moreover, monetary policy makers take into account their expectations about the future path of output and inflation as any action taken by the central bank needs some time to take effect. The standard approach is based on the assumption that these expectations can be fully recovered from the current and lagged values of the variables included in the VAR.[2] Consequently, the VAR has to comprise the relevant information the policy maker's expectations are based on.

With respect to the Federal Reserve, Greenbook projections provide now- and forecast information of the main economic indicators compiled for each FOMC meeting. These projections reflect the real-time information set of the central bank based on the information of various aggregated and disaggregated indicators and different forecasting models.[3] Consequently, we do not have to make ad hoc assumptions with regard to the unobservable expectation formation process of the policy maker, publication dates of macroeconomic variables, and the selection of potentially leading indicators. One caveat is that they are conditional forecasts based on a hypothetical path for the monetary policy and they are not intended to forecast this path (Faust and Wright, 2008).

Using economic projections that are indented to estimate the economic state unconditionally of the monetary policy decision in the VAR has consequences for the computation of impulse response functions, especially with respect to the revisions to previous projections. Econometrically, revisions to the policy maker's information set affect the systematic component of monetary policy and, thus, the estimated monetary policy shocks. In their real-time data VAR, Croushore and Evans (2006) assume that future revisions to period t data vintages, h^{t+s}_t, follow a stationary process and are independent of period t structural shocks, i.e. $\frac{\partial h^t+s}{\partial \varepsilon_t} = 0 \;\; \forall s > 0$. This assumption seems implausible for Greenbook projections which are, by construction, not intended to forecast exogenous monetary policy shocks. In a subsequent period, however, these shocks enter the information set of the staff responsible for computing the projections and potentially

[1] We do not restrict $a_{23} = a_{24}$ and $a_{25} = a_{26} = a_{27}$ as the revisions to previous projections reflect more timely information and, thus, may have a higher weight in the monetary policy reaction function.

[2] These expectations are assumed to be a linear function of the endogenous variables included in the VAR. This linearity assumption also applies to information-rich frameworks like FAVAR (Ramey, 2016).

[3] While the Greenbook data set is compiled by the staff at the Board of Governors, these projections do not have to represent the expectations of the FOMC members one-to-one. However, the Humphrey-Hawkings report to the Congress may represent the expectations of the policy maker more directly, but is only available on an semiannual basis (see Orphanides and Wieland, 2008).

help to revise previous projections. Sargent (1989) studies an optimal filtering method for a data agency that observes signals contained by measurement error and which aims to provide an optimal estimate of the true state of the economy in terms of different data vintages, i.e. preliminary, revised, and final data. With respect to data revisions, he shows that an efficient estimate of current and lagged vintage data requires a joint likelihood function which is based on all available information. Consequently, efficient revisions to past preliminary estimates depend on the current information set, i.e. $\mathbb{E}(h^t_{t-1}|y^t_t, y^t_{t-1}, \ldots)$.[4]

2.3 Modeling the Data Revision Process

In general, we assume that new information about macroeconomic variables enter the central bank's information set, Ω_t, through a new vintage of Greenbook projections, either as the current period's forecast, $y^t_{t+\tau}$ for $\tau \geq 0$, or as revisions to lagged projections, $h^t_{t+\tau-\ell}$ for $\tau \geq 0$ and $\ell > 0$.

As shown by Aruoba (2008) and Jacobs and van Norden (2011), measurement errors in major macroeconomic variables are characterized by complex dynamics. Gathering new information of the state of the economy may cause statistical offices to revise variables for consecutive periods, e.g. new tax return information for a given year may cause changes in several subsequent quarters $y^t_t, y^t_{t-1}, y^t_{t-2}, \ldots$ Revisions may be also correlated across different vintages, $\mathbb{E}\left(h^t_{t-2}|h^{t-1}_{t-2}\right) \neq 0$. As these official statistics are used by the staff at the Board of Governors to produce their forecasts, Greenbook projections should inherit these properties. Further, as Greenbook projections are jointly produced using multivariate approaches, revisions may be correlated across variables.

We include the revisions of previous Greenbook projections as additional variables in the VAR that respond to lags of the monetary policy instrument, i.e. to the monetary policy shock, and lags of real-time data. Consequently, we model revisions as efficient estimates given all available information in the sense of Sargent (1989). With respect to contemporaneous interactions, we assume that innovations in the projection of one variable affect also other variables of the same Greenbook vintage. Further, we allow for innovations to revisions of past Greenbook projections to affect current projections contemporaneously, but restrict the other way around, at least for the baseline specification. The same applies to revisions to past observations on different lags.[5] Consequently, the real-time information block of a VAR can be represented as:

$$h^t_{t-2} = c_1 + f(x_t) + \varepsilon_{t,1}, \tag{13}$$

$$h^t_{t-1} = c_2 + f(x_t) + a_1 h^t_{t-2} + \varepsilon_{t,2}, \tag{14}$$

$$y^t_t = c_3 + f(x_t) + a_2 h^t_{t-2} + a_3 h^t_{t-1} + \varepsilon_{t,3}, \tag{15}$$

$$s_t = c_4 + f(x_t) + a_4 h^t_{t-2} + a_5 h^t_{t-1} + a_6 y^t_t + \varepsilon^{mp}_t, \tag{16}$$

where $x_t = \begin{bmatrix} s_{t-1} & s_{t-2} & y^{t-1}_{t-1} & y^{t-2}_{t-2} & h^{t-1}_{t-2} & h^{t-2}_{t-3} & h^{t-1}_{t-3} & h^{t-2}_{t-4} \end{bmatrix}$ denotes past observations.

[4]Further, as we use the mid-quarter FOMC meeting in our empirical exercise, the mid-quarter monetary policy shock may have a considerable effect on end-of-quarter macroeconomic variables. This effect gets amplified when we study a forward looking monetary policy reaction function.

[5]These restrictions are necessary for an unique solution of the contemporaneous coefficient matrix when using a non-recursive identification scheme. We test the robustness of our results by using a sign identification scheme where we do not have to impose these restrictions.

3 Model, Data, and Bayesian Estimation

In this section we describe how we estimate a joint econometric model of the real-time central bank reaction function and final revised macroeconomic variables. A joint modeling is required for two reasons. First, the true monetary policy shock has to be orthogonal to the real-time information set of the policy maker. Yet, we are predominantly interested in the shock responses of the true value of a variable, best approximated by the final revised value. Second, the identification of monetary policy shocks requires to estimate the systematic component of monetary policy decisions, i.e. the monetary policy reaction function (Leeper et al., 1996). Based on the previous section, our approach builds on the assumption that Greenbook projections summarize the real-time information set policy makers condition their decision on. Methodologically, we implement this by restricting the reduced-form VAR as well as estimating an appropriately specified contemporaneous coefficient matrix. In doing so, we treat the final revised macroeconomic variables as exogenous to the monetary policy equation.

3.1 Estimating a Monetary Policy SVAR with Real-time Data

Suppose an n-variate SVAR model in its general form:

$$y_t' A_0 = \sum_{\ell=1}^{p} y_{t-l}' A_\ell + c + \varepsilon_t', \qquad \text{for } 1 \leq t \leq T. \tag{17}$$

Alternatively, the model (17) can be written in compact form as:

$$y_t' A_0 = x_t' A_+ + \varepsilon_t', \tag{18}$$

where $A_+' = [A_1' \ldots A_p' c']$ and $x_t' = [y_{t-1}' \ldots y_{t-p}' 1]$. The reduced-form representation of the structural model (18) is:

$$y_t' = x_t' B + u_t', \tag{19}$$

where $B = A_+ A_0^{-1}$, $u_t' = \varepsilon_t' A_0^{-1}$, and $E[u_t u_t'] = \Sigma = (A_0 A_0')^{-1}$.

We restrict the monetary policy reaction function to information that is available in real time, namely Greenbook projections and predetermined indicators such as commodity prices. Thus, we split the data vector y_t into five blocks: n_{GB} variables, y_t^{GB}, comprising the Greenbook projections and the data revision process, n_T final variables, y_t^T, which are subject to recurring data revisions and could not be observed by the central bank in real time, n_t control variables that are divided into two blocks that are either predetermined, $y_t^{1,t}$, or contemporaneously not observable from the perspective of the central bank, $y_t^{2,t}$. Finally, we approximate the monetary policy variable, s_t, by the short-term interest rate, i_t. Then it holds that $n = n_{GB} + n_T + n_t + 1$, with n being the dimension of y_t.

$$y_t' = \begin{bmatrix} y_t^{GB} & y_t^T & y_t^{1,t} & i_t & y_t^{2,t} \end{bmatrix}. \tag{20}$$

In order to ensure that final revised information about the economic state does not enter the monetary policy equation, we have to restrict both the contemporaneous, A_0, and the lagged structural coefficient matrices, A_ℓ, in eq. (17). The latter is necessary to ensure that the central bank does not learn about unexpected innovations in the final data through the lagged feedback of the real-time variables. Specifically, we restrict the reduced-form model (19) and the contemporaneous coefficient matrix A_0 so that the final data vector $y^T_{t-\ell}, 0 < \ell \leq p$, does not enter the monetary policy reaction function. By appropriately restricting the estimated reduced-form VAR and the contemporaneous coefficient matrix A_0 we ensure that the necessary restrictions carry over to the structural coefficient matrix A_+.

We estimate the VARs with Bayesian techniques. Due to the restrictions on the lagged coefficient matrices, we use an independent Normal-Wishart prior for the reduced-form VAR and estimate the model using a standard Gibbs-sampling algorithm. Given that our benchmark model includes many free parameters, we use a Minnesota-style prior to prevent overfitting.[6] In Appendix B we provide the details of the priors and the estimation procedure.

3.2 Variables and Data in the Baseline VAR

The baseline VAR includes six macroeconomic variables: real GDP, GDP deflator, an index of commodity prices, federal funds rate (as the monetary policy variable), total reserves, and non-borrowed reserves. The set of endogenous variables is the same as in Croushore and Evans (2006) and Arias et al. (2019). All variables are quarterly and taken from FRED except of the commodity price index which is taken from the replication files of Ramey (2016). Further, we add Greenbook data to our VAR. Following the discussion in section 2.3, we use the Greenbook projections for real GDP growth and the GDP deflator.[7] Specifically, we use the data of the mid-quarter meeting.[8] Further, we construct revision series for every variable for as many periods as the lag-length of the VAR. Following Aruoba (2008), these revisions are defined on the growth rates and are denoted for variable x as

$$h^t_{t+f-\tau} = x^t_{t+f-\tau} - x^{t-1}_{t+f-\tau},$$

where $0 \leq f \leq 4$ is the forecast horizon and $1 \leq \tau \leq p$ denotes the lag order of the variable revised. As the Greenbook data is generically in annualized growth rates, we cast all variables except the federal funds rate in this way.

The maximum sample period would be 1967Q3 to 2013Q4 due to the availability of the Greenbook data. In the baseline VAR the lag order is $p = 3$ and the sample period ends in 2007Q2 due to the Global Financial Crisis. The vintage for the revised data is October 2019. We treat this data vintage as final revised as it is more than five years after our sample period ends. Further, using growth rates mitigates the issues associated with benchmark revisions and the transition from GNP to GDP in the Greenbook data.

3.3 Identificating Monetary Policy Shocks

The monetary policy shock is identified using two schemes based on a nonrecursive ordering and a mixture of sign and exclusion restrictions. While the nonrecursive scheme makes less assumptions regarding the monetary policy reaction function, the latter approach allows for a more flexible Greenbook information process. However, the higher flexibility of the latter is gained by a more pronounced identification

[6] In Appendix C, we show the robustness of our main results to use the dummy-observation priors following Sims and Zha (1998) in conjunction with the block-recursive algorithm of Zha (1999) and Waggoner and Zha (2003).

[7] While the FOMC uses PCE inflation as their main inflation indicator nowadays, we use the GDP deflator as this series is available for a much longer sample period in the Greenbook data set. Similar, we use real GDP growth instead of an output gap measure as the official Greenbook output gap vintages are not available before 1996.

[8] See Orphanides (2001) for a discussion of the advantages using the information corresponding to the February, May, August, and Novemeber FOMC meetings.

uncertainty due to the partial and set identification strategy. The nonrecursive identification scheme is an adoption of the well understood recursive identification approach discussed in Christiano et al. (1999) and many others. We use this as our baseline model to investigate how the real-time availability of macroeconomic indicators affects the identification of monetary policy shocks and the systematic component of monetary policy. In a second step, we use the more agnostic sign restriction approach to test the robustness of our results across several sign restriction schemes widely used in the literature.

Both approaches have in common that there should be no feedback, neither contemporaneously nor through lagged values, from the final output and price inflation to the monetary policy variable. Further, as it is standard in the literature, we assume that the policy maker reacts only with a lag to movements in total reserves and nonborrowed reserves. Importantly, the restrictions of the A_0 matrix in conjunction with an appropriate specification of the reduced-form estimation discussed in Section 3.1 guarantees the exclusion restrictions in the lagged coefficient matrices A_ℓ.

In general, we restrict the information set available to economic agents other than the policy maker as much as necessary to avoid feedbacks from other equations in the VAR to the monetary policy reaction function. Thus, we assume that new information enters the Fed's information set only through the Greenbook projections. With respect to the Greenbook information process, y_t^{GB}, we suppose that it is a vector of Greenbook projections and revisions to past projections. We model this information process as flexible as possible to allow for potential interdependence in projections across indicators and across horizons as well as data vintages.

As for the nonrecursive scheme, we impose the following contemporaneous zero restrictions on the matrix A_0:

$$\begin{bmatrix} u_t^{GB} & u_t^T & u_t^{1,t} & u_t^i & u_t^{2,t} \end{bmatrix} \begin{bmatrix} A_0^{11} & A_0^{12} & A_0^{13} & A_0^{14} & A_0^{15} \\ 0 & A_0^{22} & 0 & 0 & 0 \\ 0 & 0 & A_0^{33} & A_0^{34} & A_0^{35} \\ 0 & 0 & 0 & A_0^{44} & A_0^{45} \\ 0 & 0 & 0 & 0 & A_0^{55} \end{bmatrix} = \begin{bmatrix} \varepsilon_t^{GB} & \varepsilon_t^T & \varepsilon_t^{1,t} & \varepsilon_t^{mp} & \varepsilon_t^{2,t} \end{bmatrix}, \qquad (21)$$

where the elements A_0^{ij} represents matrices of coefficients.

The first row of A_0 represents the Greenbook information process and is modeled as described in Section 2.3: A_0^{11} is block upper-triangular and there are no restrictions between different variables of the same horizon. By setting $A_0^{12} \neq 0$, we allow Greenbook forecasts to affect final output and prices. Implicitly, we assume that the other economic agents are as good as the central bank in forecasting the future path of output and prices. While this assumption appears ad hoc, it reflects the predeterminedness of expectations.

We use the additional space generated by the exclusion restrictions related to the final revised data to increase the flexibility of the the contemporaneous Greenbook information process. Specifically, we allow output growth and inflation forecasts of the current projection as well as revisions to the same lagged vintage to be interdependent. Further, we do not restrict the contemporaneous interactions between Greenbook forecasts and revisions of last periods' forecasts.

