Exchange rate effects of US monetary policy – A multi-dimensional analysis using identification through heteroscedasticity*

Marc Burri† Daniel Kaufmann‡ §¶

November 19, 2024

Abstract

We identify the dynamic causal effects of monetary policy shocks on the exchange rate for the United States. We propose an IV-estimator, which allows us to combine identification through heteroscedasticity with recursive zero restrictions to disentangle an interest rate target, path (forward guidance), and term premium (asset purchases) shock. A target shock temporarily appreciates the USD. But the effect vanishes after about 10 working days. We find similar effects for a path shock. There is no evidence of a relevant term premium shock. Our findings suggest that monetary policy affects the exchange rate predominantly through changes in the interest rate target and forward guidance.

JEL classification: E41, E43, E44, E52, E58, C32

Keywords: Monetary policy shocks, exchange rate, forward guidance, large-scale asset purchases, identification through heteroscedasticity

*We thank Martin Huber, Leif Anders Thorsrud, Eric Swanson, Mark W. Watson, Linyan Zhu, as well as participants at the IRENE PhD Meeting in Neuchâtel, the SSES Annual Congress in Lucerne, and the Workshop on Applied Macroeconomics and Monetary Policy in St. Gallen, for helpful comments.

†University of Neuchâtel, Institute of Economic Research, Rue A.-L. Breguet 2, CH-2000 Neuchâtel, marc.burri@unine.ch

‡University of Neuchâtel, Institute of Economic Research, Rue A.-L. Breguet 2, CH-2000 Neuchâtel, daniel.kaufmann@unine.ch

§KOF Swiss Economic Institute

¶Corresponding author

1 Introduction

How do monetary policy decisions affect the exchange rate? To answer this question, economists resorted to theoretical and empirical approaches (Bjørnland, 2009; Dornbusch, 1976; Eichenbaum & Evans, 1995; Rogoff, 2002; Schmitt-Grohé & Uribe, 2022). However, there is no consensus about the size and persistence of the effects. Indeed, there is still a controversy about whether the exchange rate immediately overshoots, as in the theory by Dornbusch (1976). Theoretically, the response depends on rigidity in goods markets and the monetary policy regime (see, e.g., Benigno, 2004). Empirically, the response depends on the sample period (Kim et al., 2017) and the identification scheme (Bjørnland, 2009; Scholl & Uhlig, 2008). Some authors suggest that the exchange rate does not overshoot at all (Schmitt-Grohé & Uribe, 2022), or displays a delayed overshooting, for example, due to information rigidity (Müller et al., 2023). In addition, there is little evidence on whether different monetary policies, such as changes in the interest rate target, forward guidance, or large-scale asset purchases, affect the exchange rate differently.

This chapter aims to fill this gap. Our main contribution is twofold. First, we propose to combine a heteroscedasticity-based identification scheme with recursive zero restrictions and estimate the impulse responses with an instrumental variables (IV) approach. This allows us to identify multiple orthogonal monetary policy shocks exploiting the term structure of interest rates. Second, we apply our approach to investigate how various monetary policy shock dimensions in the United states affect the USD exchange rate at high (daily) and low (monthly) frequency.

Our identification strategy rests on two insights. First, we can identify a linear combination of a multi-dimensional monetary policy shock through heteroscedasticity, that is, using the difference in the variance of financial market variables during monetary policy event days and other days. Second, if we impose further restrictions, we can recover the underlying multiple dimensions of the monetary policy shock. Specifically, we impose recursive zero restrictions to identify a shock to the short-term interest rate (target shock), medium-term interest rate (path shock or forward guidance), and term spread (term premium shock or large-scale asset purchases). The zero restrictions impose that a path shock has no immediate impact on the short-term interest rate, while the term premium shock has no immediate impact on short- and medium-term interest rates. We show that dynamic causal effects can be estimated separately for every shock with a modification of the IV approach by Rigobon and Sack (2004). In addition, we can test for weak instruments and provide evidence on the existence of each shock by computing heteroscedasticity-robust F-statistics proposed by Lewis (2022b). Finally, we show how to estimate the monetary policy shock series from the term structure of interest rates, extending the procedure by Bu et al. (2021). This allows us to estimate the impulse responses of low-frequency macroeconomic variables and compare our shocks with existing high-frequency monetary policy surprises.