In the second identification scheme, we impose a mixture of sign and exclusion restrictions. As this identification strategy does not build on a specific ordering of the variables to identify the A_0 matrix, the variables are ordered to establish a block exogeneity structure in the coefficient matrices A_0 and A_ℓ. Specifically, we split the data vector y_t in a monetary policy block, consisting of the Greenbook data, y_t^{GB}, timely reacting real-time data, $y_t^{1,t}$, and the policy rate, i_t, and a non-policy block, spanning the slow moving real-time data, $y_t^{2,t}$, and final revised macroeconomic variables, y_t^T.

$$\tilde{y}_t' = \begin{bmatrix} y_t^{GB} & y_t^{1,t} & i_t & y_t^{2,t} & y_t^T \end{bmatrix}. \tag{22}$$

We identify the monetary policy shock using sign restrictions in the policy block and exclusion restrictions with respect to the non-policy block. Specifically, we impose the restrictions that a contractionary monetary policy shock leads to a decrease in real GDP, the GDP deflator, commodity prices, and nonborrowed reserves on impact and in the first period after the shock.

We implement the block exogeneity by using a subrotation matrix Q^*. Specifically, for each draw of the reduced-form covariance matrix Σ, we compute the Cholesky decomposition denoted Σ_{tr}. A draw of A_0 can then be computed by:

$$A_0 = \Sigma_{tr}^{-1} Q' = \Sigma_{tr}^{-1} \begin{bmatrix} Q^* & 0 \\ 0 & I \end{bmatrix}', \tag{23}$$

where the subrotation matrix Q^* rotates the policy block of the reordered $\tilde{y}_t$ such that the first shock satisfies the sign restrictions. The prior on the rotation is uniform in the subspace of all orthonormal matrices that satisfy the sign restrictions. The construction of the matrix Q maintains the orthogonality of the shocks. Further, A_0^{-1} satisfies the contemporaneous impact restrictions on inflation, commodity price inflation, and nonborrowed reserves.

For both identification schemes, we report results based on 10.000 draws from the Gibbs sampler after discarding the first 90.000 draws. For every draw of the reduced-form coefficients, we check the stability of β, i.e. the roots are within the unit circle, and proceed only with draws that are stable. For every draw of β and Σ, we estimate A_0 according to the identification strategies described above.

4 Results

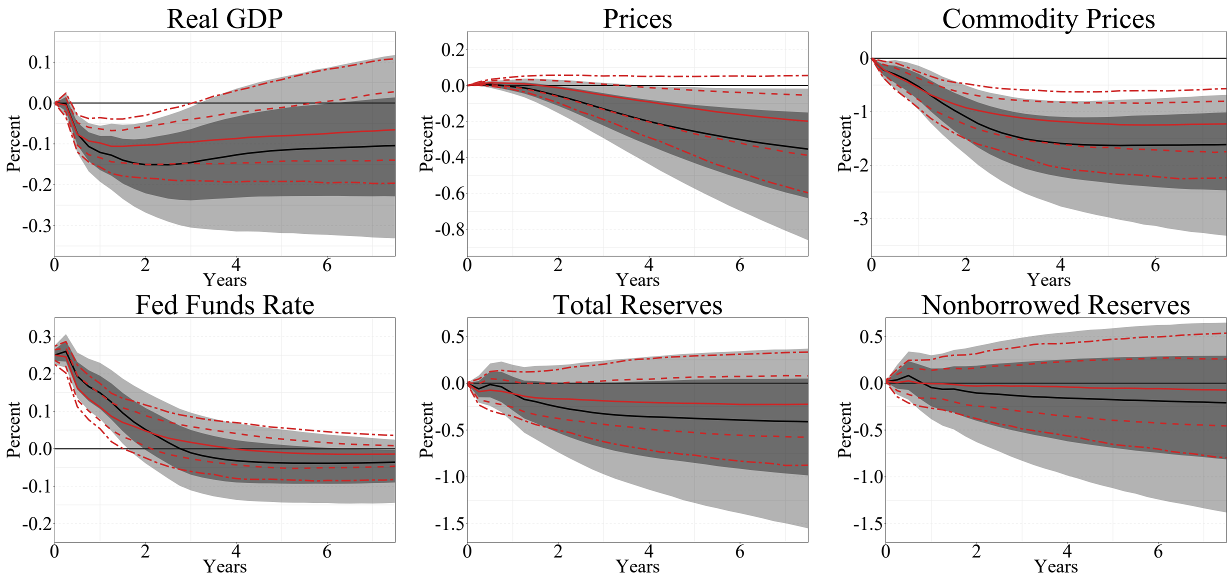
4.1 The Effect of Monetary Policy Shocks

To analyze how the real-time availability of macroeconomic indicators affects the identification of monetary policy shocks and the transmission to the economy, we estimate the SVAR twice. First, we follow the standard approach in the literature and condition monetary policy on final data. Specifically, we assume that the monetary policy variable, i.e. the federal funds rate, reacts contemporaneously to innovations in output growth, inflation, and commodity price inflation.[9] In our second specification, we account for the fact that central banks have to rely on forecasting the current state of the economy as final revised data is not available. As discussed above, we extend the vector of endogenous macroeconomic variables by Greenbook projections of output growth and inflation as well as revisions in previous estimates. Accordingly, we restrict the information set of the central bank in our VAR estimation to the contemporaneous Greenbook data and commodity prices as well as lags of these variables and reserves. In our baseline specification we use the nonrecursive identification strategy laid out above and employ the Greenbook nowcast. In a second step, we will test how using Greenbook forecasts two and four quarters ahead affects the analysis.

Figure 1 displays the impulse responses from a monetary policy shock in a VAR system with final data

[9] In terms of Equation (17) and (20), we set $y_t^{GB} = \{\}$.

Figure 1: Impulse Responses to a Nonrecursive Identified Monetary Policy Shock



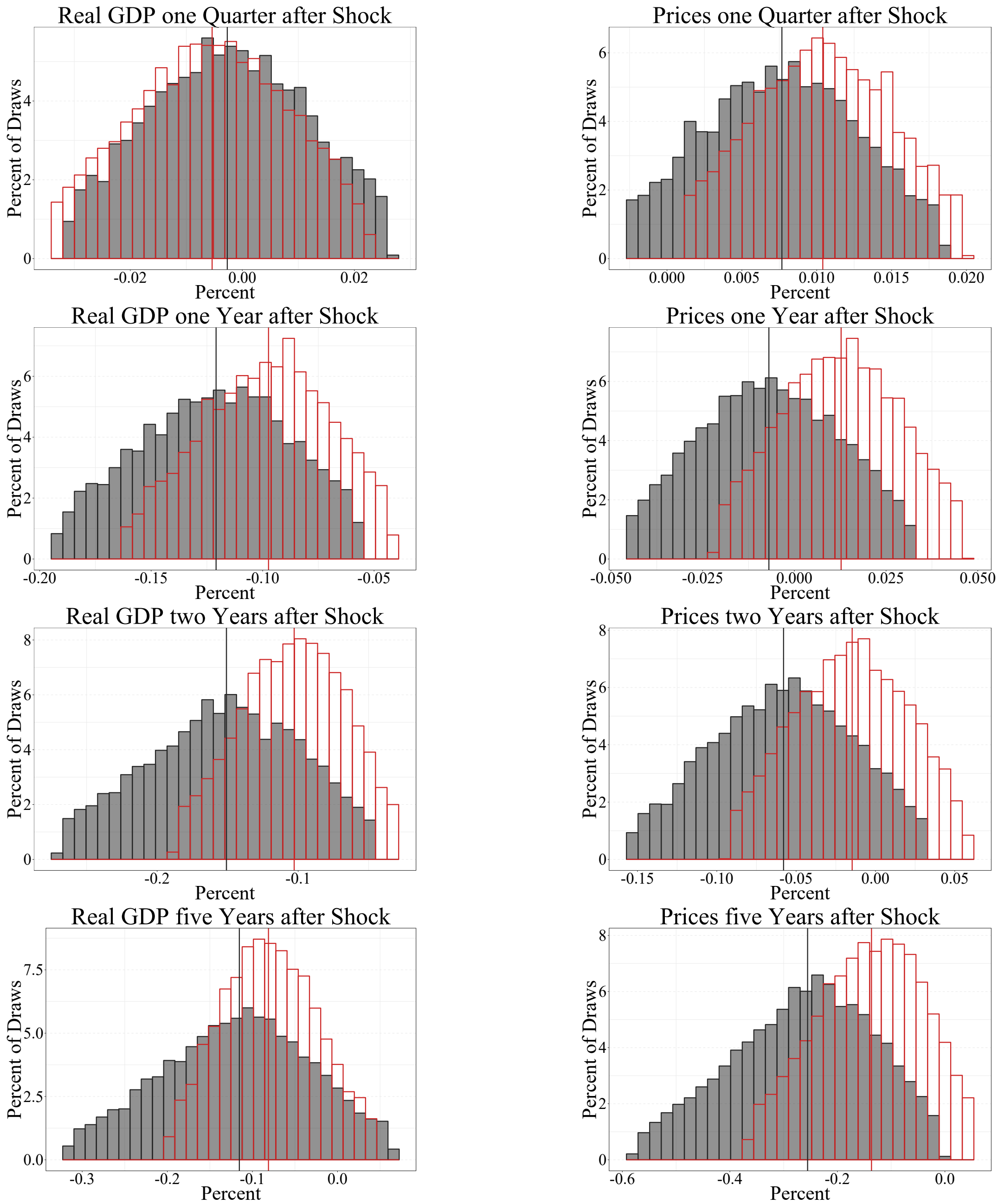
Notes: This figure shows responses to a 25 Bp contractionary monetary policy shock as identified with a nonrecursive identification scheme. The red solid line and dashed lines depict the median impulse response function and the 68% and 90% pointwise credible sets, respectively, of the VAR specification with final data only. The solid black line and the gray shaded bands depict the distribution of impulse responses for the model with Greenbook projections in the central bank information set. Sample period: 1967Q3-2007Q2.

and with real-time data in the monetary policy equation. The solid black line and the grey shaded bands show the pointwise median responses and the corresponding 68 percent and 90 percent pointwise credible bands for the model including the Greenbook projections in the central bank information set, respectively. We cumulated the responses of real GDP growth and GDP deflator inflation to see the response of output and the general price level. For comparison, red solid line and dashed lines depict the pointwise median impulse response function and the 68 percent and 90 percent pointwise credible sets, respectively, of the VAR specification with final data only. We normalized the two monetary policy shocks so that they cause a posterior median increase in the federal funds rate of 25 basis points on impact.

Both specifications show responses in line with economic theory (see, among many others, Christiano et al., 1999; Ramey, 2016). A contractionary policy shock leads to a decrease in output, prices, and total reserves. The negative response of output has a high posterior probability for the first two years before the shock response eventually dies out. The zero is not contained in the 90 percent credible sets of both models for the first periods after the shock. In contrast, the response of the general price level is more protracted and it takes more than a year before a considerable probability mass indicates a decline. In both specification, a sizeable posterior probability mass of the responses gives rise to a counterintuitive increase in prices in the first periods after a contractionary monetary policy shock. However, the price puzzle is less pronounced in the specification using real-time data in the monetary policy reaction function. The response of nonborrowed reserves is not precisely estimated and close to zero in both specifications.

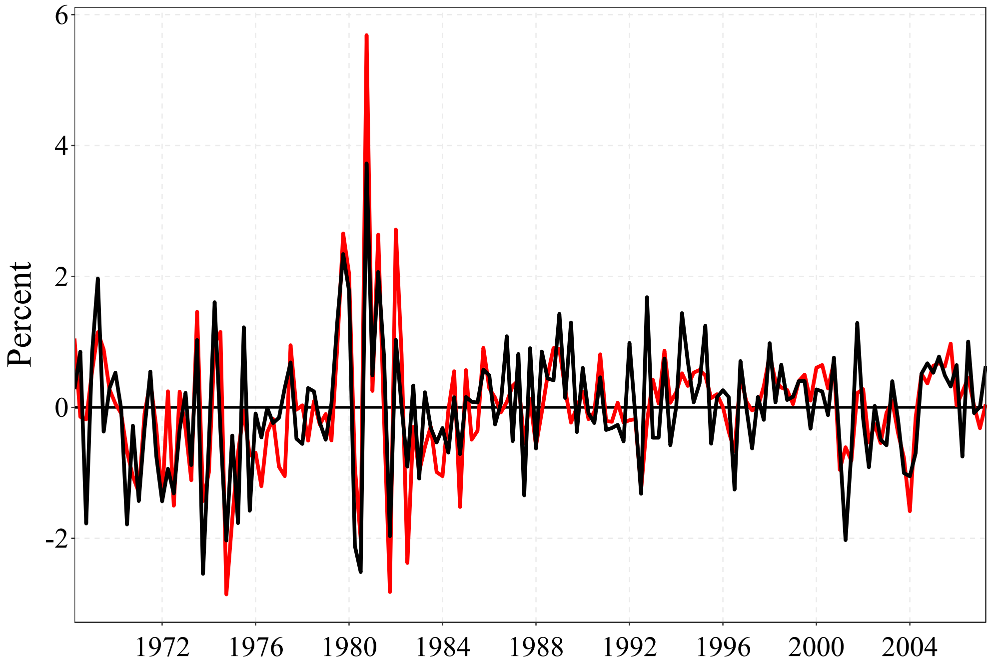
While the qualitative results are quite similar, expanding the vector of endogenous variables by the Greenbook data results in higher sample uncertainty and, thus, wider credible sets. However, the credible sets do not widen symmetrically when going from the final data to the real-time information model. Restricting the information set of the central bank to real-time information leads to a considerable stronger countercyclical effect of monetary policy. Figure 2 shows the histograms of the responses of real GDP

Figure 2: Histograms of the Responses to a Nonrecursive Identified Monetary Policy Shock



Notes: This figure shows the distribution of impulse responses (90% pointwise credible set) to a 25 Bp contractionary monetary policy shock as identified with a nonrecursive identification scheme. The red-rimmed bars indicate impulse response functions estimated from the VAR specification with final data only. The grey bars depict the distribution of impulse responses for the model with Greenbook projections in the central bank information set. Vertical lines show the median response. Sample period: 1967Q3-2007Q2.

Figure 3: Estimated Monetary Policy Shocks



Notes: The red line shows the posterior median monetary policy shocks estimated from VARs using final revised data and black line using real-time data. Sample period: 1967Q3-2007Q2.

and GDP deflator on different horizons. The grey bars depict the distribution of impulse responses for the model using Greenbook projections in the central bank information set, while the red-rimmed bars show the respective distribution of the final revised data SVAR. The vertical lines display the median response. Two observations stand out. First, around one-third of the draws imply a more pronounced decrease in output, prices, and commodity prices after a contractionary monetary policy shock. The difference in the posterior median response of the real-time information and the final revised data model is the largest about one to two years after the shock. For real GDP (GDP deflator), the posterior medians are -0.10 (-0.01) percent and -0.15 (-0.06) percent for the final revised data and the real-time information specification, respectively, two years after the shock. Second, in both models, there is a considerable posterior probability mass that implies a price puzzle one quarter after the shock. While it takes less than a year for the posterior median in the model with real-time information to turn negative, the posterior median of the final data specification is barely below zero even two years after the shock.

Overall the results imply that one would considerably underestimate the overall effect of unsystematic monetary policy actions. This is to some extend in contrast to the findings of Croushore and Evans (2006). Based on specific assumptions about the revision process, they report rather a less persistent and less pronounced effect of monetary policy on output and prices in their real-time data model compared to the final revised data VAR. Though, the differences are not statistically significant from a frequentist perspective.

To investigate the cause for the more pronounced effect of monetary policy shocks in the real-time data model, we analyze differences in the estimated monetary policy shocks and in the policy reaction function. Figure 3 shows the median monetary policy shocks using real-time information and the shock series estimated using final revised data. Both series are highly correlated (0.75), display a similar timing in terms of peak and troughs, and have the same sign most of the time. However, the magnitude and the qualitative implication for the historical policy assessment display notable differences for specific episodes. As reported in Croushore and Evans (2006), we find that using final data overestimates the magnitude of exogenous monetary policy action during the first term of Fed chairman Paul Volcker. In contrast, monetary policy shocks employing final data appear to underestimate the magnitude of exogenous policy shocks during the late 1980s and 1990s. In line with the results presented in Appendix A, this implies that employing final revised data for monetary policy analysis may partly identify what were actually systematic policy reactions to imperfect real-time data as exogenous policy actions, and vice versa.

4.2 The Systematic Component of Monetary Policy

In this section, we study how monetary policy systematically reacts to innovations in macroeconomic variables. As discussed in Leeper et al. (1996), identifying monetary policy shocks in a SVAR goes hand in hand with specifying a monetary policy reaction function. Based on the SVAR representation in Equation (18) and assumingF for the ease of notation that the monetary policy variable is ordered first and the monetary policy shock is the first one in ε_t, the monetary policy equation can be written as:

$$i_t = \sum_{j=2}^{n} y'_{j,t} \psi_{0,j} + \sum_{\ell=1}^{p} \sum_{j=1}^{n} y'_{j,t-\ell} \psi_{\ell,j} + \sigma_{mp} \varepsilon_{mp,t}, \tag{24}$$

where the systematic component of monetary policy is portioned into the contemporaneous and lagged determinants. Let $a_{\ell,ij}$ denote the (i, j) element of A_ℓ, $\psi_{0,j} = -a_{0,j1}/a_{0,11}$ and $\psi_{\ell,j} = a_{\ell,j1}/a_{0,11}$ represent the elasticities of the monetary policy variable to the macroeconomic variables in the VAR.

Table 1 reports the estimated contemporaneous, $\psi_{0,j}$, cumulative ψ_j^{cum}, and long-run coefficients, ψ_j^{long} of the monetary policy reaction function. While the cumulative coefficients are computed as:

$$\psi_j^{cum} = \sum_{\ell=0}^{p} y'_{j,t-\ell} \psi_{\ell,j},$$

Sims and Zha (2006) define the long-run coefficients as:

$$\psi_j^{long} = \psi_j^{cum}/(1 - \psi_i^{cum}),$$

where ψ_i^{cum} is the cumulative coefficient of the policy variable, i.e. the federal funds rate.

The median response of monetary policy to output growth, inflation, and commodity price inflation is always positive and, except for the final data estimates, this is also true at a 90 percent credibility level (not reported) in most cases. The posterior estimates are broadly in line with the recent SVAR findings of Caldara and Herbst (2019). Similar to the single-equation policy rule estimates of Orphanides (2004), we find higher median responses to inflation when using real-time available data compared to final data. For contemporaneous and cumulative responses the median estimates are about twice as large. With respect to the cumulative elasticities, the final revised data suggest an implausible high weight on output growth compared to the estimate for inflation. As reported in Arias et al. (2019), the response to commodity prices is considerably smaller.

The estimated long-run coefficients for the response of the federal funds rate to output growth and inflation evaluated at the posterior median are in line with the Taylor principle. Monetary policy reacts to a positive innovation in these variables with a more than one-to-one increase in the policy rate. Thus, monetary policy acts countercyclically by stabilizing output and prices. With respect to the relative weight

Table 1: Coefficients in the Monetary Policy Reaction Function

	Final Data			Real-time Data		
Panel A: Contemporaneous						
$\psi_{0,\Delta y}$	0.027	[0.001	0.050]	-		
$\psi_{0,\pi}$	0.108	[0.028	0.176]	-		
$\psi_{0,\Delta y^{GB}}$	-			0.088	[0.052	0.123]
$\psi_{0,\pi^{GB}}$	-			0.173	[0.104	0.239]
$\psi_{0,\pi^{c}}$	0.015	[0.010	0.019]	0.011	[0.006	0.015]
Panel B: Cumulative						
$\psi^{cum}_{\Delta y}$	0.161	[0.122	0.200]	-		
ψ^{cum}_{π}	0.098	[0.054	0.141]	-		
$\psi^{cum}_{\Delta y^{GB}}$	-			0.147	[0.107	0.187]
$\psi^{cum}_{\pi^{GB}}$	-			0.178	[0.129	0.226]
$\psi^{cum}_{\pi^{c}}$	0.027	[0.020	0.034]	0.014	[0.008	0.021]
ψ^{cum}_{i}	0.968	[0.939	1.000]	0.929	[0.898	0.959]
$\psi^{cum}_{\Delta TR}$	-0.025	[-0.043	-0.007]	-0.026	[-0.042	-0.009]
$\psi^{cum}_{\Delta NBR}$	0.016	[-0.004	0.032]	0.017	[0.012	0.032]
Panel C: Long Run						
$\psi^{long}_{\Delta y}$	3.555	[-1.003	9.697]	-		
ψ^{long}_{π}	2.420	[0.629	5.189]	-		
$\psi^{long}_{\Delta y^{GB}}$	-			2.050	[1.219	3.735]
$\psi^{long}_{\pi^{GB}}$	-			2.491	[1.906	3.614]
$\psi^{long}_{\pi^{c}}$	0.606	[-0.186	1.571]	0.192	[0.086	0.427]
$\psi^{long}_{\Delta TR}$	-0.493	[-1.573	0.350]	-0.359	[-0.738	-0.118]
$\psi^{long}_{\Delta NBR}$	0.285	[-0.418	1.193]	0.234	[0.140	0.551]

Note: This table reports the posterior median estimates of the contemporaneous, cumulative, and long-run coefficients in the monetary policy reaction function for the VAR with only final data and with real-time consistent central bank information. The 68% credible sets are reported in brackets. Sample period: 1967Q3-2007Q2.

of inflation to output growth in the monetary policy reaction function, both specifications yield different results. While the long-run coefficients in the specification with final data imply a higher weight on output growth than on inflation, the specification with real-time available information yields the opposite. Further, the coefficients based on final revised data are less precisely estimated and the 68 percent credible sets contain the zero in all cases except for inflation.

Finally, both models yield a high degree of policy inertia, though, significantly lower than one in case of the real-time consistent specification. As a considerable amount of draws imply a cumulative elasticity of $\psi_i^{cum} > 1$ for the model where the central bank contemporaneously reacts to final data, the distribution of the long-run coefficients is distorted for this specification. Thus, the posterior median estimates of the final data VAR have to be interpreted with caution as these draws have questionable implications for the conduct of monetary policy.

4.3 Assumptions on the Revision Process

In our baseline model, we do not restrict the response of revisions to structural shocks. In contrast, Croushore and Evans (2006) assume that future revisions to period t data vintages, h_t^{t+s}, and measurement errors with respect to the true data value are independent of period t structural shocks when computing impulse response functions. But, given that we look specifically at the revisions of the Greenbook projections, we argue that it is necessary to allow for an interdependence between monetary policy shocks and subsequent revisions.

To investigate whether our results are driven by the assumptions placed on the revision process or the difference between Greenbook projections and the available official data estimates, we analyze the estimated effects of monetary policy shocks on revisions. Further, we mimic the approach of Croushore and Evans (2006) through restricting the response of Greenbook revisions to lagged innovations in all other endogenous variables to be zero. Consequently, revisions to previous Greenbook projections, h_t^{t+s}, are independent of the monetary policy shock, ε_t^{mp}, and all other exogenous innovations in the real economy block of our SVAR model.[10]

In general, there are two metrics to assess the impact of monetary policy shocks on future revisions: i) revisions to a specific quarter in the periods after the shock may be correlated with the shock and ii) shocks may impact the revision series across data vintages. Specifically, we compute the response function of the revisions to the nowcast of real GDP growth and GDP deflator growth due to the monetary policy shock as follows:

$$\frac{\partial h_t^{t+s}}{\partial \varepsilon_t^{mp}}, \qquad 1 \leq s \leq 3, \tag{25}$$

and the response of the series of revisions $h_{t-\ell}^{t}$:

$$\frac{\partial h_{t-\ell}^{t}}{\partial \varepsilon_t^{mp}}, \qquad 1 \leq \ell \leq 3, \tag{26}$$

where the maximum length of s and ℓ is determined by the lag length of our VAR model. Table 2 shows the cumulated response of h_t^{t+s} to a monetary policy shock in t separately for real GDP and the GDP

[10] Specifically, in terms of Equation (31), we restrict the reduced-from VAR so that the respective coefficients in the matrices B_ℓ^{31}, B_ℓ^{41} and B_ℓ^{51} are zero.

Table 2: Revisions h_t^{t+s}: 1967Q3-2007Q2

	Real GDP	GDP deflator
h_t^{t+1}	0.57	-0.23
	[0.31 0.83]	[-0.38 -0.08]
h_t^{t+2}	0.61	-0.20
	[0.33 0.91]	[-0.36 -0.02]
h_t^{t+3}	0.50	-0.21
	[0.20 0.80]	[-0.38 -0.03]

Note: This table shows the estimated responses of the revisions to a 25 Bp contractionary monetary policy shock. The 68% credible sets are reported in brackets. Sample period: 1967Q3-2007Q2.

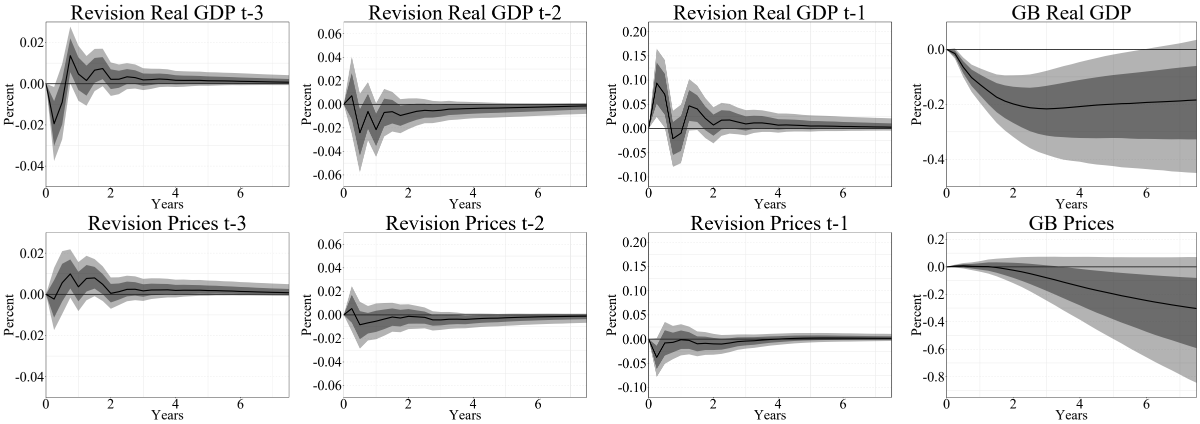
deflator.[11] Figure 4 shows the responses of the revision series $h_{t-\ell}^{t}$ for $\ell = 1,2,3$ as they are included in our reduced-form VAR. Both sets of results stem from our baseline specification, building on a non-recursive identification strategy, the nowcast of the Greenbook projection, and the sample period 1967Q3-2007Q2.

We find that Greenbook projection revisions respond considerably to a monetary policy shock. Similar to the unconditional means reported in Appendix A, the revisions to real GDP growth projections are substantially larger than revisions to inflation. Further, the magnitude of revisions shrinks the longer ago the reference period for the revision is. With respect to the sign of the revisions, we find a complex pattern. Considering the revisions to a projection for a specific quarter, we find that the real GDP growth projection is revised upwards after a contractionary monetary policy shock in the same quarter, while a GDP deflator projection is significantly revised downwards. The impulse response functions of the revision series included in the VAR show a similar pattern, though the signs of the responses alternate in the first quarters after the shock. Further, the response of the Greenbook projections mimics the response of the final data. This is in line with the presumption that the monetary policy shocks are not anticipated when preparing the Greenbook projections.

Economically, the response of revisions to monetary policy shocks could be the result of two opposing effects. First, the quarterly frequency of our analysis obscures an endogeneity problem. As we only analyze the mid-quarter FOMC decisions, an exogenous monetary policy shock has about six weeks to affect the macroeconomic variables in our VAR. While the monetary policy shock might be a response to the nowcast about the economic state in a given quarter, the true economic state in the respective quarter is also affected by the shock. This mechanism implies that monetary policy shocks should lead to a downward revision in output and price projections. Second, the Greenbook projections arguably reflect the information of all available indicators about the economic state, but the policy makers' information set may also include informal knowledge about the economic state based on their expert judgment. As a consequence, monetary policy shocks could reflect the superior knowledge of the policy maker compared to the Greenbook projection which then getting incorporated in the revision of the projection one period later. This mechanism would imply an upward revision of output and inflation projection conditional on a contractionary monetary

[11] The response functions are computed by collecting the respective impulse responses from the respective impulse response functions of the revision series included in our reduced-from VAR. The responses are collected and cumulated for every draw from the Gibbs sampler. Given the lag-order of the reduced-form VAR, we track the revisions to a specific quarter for three consecutive periods.

Figure 4: Impulse Responses to a Contractionary Monetary Policy Shock: Revisions and Greenbook Projections



Notes: This figure shows responses to a 25 Bp contractionary monetary policy shock. The solid black line and the gray shaded bands depict the median impulse response function and the 68% and 90% pointwise credible sets, respectively. The responses of revisions are not cumulated. Sample period: 1967Q3-2007Q2.