The main findings may be summarized as follows. The target, path, and term premium shocks we identify are correlated with the corresponding multi-dimensional high-frequency surprises for the United states by Swanson (2021). This suggests that our procedure is a valid alternative for countries and periods where high-frequency data is missing. In addition, we find evidence of a monetary policy target shock that affects financial markets via short-term interest rates. After a target tightening, the exchange rate immediately appreciates. Additionally, we find a path shock that affects financial markets through the 2Y interest rate. The path shock also leads to an (almost) immediate appreciation. Finally, we find evidence of a term premium shock affecting the 10Y - 2Y spread. Again, an increase in this spread appreciates the USD. For all three shocks, there is no evidence of a significantly delayed response. However, the estimation uncertainty at longer horizons is high. Therefore, we use the shocks to estimate monthly impulse responses in a structural vector-autoregression (SVAR) identified with external instruments. Although the exchange rate response is persistent, there is no evidence of a delayed overshooting puzzle.

Our first contribution relates to a large literature identifying causal effects of monetary policy using financial market data. The identification strategy is closely related to Canetg and Kaufmann (2022), who identify the effect of overnight rate and signaling shocks of central bank debt security auctions by the Swiss National Bank on the Swiss franc exchange rate. They assume the overnight rate shock immediately affects all financial market variables through a short-term interest rate. However, the signaling shock on impact affects only forward-looking variables, such as stock prices, but not the short-term interest rate. They estimate the impulse responses using a bootstrap algorithm, similar to Rigobon (2003). We show that impulse responses can be alternatively estimated with an IV approach, similar to Rigobon and Sack (2004).[1] Additionally, we show how to impose zero restrictions to disentangle multiple

[1] The advantage of IV is that it saves computational time, is readily implemented in many software packages, and there is a large literature on testing for weak instruments.

dimensions of the monetary policy shock.[2]

Following the seminal work by Kuttner (2001), most researchers use high-frequency identification schemes to identify multiple dimensions of monetary policy. The approach is based on the idea that, within a narrow window around monetary policy decisions, the only variation in financial market variables (mostly futures prices) stems from the policy decision. Gürkaynak et al. (2005) show that path surprises, associated with longer maturity interest rates, have a stronger effect on long-term interest rates than target surprises. Nakamura and Steinsson (2018) show that these high-frequency surprises comprise an 'information effect', that is, news the central bank communicates about the state of the economy. These information shocks may bias the results because they may lead to positive co-movement of interest rates and stock prices. In contrast, we would expect a negative co-movement in the case of a surprise tightening or loosening of monetary policy. Bauer and Swanson (2023b) argue that this information effect can be explained by the information available to the public before the monetary policy decision and, therefore, does not constitute inside information by the central bank. In addition, they highlight the relevance of speeches in addition to FOMC decisions. Because these monetary policy surprises are based on financial market instruments with varying maturities and because of recent non-conventional central bank policies, recent papers aim to disentangle various dimensions of monetary policy. Swanson (2021, 2024) and Altavilla et al. (2019) estimate multiple factors from a cross-section of high-frequency financial market data and rotate them so that they can be interpreted as a target, path, or large-scale asset purchase surprises.[3] Recently, Brennan et al. (2024) have shown that various measures of high-frequency surprises yield varying results.

Compared to the high-frequency literature, our approach has several advantages. High-frequency identification schemes remove background noise by computing changes in financial market variables in a very narrow window around a monetary policy announcement. This requires high-frequency data and exact knowledge of the intraday timing of the event. Our identification rests on comparing the variance-covariance of financial market variables on event and control days. The variance-covariance of financial market variables serves as a counterfactual of how markets respond in the

[2]Lewis (2022a) estimates multiple dimensions of unconventional monetary policy announcements using intraday heteroscedasticity. His approach allows for varying importance of various shocks across announcements. He also finds that forward guidance has relevant effects. However, he also finds evidence of relevant information and large-scale asset purchase shocks.

[3]Recently, Schlaak et al. (2023) show how to combine high-frequency identification schemes with heteroscedasticity. As they exploit more exogenous variation, they can test the exogeneity of the instruments. They find evidence against the validity of high-frequency monetary policy surprises.

absence of a monetary policy shock. Because our identification does not rest on the assumption that no other shocks occur during an event, we do not need to know the exact intraday timing of the event. In addition, we do not need high-frequency data and can use freely available daily data. Finally, the publication time of some events may be imprecise or completely unknown. The disadvantage is that the analysis may suffer from a weak instrument problem because daily data includes more background noise. However, standard tests exist to address this issue (Lewis, 2022b).