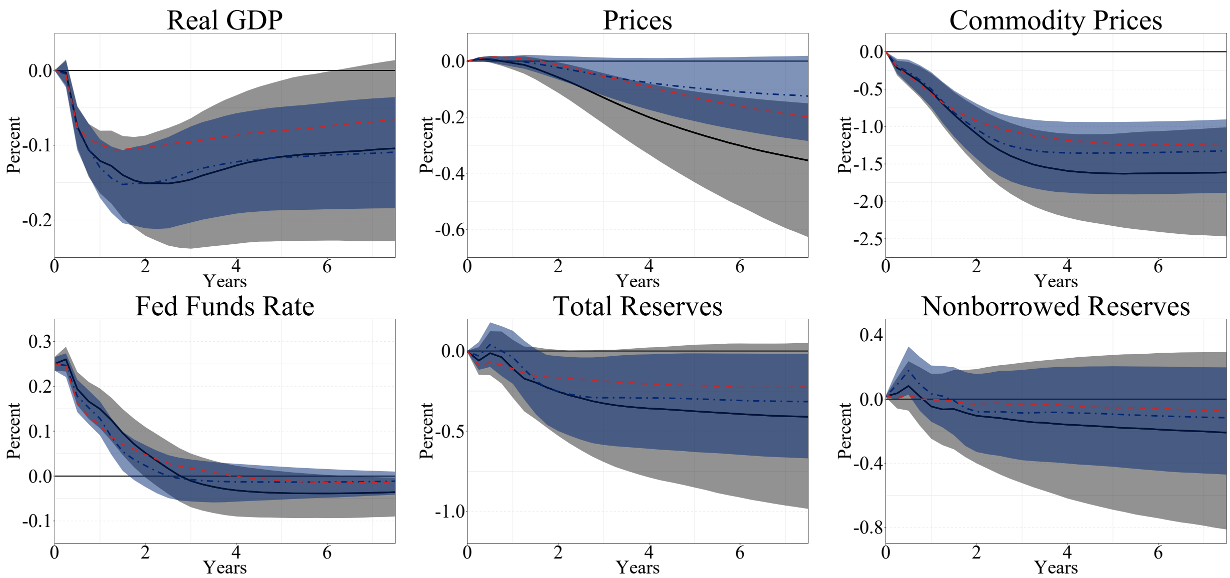
policy shock.

The results presented in Table 2 provide evidence for both of these effects and are broadly in line with the findings of Romer and Romer (2008). Analyzing the differences between the Greenbook projections and the forecasts prepared by the FOMC members for the semiannual Monetary Policy Report to the Congress, they show that using the FOMC's forecast for real GDP growth in addition to the Greenbook projections improves the predictive power. For inflation, they do not find such an effect. Further, Romer and Romer (2008) report that the difference between the Greenbook projections and the forecasts of the FOMC members are correlated with the respective Romer and Romer (2004) monetary policy shocks. In a back-of-the-envelope calculation, we compute the correlation between the cumulated revisions to the Greenbook revisions, h_t^{t+s}, and the differences between the forecasts of the FOMC members and the Greenbook projections. We find a slight correlation of 0.25 for real GDP growth and an almost negligible correlation of 0.09 for GDP deflator growth.[12]

Figure 5 shows the impulse response functions of the endogenous macroeconomic variables to a monetary policy shock if we impose the additional restriction that the response of future revisions to a monetary policy shock is zero (blue dashed line and blue shaded area). This mimics the assumption on the revision process placed by Croushore and Evans (2006). The plots also show the impulse response functions of our baseline real-time information model (solid black line and gray shaded area) as well as the posterior median response of the final revised data model (red dashed line). The two real-time information models are remarkably similar. The only exception to this is the response of prices. Restricting the response of revisions to the monetary policy shock seems to explain the difference between the price responses found in the real-time information model and the final revised data model reported in Figure 1. Similar to Croushore and Evans (2006), we find that the response of prices is smaller in the real-time information model than in the final revised data model once we mimic their assumption about the revision process. This finding highlights

[12]We construct constant-horizon forecasts for real GDP (real GNP) growth and GDP deflator (GNP deflator) growth three quarters ahead from the Monetary Policy Report and the Greenbook data, respectively, following Orphanides and Wieland (2008). We contrast the differences between the forecasts with the cumulated revisions, h_t^{t+s}, shown in Table 2 for the available sample period 1979-2007. Due to the semiannual frequency of Monetary Policy Report and the fact that the June/July forecasts are actually based on the end-of-quarter Greenbook projection, which are not part of our analysis, the results have to be treated with caution.

Figure 5: Impulse Responses to a Nonrecursive Identified Monetary Policy Shock: Restricted Revisions



Notes: This figure shows responses to a 25 Bp contractionary monetary policy shock as identified with a nonrecursive identification scheme. The red dashed line depicts the median impulse response function of the VAR specification with final data only. The solid black line and the gray shaded band depict the median impulse response function and the pointwise 68% credible sets for our baseline real-time information set model. The blue dashed line and the blue shaded band depict the distribution of impulse responses for the model where we impose additional restrictions on the revision process. See text for details. Sample period: 1967Q3-2007Q2.

the importance of accounting for revisions to macroeconomic variables and of the assumptions placed on the revision process. With respect to the differences in the real GDP response, though quantitatively less pronounced, revisions to previous Greenbook projections do not seem to drive the difference between the real-time information and the final revised data model. Consequently, this suggests that it may be caused by the forecast error in the initial Greenbook projections.

4.4 The Effects of Forward-looking Monetary Policy

Motivated by the lag with which monetary policy actions affect the real economy, a vast literature provides evidence that the Fed has followed a forward-looking policy rule (see, among many other, Orphanides, 2001, 2004; Boivin and Giannoni, 2006). In this subsection, we report how the results of our baseline analysis change if we alter the forecast horizon of the Greenbook projections in the information set of the policy maker. While the Fed supposedly uses all the information it has, we abstain from including Greenbook forecasts for different horizons all at once to systematically investigate the impact of different projection horizons and to not overload the state space. Further, as Greenbook forecasts for four quarters ahead are not throughout available in the first years of our sample period, we have to reduce the sample period to 1974Q3-2007Q2 for this exercise.

Figure 6 displays the response of real GDP, GDP deflator, and the commodity price level to a contractionary monetary policy shock for different specifications of the policy reaction function.[13] Based on the insights provided by (Orphanides, 2004), we only change the forecast horizon of the GDP deflator in the monetary policy reaction function and use the nowcast of output.[14] Interestingly, the estimated impulse

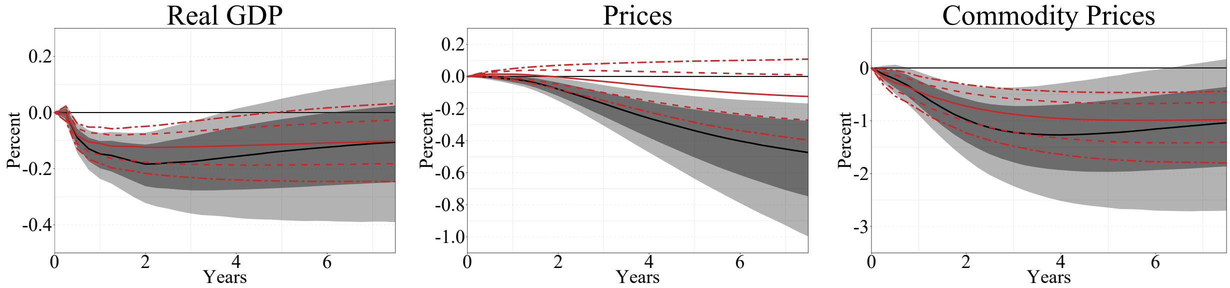
[13]The impulse response functions of the remaining variables are shown in Appendix D.

[14]In a not reported exercise, we also experimented with forecast for real GDP growth. The results yield counterintuitive re-

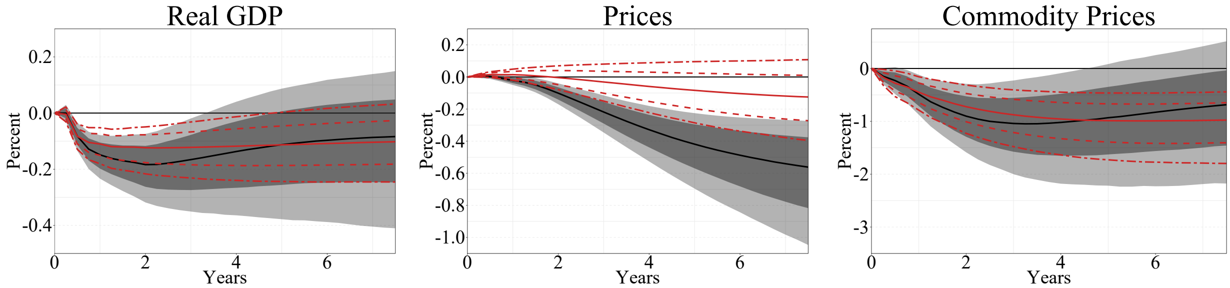
response functions imply a considerable pronounced effect on the price level. In both specifications, the one standard deviation credible sets of the final data model and the real-time information model do not overlap starting one year after the shock. Further, as shown in Appendix D, only the model using the four quarter ahead inflation forecast yields decreasing nonborrowed reserves after a contractionary monetary policy shock.

Figure 6: Impulse Responses to a Monetary Policy Shock using Greenbook Projections with different Horizons

Panel A: Real GDP Growth Nowcast, Inflation Forecast 2Q ahead



Panel B: Real GDP Growth Nowcast, Inflation Forecast 4Q ahead



Notes: This figure shows responses to a 25 Bp contractionary monetary policy shock as identified with a nonrecursive identification scheme. The red solid line and dashed lines depicts the median impulse response function and the 68% and 90% pointwise credible sets, respectively, of the VAR specification with final data only. The solid black line and the gray shaded bands depict the distribution of impulse responses for the model with Greenbook projections in the central bank information set. Sample period: 1974Q3-2007Q2.

The estimated long-run elasticities in the monetary policy reaction function do not provide a clear picture. As displayed in Panel A of Table 6, raising the forecast horizon of the Greenbook projections leads to a considerable increase in the estimation uncertainty especially for the output coefficient.[15] In case of the specification involving the four quarters ahead inflation forecast, the posterior median even turns negative. These results imply a misspecified policy reaction function while a rule based on contemporaneous values is supported by the data. However, this is in contradiction to the findings of a vast literature. A more likely explanation is that the monetary policy response has changed during the late 1970s.

Estimating single-equation policy rules with data available in real time, Orphanides (2002, 2004) do not find considerable differences in the conduct of monetary policy by the Fed before and after the Volcker chairmanship. In contrast, Boivin (2006) provides evidence for significant changes in the Fed's response to output and inflation throughout the 1970s and early 1980s. Based on the results of Boivin (2006), we estimate the models again for the 1983Q1-2007Q2 period.[16]

sponses of output.

[15] Again, the results for the reserves are omitted to save space.

[16] Due to the availability of Greenbook data, the period before 1983 is too short for a consistent estimation of the coefficients in the policy reaction function.

Table 3: Long-run Coefficients in the Monetary Policy Reaction Function across Forecast Horizons

	Panel A: 1974Q3 - 2007Q2			Panel B: 1983Q1 - 2007Q2		
	y_t^t, π_t^t	y_t^t, π_t^{t+2}	y_t^t, π_t^{t+4}	y_t^t, π_t^t	y_t^t, π_t^{t+2}	y_t^t, π_t^{t+4}
$\psi^{long}_{\Delta y^{GB}}$	2.50	2.89	-2.36	1.40	0.97	1.04
	[1.37 5.56]	[0.40 8.66]	[-13.75 12.75]	[0.83 2.49]	[0.65 1.45]	[0.54 1.87]
$\psi^{long}_{\pi^{GB}}$	2.87	2.99	1.22	2.31	2.28	2.19
	[2.07 4.95]	[1.19 6.39]	[-3.18 6.01]	[1.69 3.06]	[1.93 2.73]	[1.88 2.54]
$\psi^{long}_{\pi^c}$	0.28	0.29	-0.11	0.05	-0.01	-0.00
	[0.11 0.70]	[-0.10 0.96]	[-1.30 1.31]	[-0.01 0.18]	[-0.05 0.04]	[-0.04 0.05]
ψ^{cum}_i	0.94	0.97	1.00	0.93	0.90	0.90
	[0.91 0.98]	[0.94 1.00]	[0.96 1.04]	[0.90 0.97]	[0.87 0.93]	[0.86 0.94]

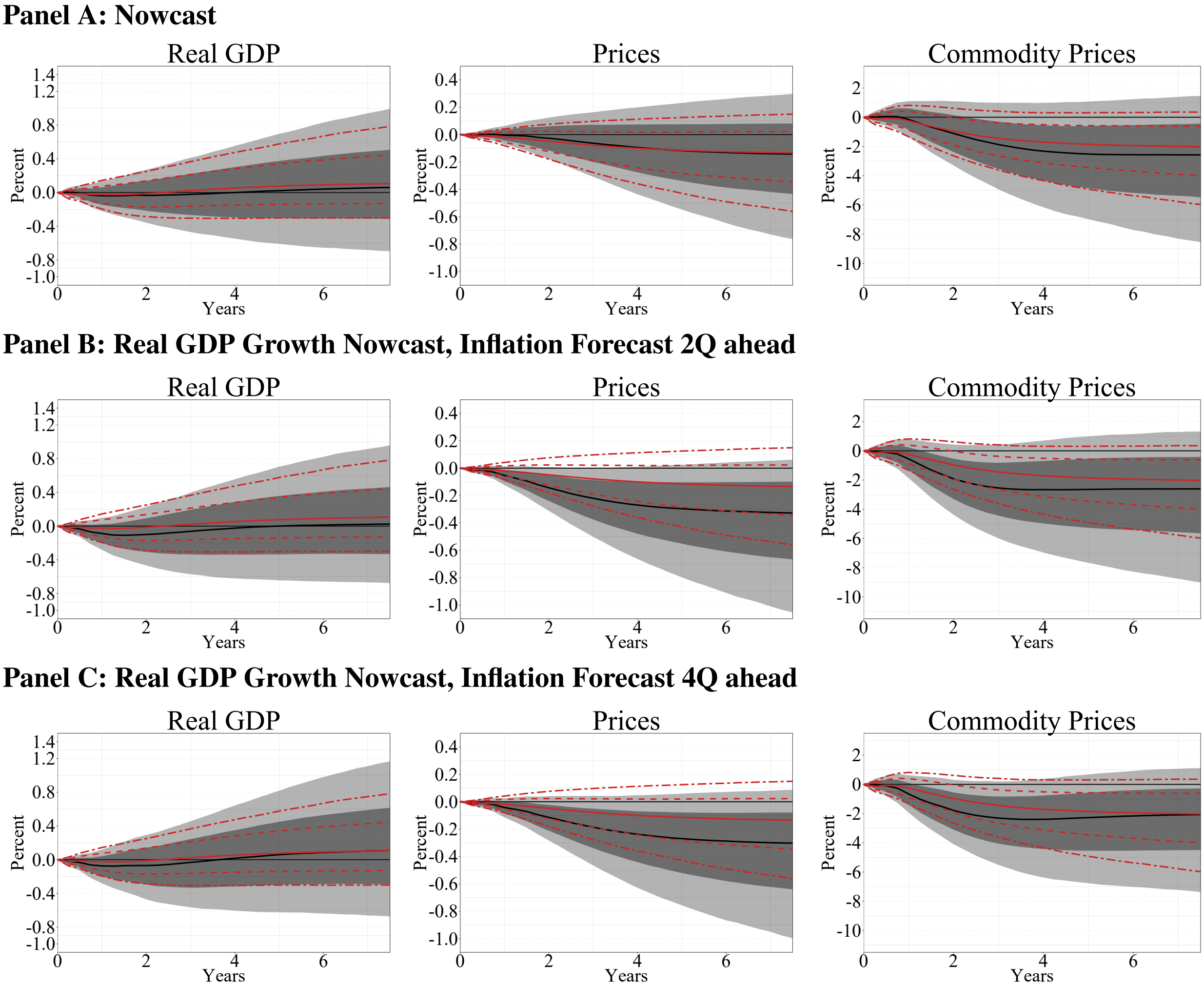
Note: This table reports the posterior median estimates of the long-run coefficients in the monetary policy reaction function using different Greenbook forecast horizons. The 68% credible sets are reported in brackets.

Compared to the full sample, the results tabulated in Panel B of Table 3 reveal two interesting patterns. First, in line with the single-equation policy rule estimates of Orphanides (2004), the response of the Fed to output is sizably lower. While the posterior median estimate of the long-run inflation elasticity is above two for all forecast horizons, the median output growth elasticity shrinks in half. Similarly, the response to commodity price movements is lowered and the 0 is well contained in the 68 percent credible set for all specifications. Arias et al. (2019) report a similar finding using a final revised data VAR. Compared to the pure nowcast specification, the forward looking models have a somewhat lower posterior median estimate for the policy inertia.

The impulse response functions for the post 1983 sample period in Figure 7 reemphazise the common finding that identification strategies based on a zero contemporaneous response of output to monetary policy shocks are not robust to reducing the estimation period to the Great Moderation. As documented by Barakchian and Crowe (2013) and Ramey (2016), standard identification strategies imply an increase in output following a contractionary policy shock rather than a fall when the estimation starts in the 1980s. Overall, we find a similar effect for the response of output in our real-time information setup. When using the Greenbook nowcast of the inflation rate in the monetary policy reaction function (Panel A), the response of real GDP is highly imprecisely estimated and the posterior median is close to zero. However, when supposing that the Fed acts forward looking and uses forecasts of inflation two or four quarters ahead, the posterior median is negative for an extended time and, at least for the first year after the shock, the respective 68 percent credible sets barely contain the zero. With respect to the response of GDP deflator, the results obtained for the full sample appear to be robust to the shortened sample period.

In summary, the estimates presented in this section point towards a stronger countercyclical impact of monetary policy shocks when conditioning on real-time available information. Using different specifications of the Fed's information set and reducing the sample period to the post Volcker period, we could reconstruct many of the empirical findings provided by the policy rule literature. Specifically, we find that using forecasts of inflation in the estimated monetary policy reaction function provides a better fit, i.e. in terms of the estimated impulse response functions and the policy reaction function. Further, a detailed investigation of the reaction function reveals that an accurate description of the historical policy requires a sample split at the end of the Volcker chairmanship.

Figure 7: Impulse Responses to a Monetary Policy Shock using different Greenbook Projections: Great Moderation

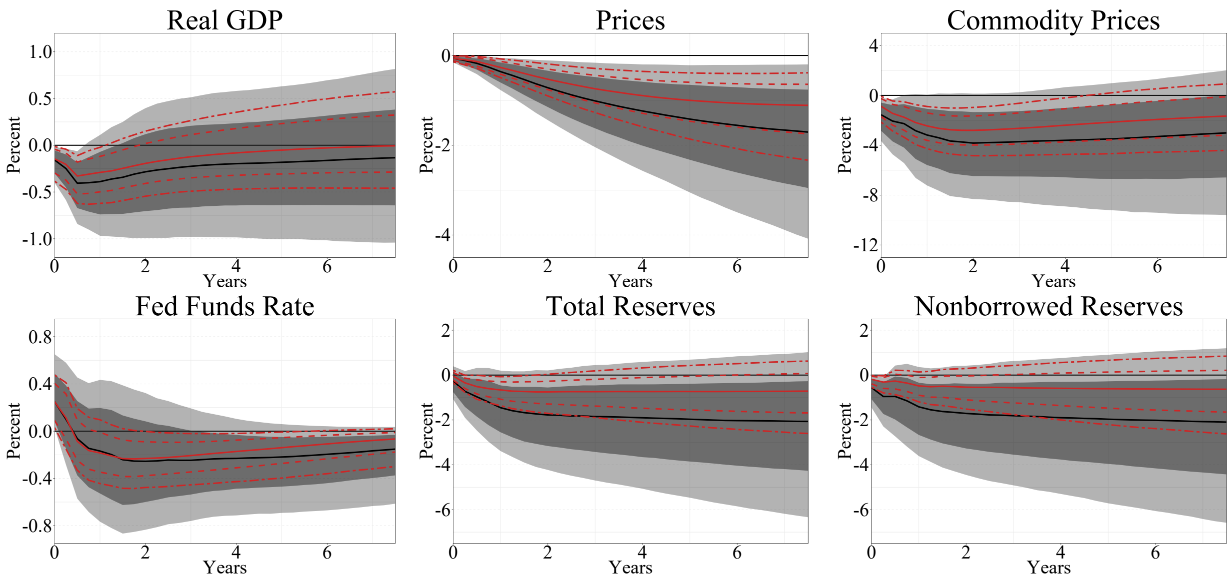


Notes: This figure shows responses to a 25 Bp contractionary monetary policy shock as identified with a nonrecursive identification scheme. The red solid line and dashed lines depicts the median impulse response function and the 68% and 90% pointwise credible sets, respectively, of the VAR specification with final data only. The solid black line and the gray shaded bands depict the distribution of impulse responses for the model with Greenbook projections in the central bank information set. Sample period: 1983Q1-2007Q2.

5 Sign-Identified Monetary Policy Shocks

In this section, we discuss the robustness of our results if we use an alternative identification strategy. Specifically, we identify the dynamic effects of monetary policy shocks based on the mixture of sign and zero restrictions presented in Section 3.3. As demonstrated by Ramey (2016) and Barakchian and Crowe (2013), standard identification strategies that rely on a zero restriction for the contemporaneous impact of monetary policy on output lead to counterintuitive results especially for the Great Moderation period. While different sign restriction schemes have proven to provide meaningful results also in the post 1983 period, we test the robustness of the results obtained above by imposing a set of restrictions that are consistent with standard DSGE models. In Appendix F, we test the robustness of our results using different identification

Figure 8: Impulse Responses to a Sign Identified Monetary Policy Shock



Notes: This figure shows responses to a 25 Bp contractionary monetary policy shock as identified with sign restrictions. The red solid line and dashed lines depicts the median impulse response function and the 68% and 90% pointwise credible sets, respectively, of the VAR specification with final data only. The solid black line and the gray shaded bands depict the distribution of impulse responses for the model with Greenbook projections in the central bank information set. Sample period: 1967Q3-2007Q2.

strategies that are agnostic with respect to the output response. Doing so, we identify necessary restrictions to pin down monetary policy shocks in a real-time information setting.

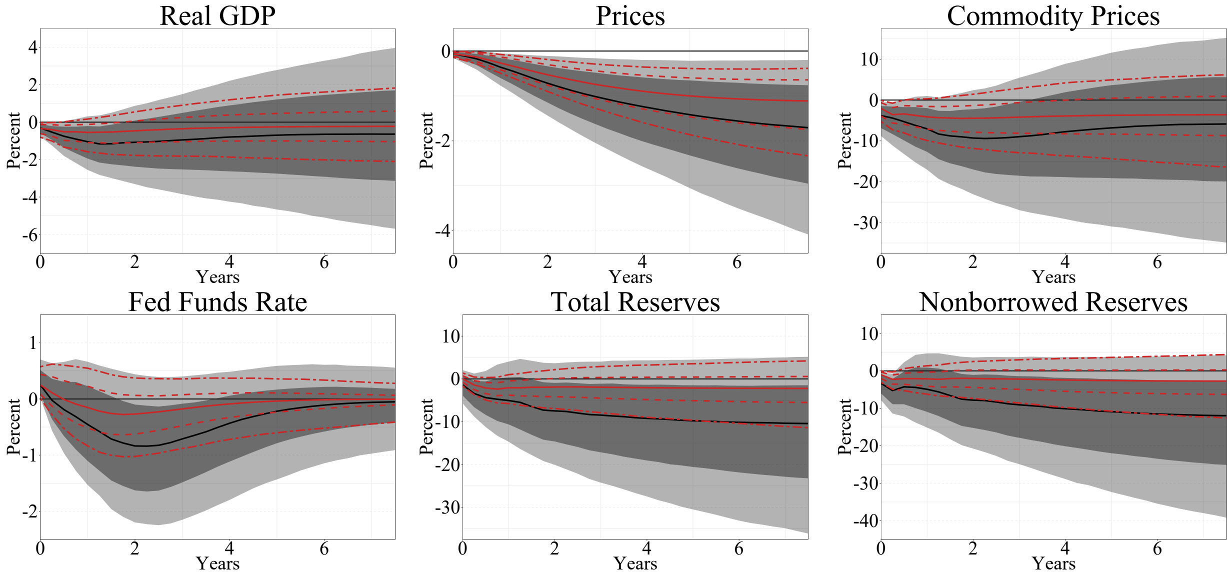
We identify a monetary policy shock by imposing that a contractionary monetary policy shock increases the federal funds rate and lowers output, prices, and nonborrowed reserves. Following Canova and Gambetti (2009), we impose these restrictions for the first period. We implement the sign restrictions by discipline the subrotation matrix Q^* and compute the matrix A_0 following Equation (23). Thus, we use exclusion restrictions in the monetary policy reaction function with respect to final revised output growth and inflation.

Using set identification allows us to identify monetary policy shocks without restricting the Greenbook revision process. While we had to impose ad hoc restrictions with respect to the contemporaneous impact of revisions among different lags when using the nonrecursive identification approach, we can proceed without any contemporaneous restrictions on the Greenbook revision process in this section. This is in line with the findings of Jacobs and van Norden (2011) and Kishor and Koenig (2012) who documented that measurement errors in official data releases follow more complex dynamics than what pure news and noise models would imply.

Figure 8 shows the median posterior impulse response functions and the 68 percent and 90 percent credible bands of the endogenous variables to a contractionary 25 basis points (median) monetary policy shock.

The robust identification strategy yields results for the full sample quite in line with the findings obtained with the non-recursive identification strategy reported in Figure 1. A contractionary policy shock leads output to decrease with the one standard deviation credible set not containing the zero for about two years. Though, the output response is more short-lived than in the baseline model. Prices fall persistently with no probability mass implying counterintuitive price movements. The reserve measures show a sustained fall with no evidence for a liquidity puzzle for the one standard deviation credible set. In line with our baseline

Figure 9: Impulse Responses to a Sign Identified Monetary Policy Shock: Great Moderation



Notes: This figure shows responses to a 25 Bp contractionary monetary policy shock as identified with sign restrictions. The red solid line and dashed lines depicts the median impulse response function and the 68% and 90% pointwise credible sets, respectively, of the VAR specification with final data only. The solid black line and the gray shaded bands depict the distribution of impulse responses for the model with Greenbook projections in the central bank information set. Sample period: 1983Q1-2007Q2.

result, the real-time information specification has more probability mass for a more pronounced monetary policy impact on output and prices, in particular, compared to the final data model. However, the estimates are less precise due to the higher identification uncertainty when using sign restrictions.

Figure 9 plots the impulse response functions for a 25 Bp contractionary monetary policy shock during the Great Moderation period 1983-2007. Based on the insights obtained above, we use the four quarters ahead Greenbook projection for inflation to estimate the real-time consistent monetary policy reaction function. Compared to the full sample, the results are qualitatively similar, but quantitatively much larger. In contrast to Figure 8, the impact response of the federal funds rate is more dispersed and dies out less quickly. There is a considerable posterior probability mass on structural models that rather implies almost no change in the federal funds rate in the first year after the shock in the final revised data and the real-time data specification. In Appendix E, we show the impulse response functions of the robust identification scheme for the Great Moderation period where we additionally impose the restriction that the federal funds rate is positive but decreasing in the first year after the shock. The obtained impulse response functions are considerably dampened but qualitatively similar.

6 Conclusion

In this paper, we investigate the effects of monetary policy when controlling for the real-time available information of the policy maker using nonrecursive and set-identified SVARs. Carefully modeling the information set and the revisions to previous projections of the economic state allows us to decompose movements of the policy rate into a systematic component and a monetary policy shock in real time. Further, we test the effect of conditioning the monetary policy reaction function on economic projections for different horizons. We find that monetary policy shocks that are orthogonal to these economic projections have a stronger effect on output and prices compared to what conventional final revised data SVARs suggest. Further, investigating the estimated monetary policy reaction function, we provide evidence for a shift in the responsiveness of the Fed to output measures during the Volcker chairmanship and for a forward-looking monetary policy conduct with respect to expected inflation during the Great Moderation period. In contrast to the seminal work of Croushore and Evans (2006), our findings indicate that accounting for the real-time nature of monetary policy conduct does make a quantitative difference.

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Appendices

A A Measurement Error Perspective: News versus Noise

In this appendix, we briefly present how and why not accounting for the revisions to real-time available macroeconomic variables may distort ex post structural analyses. Fundamentally, the process of data revisions either reduces the noise with respect to an earlier estimate or it adds news to an otherwise optimal forecast given the information available in real time (Croushore, 2011). In this paper, we use Greenbook projections as a proxy for the real-time information set of the Fed. Supposing that the Greenbook projections represent optimal forecasts of the economic state based on real-time data, data revisions by the statistical agency to the input data directly translate into revisions of the back-, now-, and forecasts.

Denote the final value of a variable as x_t^T, the data vintage released at time t, as x_t^t, and the measurement error in vintage t of x_t as η_t^t, respectively.

1. If η_t^t is news:

$$x_t^T = x_t^t + \eta_t^t \qquad x_t^t \perp \eta_t^t \tag{27}$$

   In this case, future revisions $h_t^{t+\tau}$ are not predictable by current information.

2. If η_t^t is noise:

$$x_t^T - \eta_t^t = x_t^t \qquad x_T^t \perp \eta_t^t \tag{28}$$

   As $cov(x_t^t, h_t^{t+\tau}) \neq 0$, future revisions in x_t^t are potentially predictable by information available in t.

With respect to central bank reaction functions, one can show that measurement errors may lead to a critical bias between the estimates using final revised and real-time data depending on the nature of η_t^t. To simplify, suppose that the central bank sets the policy variable s_t as a function of current and lagged values of the vector x_t as known in real time.

$$s_t = a_1 s_{t-1} + a_2 x_t^t + a_3 x_{t-1}^t + \varepsilon_t^{mp}. \tag{29}$$

Estimating Equation 29 using final data yields:

$$\begin{aligned} s_t &= \hat{a}_1 s_{t-1} + \hat{a}_2 x_t^T + \hat{a}_3 x_{t-1}^T + \hat{e}_t, \\ &= \hat{a}_1 s_{t-1} + \hat{a}_2 (x_t^t + \eta_t^t) + \hat{a}_3 (x_{t-1}^t + \eta_{t-1}^t) + \hat{e}_t. \end{aligned} \tag{30}$$

This implies two things. First, only if η_t^t is pure news, $cov(x_t^t, \eta_t^t) = 0$, estimating Equation (30) by OLS recovers the true weights in the central bank reaction function. This is also affecting other statistics of interest like impulse response functions. Second, the estimated monetary policy shock, $\hat{e}_t$, and the true monetary policy shock, ε_t^{mp}, differ by the measurement error, $\hat{e}_t = \varepsilon_t^{mp} - \hat{a}_2(\eta_t^t) - \hat{a}_3(\eta_{t-1}^t)$. As estimated monetary policy shocks are orthogonal to the measurement error, the estimation bias affects the decomposition into systematic and unsystematic policy movements. In case of pure news, $cov(x_t^T, \eta_t^t) \neq 0$ implies that future revisions in x_t^t are attributed to the systematic component of monetary policy despite having been unpredictable by the central bank in real time. In contrast, if η_t^t is pure noise, $cov(x_t^t, h_t^{t+\tau}) \neq 0$, the estimated

Table 4: Revision Means

	h_{t-1}^{t}		h_{t-2}^{t}		h_{t-3}^{t}	
Panel A: Real GDP Growth						
1967Q3-2007Q2:	0.11	(0.46)	0.19	(0.00)	−0.01	(0.75)
1983Q1-2007Q2:	0.26	(0.06)	0.12	(0.07)	0.05	(0.17)
Panel B: GDP Deflator Inflation						
1967Q3-2007Q2:	−0.06	(0.53)	0.11	(0.03)	−0.03	(0.34)
1983Q1-2007Q2:	−0.08	(0.40)	0.05	(0.27)	0.00	(0.77)

Note: This table shows the sample mean. p-values in parentheses. Newey–West heteroskedasticity- and autocorrelation-consistent standard errors are used to compute the test of significance for the means. Sample period: 1967Q3-2007Q2.

monetary policy shocks are orthogonal to future revisions that actually could have been foreseen by the policymaker in real time.

As a first step, we estimate the unconditional mean of revisions to Greenbook nowcasts. If the initial projections are an unbiased estimate of the final value, revisions should be mean zero. Aruoba (2008) shows that this is not the case for initial announcements of official US macroeconomic variables. Our results presented in Table 4 provide evidence that the real-time revisions to Greenbook revisions are characterized by non-zero mean, especially for real GDP growth. This implies that the initial Greenbook nowcasts are at least partially biased estimates of the subsequently revised projections. Further, the unconditional means appear to have shifted around the early 1980s.

Next, we test whether the real-time revisions in the Greenbook projections reflect pure news or pure noise. While there is a large strand of literature analyzing final revisions in official data announcements, i.e. the difference between first and final data vintages, we examine the first three revisions in the Fed staff projections (see, for example, Aruoba, 2008). We do so to check whether these revisions add new information to the information set of the policy maker. Based on the insights gained above, this would make it necessary to take them into account for policy analysis.

Following Mankiew and Shapiro (1986), we regress the last available vintage of a macroeconomic variable on the Greenbook nowcast and vice versa to test the pure noise and pure news hypothesis, respectively. The joint hypothesis in both specifications is that the intercept and the slope parameter are zero Table 5 presents the F-statistics of the Wald tests for the Greenbook real GDP growth and GDP deflator inflation nowcasts.

The general conclusion of Table 5 is that we can reject both hypotheses, i.e. that revisions to Greenbook projections are pure news and pure noise, for Greenbook nowcasts. As discussed in Aruoba (2008), these hypotheses are mutually exclusive but not collectively exhaustive. Based on the discussion above, we also look at the correlation between revisions and final vintages and real-time announcements. A significant correlation between revisions and final data implies that the initial projection is an efficient forecast and subsequent revisions represent news. In contrast, correlation between revisions and the first projection indicate that the initial announcement is a noisy estimate of the final value and revisions represent mostly a change in the measurement error. As shown in Table 6, the estimated correlation coefficients provide evidence for both a substantial amount of news and noise in Greenbook revisions. Assuming a forward-looking central bank and repeating the exercise for two quarters ahead Greenbook projections of real GDP

Table 5: Pure news versus pure noise hypothesis: Greenbook nowcasts

	1967Q3-2007Q2		1967Q3-1978Q4		1984Q1-2007Q2	
Panel A: Real GDP Growth						
news:	7.13	(0.00)	1.10	(0.34)	8.37	(0.00)
noise:	42.24	(0.00)	7.04	(0.00)	61.60	(0.00)
Panel B: GDP Deflator Inflation						
news:	8.04	(0.00)	4.42	(0.02)	28.23	(0.00)
noise:	1.28	(0.28)	5.34	(0.01)	2.64	(0.08)

Note: This table reports the F-statistics of the Wald tests for the joint hypothesis that the intercept is zero and the slope coefficient is one. p-values in parentheses. See text for details.

Table 6: Correlation between Revisions and Final and Real-Time Data: Greenbook nowcasts

	h_t^{t+1}		h_t^{t+2}		h_t^{t+3}	
Panel A: Real GDP Growth						
y_t^f	0.33	(0.00)	0.31	(0.00)	0.08	(0.29)
y_t^{GB}	-0.06	(0.43)	0.06	(0.42)	-0.06	(0.43)
Panel B: GDP Deflator Inflation						
y_t^f	0.11	(0.18)	0.25	(0.00)	-0.14	(0.08)
y_t^{GB}	-0.11	(0.16)	0.24	(0.00)	-0.16	(0.04)

Note: This table reports the estimated correlation coefficients between revisions and final and real-time data vintages, respectively. p-value of the correlations are given in parentheses. Sample period: 1967Q3-2007Q2.

growth and inflation does not qualitatively change the results.

B Model Estimation

The reduced-form VAR (19) is estimated by imposing the following restrictions on the lagged coefficient matrices B_ℓ:

$$B_\ell = \begin{bmatrix} B_\ell^{11} & B_\ell^{12} & B_\ell^{13} & B_\ell^{14} & B_\ell^{15} \\ 0 & B_\ell^{22} & 0 & 0 & 0 \\ B_\ell^{31} & B_\ell^{32} & B_\ell^{33} & B_\ell^{34} & B_\ell^{35} \\ B_\ell^{41} & B_\ell^{42} & B_\ell^{43} & B_\ell^{44} & B_\ell^{45} \\ B_\ell^{51} & B_\ell^{52} & B_\ell^{53} & B_\ell^{54} & B_\ell^{55} \end{bmatrix}, \tag{31}$$

where B_ℓ^{ij} denotes matrices according to the dimensions of the respective data vectors, n_{GB}, n_T, and n_t, respectively.

Combining the estimated matrices B_ℓ with an appropriate contemporaneous coefficient matrix, A_0, the lagged structural coefficient matrices, A_ℓ, ensure that final revised information about the economic state does not enter the monetary policy equation. Specifically, we have to impose the following restrictions for the contemporaneous coefficient matrix:

$$A_0 = \begin{bmatrix} A_0^{11} & A_0^{12} & A_0^{13} & A_0^{14} & A_0^{15} \\ 0 & A_0^{22} & 0 & 0 & 0 \\ A_0^{31} & A_0^{32} & A_0^{33} & A_0^{34} & A_0^{35} \\ A_0^{41} & A_0^{42} & A_0^{43} & A_0^{44} & A_0^{45} \\ A_0^{51} & A_0^{52} & A_0^{53} & A_0^{54} & A_0^{55} \end{bmatrix}. \tag{32}$$

This implies for the lagged coefficient matrices A_ℓ the following form:

$$A_\ell = \begin{bmatrix} A_\ell^{11} & A_\ell^{12} & A_\ell^{13} & A_\ell^{14} & A_\ell^{15} \\ 0 & A_\ell^{22} & 0 & 0 & 0 \\ A_\ell^{31} & A_\ell^{32} & A_\ell^{33} & A_\ell^{34} & A_\ell^{35} \\ A_\ell^{41} & A_\ell^{42} & A_\ell^{43} & A_\ell^{44} & A_\ell^{45} \\ A_\ell^{51} & A_\ell^{52} & A_\ell^{53} & A_\ell^{54} & A_\ell^{55} \end{bmatrix}. \tag{33}$$

Obviously, more identification assumptions about A_0 are necessary to solve for the monetary policy shock. For the non-recursive identification strategy, the contemporaneous coefficient matrix A_0 is as follows:

$$u_t' \begin{bmatrix} x & x & x & x & x & x & x & x & x & x & x & x & x & x \\ x & x & x & x & x & x & x & x & x & x & x & x & x & x \\ 0 & 0 & x & x & x & x & x & x & x & x & x & x & x & x \\ 0 & 0 & x & x & x & x & x & x & x & x & x & x & x & x \\ 0 & 0 & 0 & 0 & x & x & x & x & x & x & x & x & x & x \\ 0 & 0 & 0 & 0 & x & x & x & x & x & x & x & x & x & x \\ 0 & 0 & 0 & 0 & x & x & x & x & x & x & x & x & x & x \\ 0 & 0 & 0 & 0 & x & x & x & x & x & x & x & x & x & x \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & x & x & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & x & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & x & x & x & x \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & x & x & x & x \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & x & x \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & x \end{bmatrix} = \varepsilon_t',$$

where u_t' is

$$u_t' = \begin{bmatrix} u_{h_y^3} & u_{h_\pi^3} & u_{h_y^2} & u_{h_\pi^2} & u_{h_y^1} & u_{h_\pi^1} & u_{GB_y} & u_{GB_\pi} & u_{\Delta y} & u_\pi & u_{\pi^c} & u_i & u_{\Delta TR} & u_{\Delta NBR} \end{bmatrix}$$

and x denotes an unrestricted coefficient. The monetary policy equation is given by the 12-th column of A_0.

For the sign restriction scheme, the A_0 matrix is:

$$\begin{bmatrix} u_t^{GB} & u_t^{1,t} & u_t^i & u_t^{2,t} & u_t^T \end{bmatrix} \begin{bmatrix} - & x & x & x & x \\ x & x & x & x & x \\ + & x & x & x & x \\ 0 & 0 & 0 & x & x \\ 0 & 0 & 0 & 0 & x \end{bmatrix} = \begin{bmatrix} \varepsilon_t^{mp} & \varepsilon_{1,t} & \varepsilon_{2,t} & \varepsilon_{3,t} & \varepsilon_{4,t} \end{bmatrix}. \tag{34}$$

We estimate the VARs with Bayesian techniques. Due to the restrictions on the lagged coefficient matrices, we use an independent Normal-Wishart prior for the reduced-form VAR and estimate the model using a standard Gibbs-sampling algorithm.[17]

The independent Normal-Wishart prior with respect to β and Σ is $p(\beta,\Sigma) = p(\beta)p(\Sigma)$, where $\beta = \text{vec}\, B$ and

$$p(\Sigma \mid \underline{S}, \underline{\nu}) = IW(\underline{S}, \underline{\nu}) \propto |\Sigma|^{\frac{\underline{\nu}+n+1}{2}} \exp\left(-\frac{1}{2}\text{tr}(\underline{S}\Sigma^-1)\right)$$

$$p(\beta \mid \underline{\beta}, \underline{V}_\beta) = N(\underline{\beta}, \underline{V}_\beta) \propto \exp\left(-\frac{1}{2}(\beta - \underline{\beta})'\underline{V}_\beta^{-1}(\beta - \underline{\beta})\right).$$

We use a Minnesota-style prior to prevent overfitting caused by the many free parameters in our baseline specification. As all variables in the VAR are in growth rates, the prior mean $\underline{\beta}$ is a vector of zeros.[18] The prior covariance matrix $\underline{V}_\beta$ is diagonal and specifies the prior variance of the coefficients associated with

[17] In Appendix C, we show the robustness of our main results to use the dummy-observation priors following Sims and Zha (1998) in conjunction with the block-recursive algorithm of Zha (1999) and Waggoner and Zha (2003).

[18] Centering the prior for the own lags at the OLS estimates of an AR(1) process for the variables in y_t does not affect our results.

the i-th variable's own lag ℓ as $\lambda_1/\ell^{\lambda_4}$, with the lag of variable j, $j \neq i$ as $\lambda_2 s_i^2/(\ell^{\lambda_4} s_j^2)$, and of the intercept in equation i as $\lambda_3 s_i^2$. Following Litterman (1986), we set $\lambda_1 = \lambda_2 = 0.2$, $\lambda_3 = 100$, and $\lambda_4 = 1$. s_i^2 denotes the standard OLS estimate of the error variance for the autoregression of order p of variable i. Further, $\underline{\mathrm{S}}$ is a diagonal matrix with s_i^2 on the diagonal and $\underline{\nu} = n+3$. In a sensitivity exercise reported in Appendix C, we use a noninformative prior where $\underline{\nu} = \underline{\mathrm{S}} = \underline{\mathrm{V}}_\beta^{-1} = 0$.

The posterior is computed by using a standard Gibbs-sampling algorithm to draw the reduced-form estimates of β and Σ from their conditional posteriors:

$$
\begin{aligned}
p(\Sigma \mid y, \beta) &= IW(\bar{S}, \bar{\nu}) \\
p(\beta \mid y, \Sigma) &= N(\bar{\beta}, \bar{V}_\beta)
\end{aligned}
$$

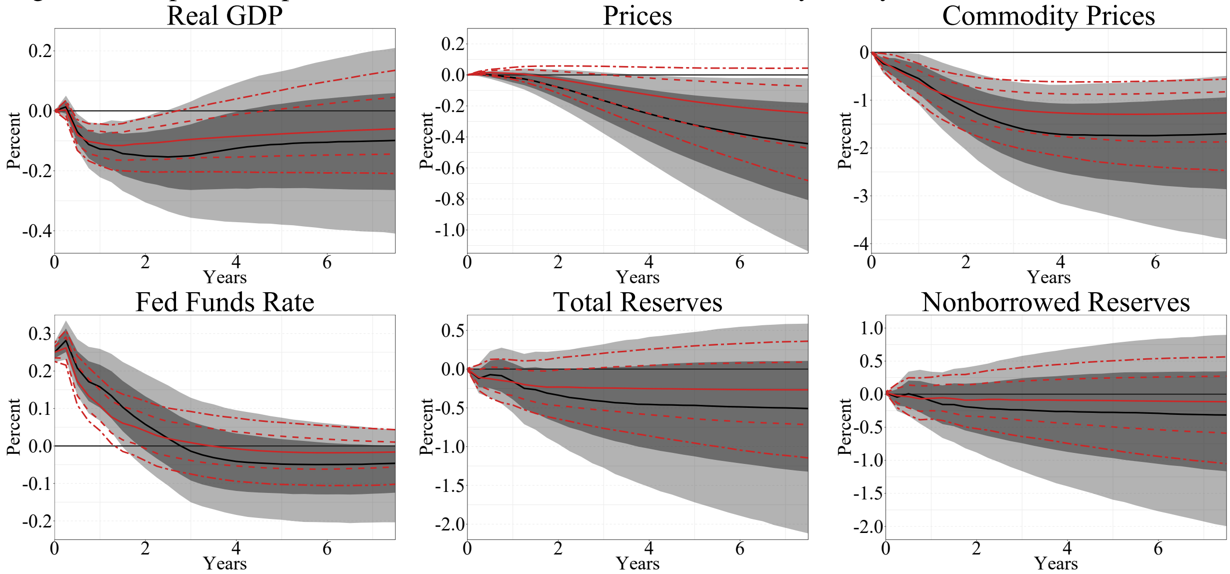
where

$$
\begin{aligned}
\bar{S} &= \underline{\mathrm{S}} + \sum_{t=1}^{T} (y_t - x_t\beta)(y_t - x_t\beta)', \\
\bar{\nu} &= T + \underline{\nu}, \\
\bar{V}_\beta &= \left(\underline{\mathrm{V}}_\beta^{-1} + \sum_{t=1}^{T} x_t' \Sigma^{-1} x_t \right)^{-1}, \\
\bar{\beta} &= \bar{V}_\beta \left(\underline{\mathrm{V}}_\beta^{-1} \underline{\beta} + \sum_{t=1}^{T} x_t' \Sigma^{-1} y_t \right).
\end{aligned}
$$

We report results based on 10.000 draws from the Gibbs sampler after discarding the first 90.000 draws. For every draw of the reduced-form coefficients, we check the stability of β, i.e. the roots are within the unit circle, and proceed only with draws that are stable. For every draw of β and Σ, we estimate A_0 according to the identification strategies described above.

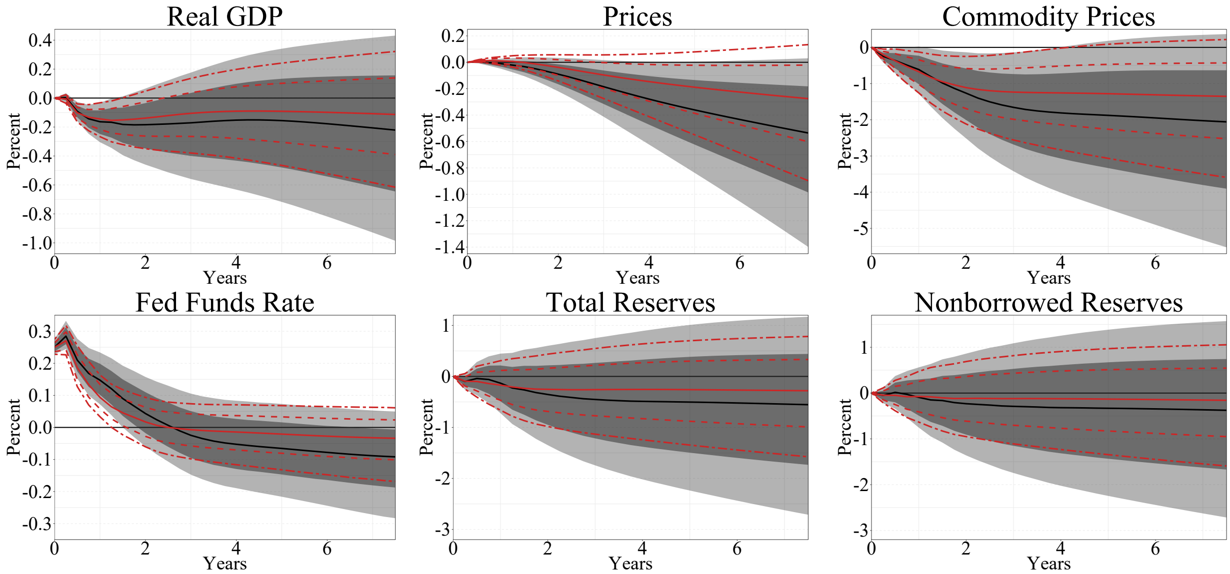
C Prior Sensitivity

Figure 10: Impulse Responses to a Nonrecursive Identified Monetary Policy Shock: Noninformativ Prior



Notes: This figure shows responses to a 25 Bp contractionary monetary policy shock as identified with a nonrecursive identification scheme. The red solid line and dashed lines depicts the median impulse response function and the 68% and 90% pointwise credible sets, respectively, of the VAR specification with final data only. The solid black line and the gray shaded bands depict the distribution of impulse responses for the model with Greenbook projections in the central bank information set. Sample period: 1967Q3-2007Q2.

Figure 11: Impulse Responses to a Nonrecursive Identified Monetary Policy Shock: Dummy Observation Prior

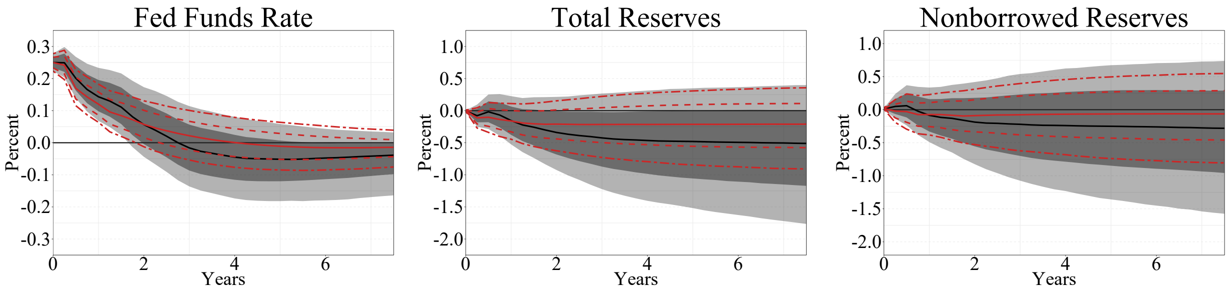


Notes: This figure shows responses to a 25 Bp contractionary monetary policy shock as identified with a nonrecursive identification scheme. The red solid line and dashed lines depicts the median impulse response function and the 68% and 90% pointwise credible sets, respectively, of the VAR specification with final data only. The solid black line and the gray shaded bands depict the distribution of impulse responses for the model with Greenbook projections in the central bank information set. Sample period: 1967Q3-2007Q2.

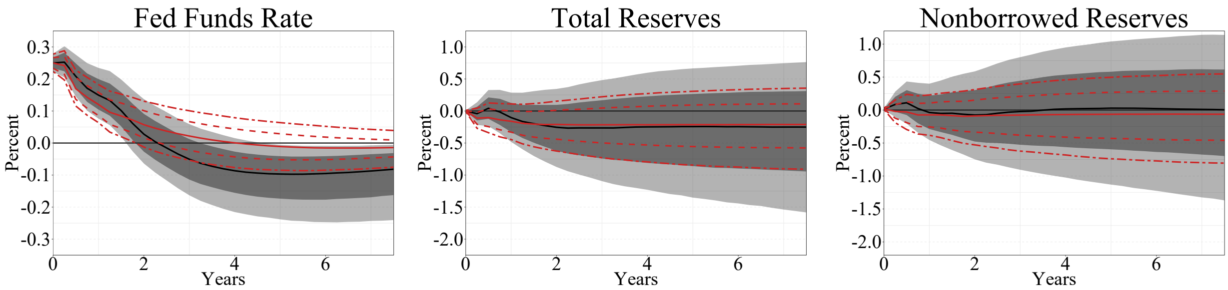
D Remaining Impulse Responses to a Monetary Policy Shock using different Greenbook Projections

Figure 12: Impulse Responses to a Monetary Policy Shock using different Greenbook Projections: 1974Q3-2007Q2

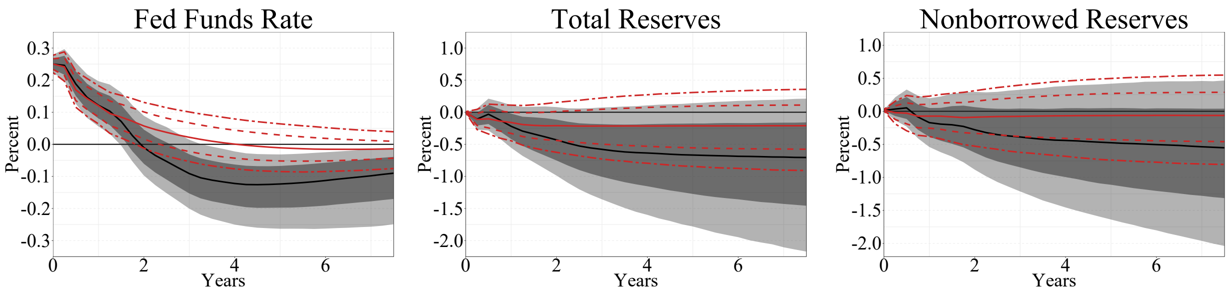
Panel A: Nowcast



Panel B: Real GDP Growth Nowcast, Inflation Forecast 2Q ahead



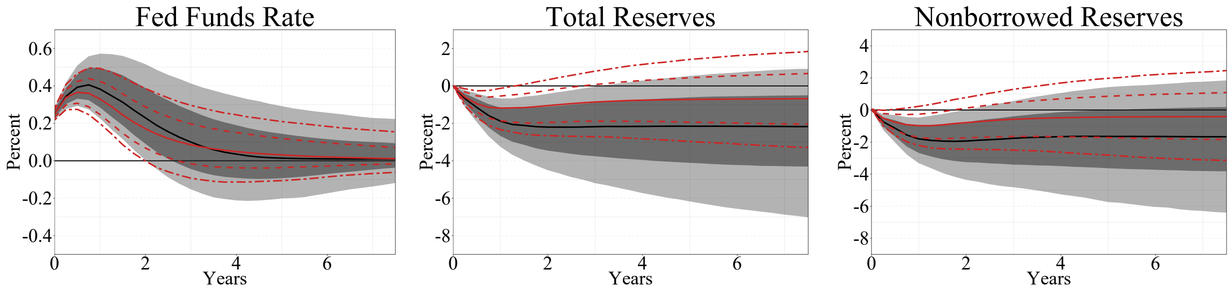
Panel C: Real GDP Growth Nowcast, Inflation Forecast 4Q ahead



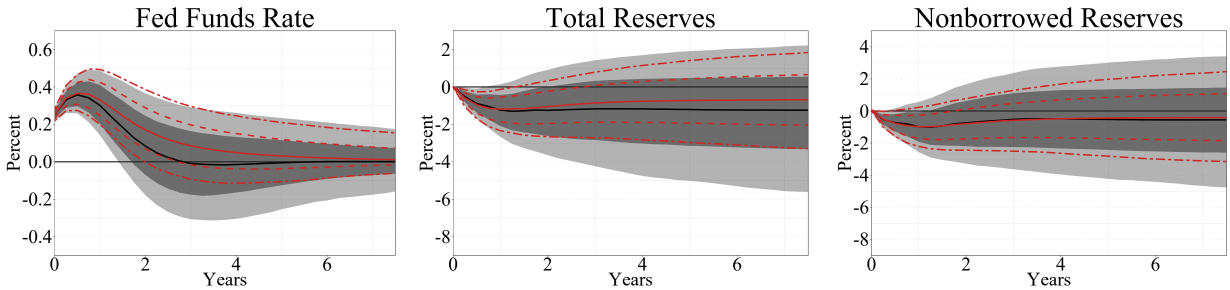
Notes: This figure shows responses to a 25 Bp contractionary monetary policy shock as identified with a nonrecursive identification scheme. The red solid line and dashed lines depicts the median impulse response function and the 68% and 90% pointwise credible sets, respectively, of the VAR specification with final data only. The solid black line and the gray shaded bands depict the distribution of impulse responses for the model with Greenbook projections in the central bank information set. Sample period: 1974Q3-2007Q2.

Figure 13: Impulse Responses to a Monetary Policy Shock using different Greenbook Projections: 1983Q1-2007Q2

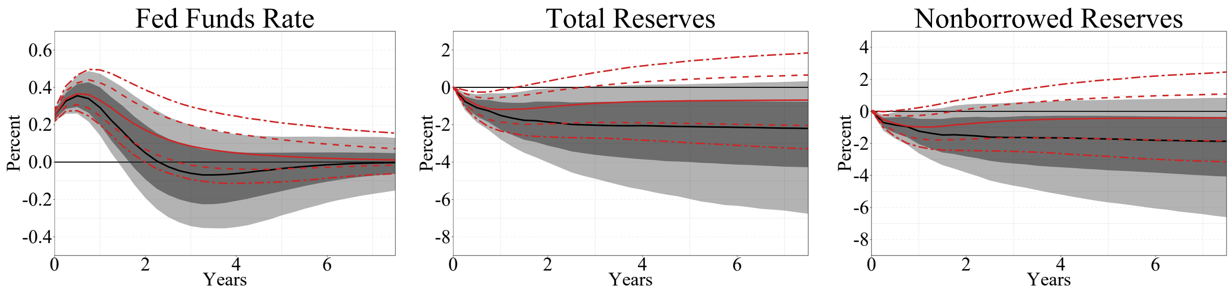
Panel A: Nowcast



Panel B: Real GDP Growth Nowcast, Inflation Forecast 2Q ahead



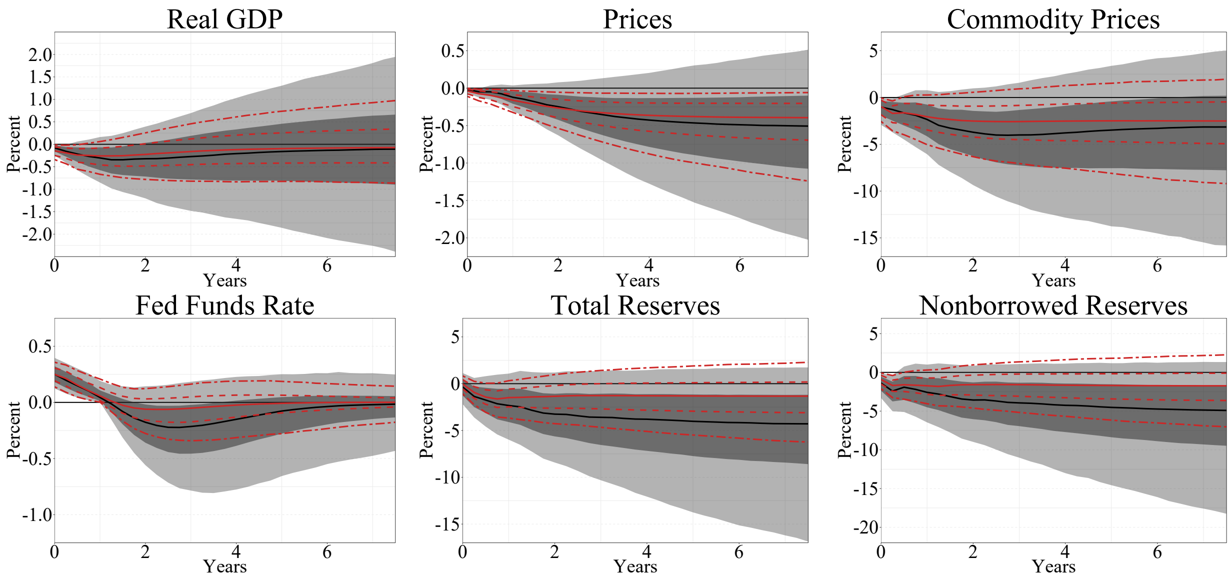
Panel C: Real GDP Growth Nowcast, Inflation Forecast 4Q ahead



Notes: This figure shows responses to a 25 Bp contractionary monetary policy shock as identified with a nonrecursive identification scheme. The red solid line and dashed lines depicts the median impulse response function and the 68% and 90% pointwise credible sets, respectively, of the VAR specification with final data only. The solid black line and the gray shaded bands depict the distribution of impulse responses for the model with Greenbook projections in the central bank information set. Sample period: 1983Q1-2007Q2.

E Impulse Responses to a Monetary Policy Shock using additional Restrictions to the Path of the Federal Funds Rate

Figure 14: Impulse Responses to a Monetary Policy Shock using additional Restrictions to the Path of the Federal Funds Rate



Notes: Figure shows responses to a 25 Bp contractionary monetary policy shock as identified with sign restrictions. The red solid line and dashed lines depicts the median impulse response function and the 68% and 95% pointwise credible sets, respectively, of the VAR specification with final data only. The solid black line and the gray shaded bands depict the distribution of impulse responses for the model with Greenbook projections in the central bank information set. Sample period: 1983Q1-2007Q2.

F Agnostic Identification of Monetary Policy Shocks

In this appendix, we test the robustness of our results using different sign identification schemes. Following the critique of Uhlig (2005), we do not impose any restrictions on the output response. To implement this, we impose the sign restriction patterns proposed by Uhlig (2005) and Arias et al. (2019).

To be agnostic about the output response due to a monetary policy shock, Uhlig (2005) suggests to impose restrictions only on GDP deflator, commodity prices, and nonborrowed reserves. Thus, we impose that a contractionary monetary policy shock leads to a decrease in these variables in the first two quarters after the shock.[19]

Recently, Arias et al. (2019) proposed to restrict the response of the policy rate to key macroeconomic variables instead of restricting the response of those variables to an innovation in the policy rate. This identification scheme involves only a minimum of restrictions that are also fully backed by conventional economic theory. Monetary policy is assumed to systematically counteract innovations in output and prices. We adjust the identification scheme to the real-time information setting by imposing that the federal funds rate contemporaneously responds to an increase in output growth and inflation projected in the Greenbook data as well as positive revisions to the last quarter's output growth and inflation.[20]

For both identification schemes, we implement the sign restrictions on the subrotation matrix Q^* and compute the matrix A_0 following Equation (23). Importantly, in all identification schemes we use exclusion restrictions in the monetary policy reaction function with respect to final revised output growth and inflation. Based on the results we obtained in the Sections 4 and 5, we focus in this exercise on the Great Moderation period. We estimate the models for the sample period 1983Q1-2007Q2 using the nowcast of real GDP growth and the four quarters ahead forecast of inflation in the real-time consistent monetary policy reaction function.[21] Again, we contrast the results with a specification using final revised data and the same sign restriction scheme. In case of the Arias et al. (2019) strategy, we impose the sign restrictions directly to the response of the federal funds rate to the final values of output growth and inflation.

Figure 15 shows the median posterior impulse response functions and the 68 percent and 90 percent credible bands of real GDP, GDP deflator, and commodity prices to a contractionary 25 basis points monetary policy shock. The results obtained with the more agnostic sign restriction schemes of Uhlig (2005) and Arias et al. (2019) are less in line with conventional wisdom compared to the impulse response functions presented in Section 5. Similar to the original findings reported in Uhlig (2005), the posterior median output response is close to zero and very imprecisely estimated. Almost half of the draws imply rather an increase in real GDP than an decrease after a contractionary policy shock. Due to the implied dynamic restrictions, the negative response of prices is more prolonged than using the robust scheme presented in Section 5. In contrast, the identification strategy of Arias et al. (2019) gives rise to a contractionary output response but for a much shorter period after the shock than what is obtained in the benchmark model. The 68 percent credible set implies a negative response of real GDP only in the first year after shock. The responses of GDP deflator and the commodity price index do not show any evidence of a contractionary effect of monetary policy. With respect to the differences between specifications involving final revised data and real-time available information, the identification scheme of Uhlig (2005) reemphasizes the stronger countercyclical effect of monetary policy only for the price level while the scheme of Arias et al. (2019)

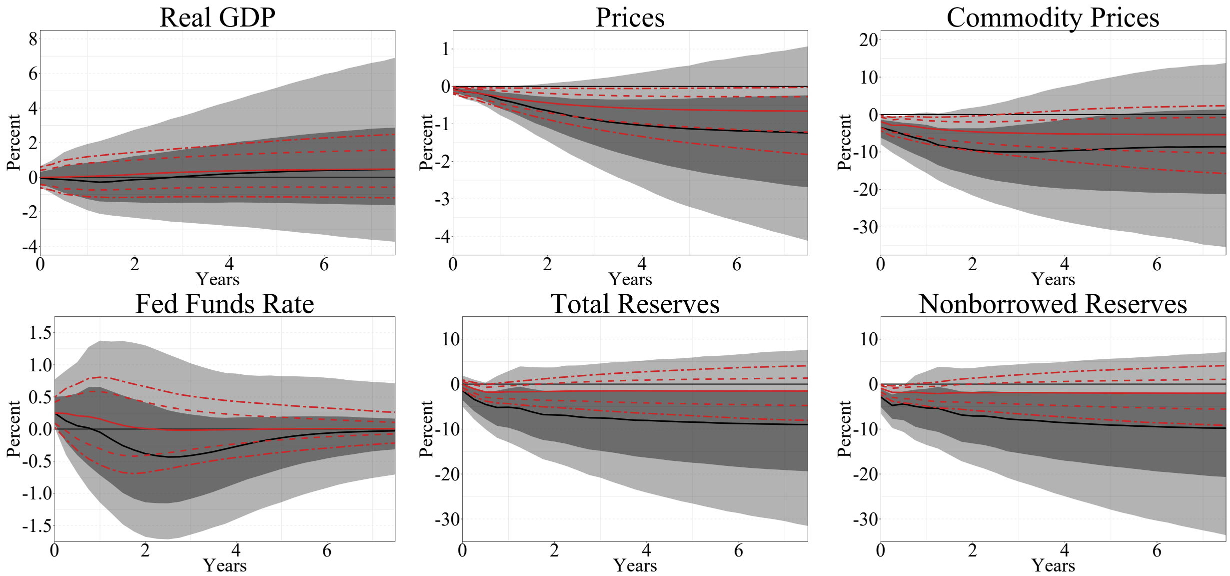
[19] Uhlig (2005) imposes the restriction for the first five months.

[20] We also tested imposing restrictions on revisions to two and three quarters ago projections, but the results are qualitatively not affected by these variations.

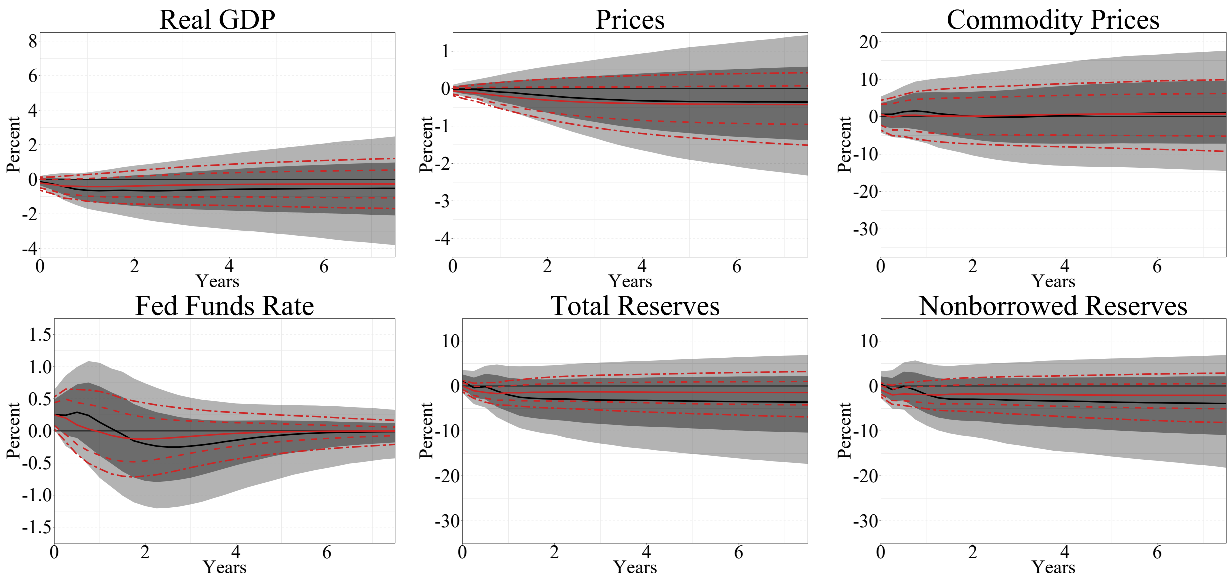
[21] Using the nowcast or the two quarters ahead inflation projection does not alter the qualitative results reported in this section.

Figure 15: Impulse Responses to a Monetary Policy Shock using different Sign Restriction Schemes

Panel A: Uhlig (2005)

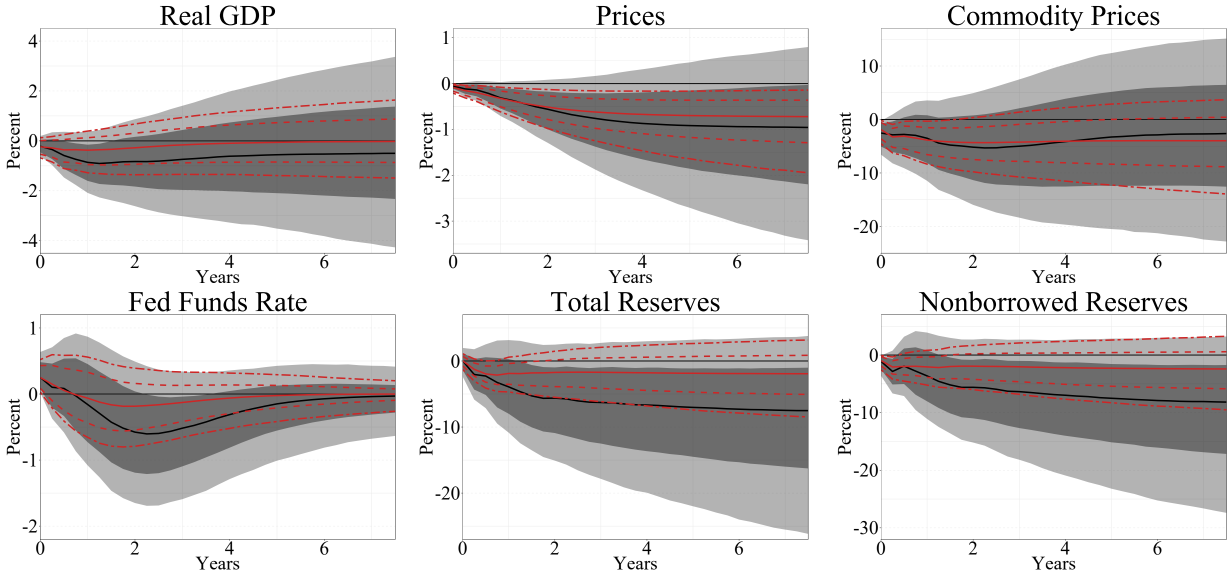


Panel B: Arias et al. (2019)



Notes: This figure shows responses to a 25 Bp contractionary monetary policy shock as identified with sign restrictions. The red solid line and dashed lines depicts the median impulse response function and the 68% and 90% pointwise credible sets, respectively, of the VAR specification with final data only. The solid black line and the gray shaded bands depict the distribution of impulse responses for the model with Greenbook projections in the central bank information set. Sample period: 1983Q1-2007Q2.

Figure 16: Impulse Responses to a Monetary Policy Shock using Adjusted Identification



Notes: This figure shows responses to a 25 Bp contractionary monetary policy shock as identified with sign restrictions. The red solid line and dashed lines depicts the median impulse response function and the 68% and 90% pointwise credible sets, respectively, of the VAR specification with final data only. The solid black line and the gray shaded bands depict the distribution of impulse responses for the model with Greenbook projections in the central bank information set. Sample period: 1983Q1-2007Q2.

shows the same only for the output response, but to a much smaller extend. Finally, the responses of all endogenous variables, except for the commodity price level and the reserve measures, are quantitatively much larger compared to our baseline specification based on a nonrecursive identification strategy. This effect seems to be driven by the amplified change in the monetary policy stance after a shock. In contrast to the outdying response of the federal funds rate displayed in Figure 1, there is a considerable posterior probability mass on structural models that rather implies an additional increase in the federal funds rate in the first year after the shock. In a not reported exercise, we additionally impose the restriction that the federal funds rate is positive but decreasing in the first year after the shock. The obtained impulse response functions are considerably dampened but qualitatively similar.

Based on the results obtained so far, we combine the on impact restrictions of Uhlig (2005) and Arias et al. (2019). On the one hand, we impose that the federal funds rate contemporaneously responds to an projected increase in output growth and inflation as well as positive revisions to last quarter's output growth and inflation. On the other hand, we also impose that monetary policy shocks have a negative effect on the final GDP deflator, commodity prices, and nonborrowed reserves on impact. The impulse response functions of all endogenous variables are displayed in Figure 16. The additional restrictions on the two price indexes and nonborrowed reserves shrink the set of structural model identified by the scheme of Arias et al. (2019). While we impose these restrictions only on the impact period, the responses of GDP deflator, commodity prices, and nonborrowed reserves are negative with high posterior probability several quarters after the shock. Compared to Figure 15, the additional restrictions affect the specifications with final revised data and real-time information differently with respect to the responses of real GDP, total reserves, and nonborrowed reserves. While the probability mass for a negative output response increases in case of the real-time consistent model, at least for the first two years after the shock, the final data model shows less evidence for a negative output response when imposing the additional impact restriction.

Further, the posterior median response dies out rather quickly. Similar observations can be made for the reserve measures. Apparently, the impact response restrictions shrink the set of impulse response functions only in case of the real-time data specification.

Summing up the results of this appendix, we show the robustness of our result to different sign restriction identification schemes that are agnostic about the output effect of a monetary policy shock. We find that not all of these schemes are directly applicable to a real-time information setup. Compared to conclusions drawn by Arias et al. (2019), we find that in a real-time setup, additional restrictions on the response on prices and nonborrowed reserves are necessary to discipline the set of structural models.