Our second contribution is related to a large literature estimating the effect of monetary policy on the exchange rate. Faust et al. (2003) use high-frequency surprises and estimate impulse responses with a VAR. They do not find evidence of a delayed overshooting of the exchange rate. Kearn and Manners (2006) estimate intraday dynamic responses for several countries. They find a statistically significant intraday effect of monetary policy on the exchange rate. Miranda-Agrippino and Rey (2022) use high-frequency monetary policy surprises in a VAR and estimate a persistent but not delayed response of the real exchange rate. Ciminelli et al. (2022) report similar findings to us, observing a peak in appreciation one week after the shock, then a gradual return to its initial level.

Delayed overshooting is mostly, but not always, found in VARs identified with zero or sign restrictions to estimate the causal effects of monetary policy on the exchange rate. Eichenbaum and Evans (1995) document a delayed overshooting puzzle using a VAR identified with zero restrictions. By contrast, Kim et al. (2017) suggest that this finding may be an artifact of including the volatile 1980s in the estimation sample. Bjørnland (2009) suggests that delayed overshooting disappears when long-term restrictions are used instead of short-term restrictions. Finally, Faust and Rogers (2003) and Scholl and Uhlig (2008) apply sign rather than zero restrictions and find little evidence in favor of delayed overshooting. However, similar to our results and Faust et al. (2003), the responses are imprecisely estimated. To the best of our knowledge, few papers examine the exchange rate response to different monetary policy shocks identified through heteroscedasticity. One notable exception is Wright (2012), who identifies monetary policy shocks at the effective lower bound through heteroscedasticity and provides the impact effect on bilateral exchange rates. However, he does not report dynamic causal effects, does not examine multiple dimensions of monetary policy, nor compares the resulting shocks to existing high-frequency surprises.

The remainder of the chapter is structured as follows. Section 2 presents the estimation and identification strategy. Section 3 presents the data and describes the baseline specification. Section 4 discusses the results before the last section concludes.

2 Estimation and identification

We identify dynamic causal effects of multiple dimensions of monetary policy in a heteroscedasticity-IV framework. We combine the IV-estimator suggested by Rigobon and Sack (2004) with recursive zero restrictions to identify orthogonal monetary policy shocks along the term structure of interest rates. In addition, we extend the approach by Bu et al. (2021) to estimate monetary policy shock series identified through heteroscedasticity via the term structure of interest rates to multi-dimensional shocks. Finally, we use these shocks as external instruments to identify a monthly SVAR.

2.1 Model and estimation

Suppose the data generating process reads:[4]

$$\begin{aligned} y_t &= \Psi\varepsilon_t + \Gamma v_t \quad \text{for } t \in P \\ y_t &= \Gamma v_t \quad \text{for } t \in C \end{aligned} \tag{1}$$

where y_t is a vector of N dependent variables, ε_t is a vector of E i.i.d. monetary policy shocks on policy event days (P), and v_t is a vector of N i.i.d. other shocks on policy event as well as control days (P and C). Furthermore, Γ and Ψ denote impact matrices of dimensions $N \times N$ and $N \times E$, respectively. Finally, we assume that Ψ is lower triangular.[5] We will justify this identifying assumption in more detail below.

Under these assumptions, we can sequentially estimate the causal impact of the E monetary policy shocks on y_t (Ψ) using a heteroscedasticity-IV estimator. The first equation of the model reads:

$$\begin{aligned} y_{1t} &= \Psi_{11}\varepsilon_{1t} + \Gamma_1 v_t \quad \text{for } t \in P \\ y_{1t} &= \Gamma_1 v_t \quad \text{for } t \in C \end{aligned} \tag{2}$$

where Ψ_{ij} denotes the ith row and jth column of Ψ and Γ_i denotes the ith row of Γ. Because Ψ is lower triangular, only the first monetary policy shock, ε_{1t}, affects y_{1t}.

As monetary policy shocks occur only on policy event days, the variance of y_{1t} differs

[4] We drop constant terms and lags of the dependent variable for ease of exposition.

[5] Canetg and Kaufmann (2022) used this assumption to identify distinct overnight and signaling effects of central bank debt security auctions.

between policy event and control days:

$$\begin{aligned} \mathbb{V}[y_{1t}] &= \quad \Psi_{11}^2\sigma_{1\varepsilon}^2 + \textstyle\sum_{n=1}^N \Gamma_{1n}^2\sigma_{nv}^2 \quad \text{for } t \in P \\ \mathbb{V}[y_{1t}] &= \qquad\quad \textstyle\sum_{n=1}^N \Gamma_{1n}^2\sigma_{nv}^2 \qquad\quad \text{for } t \in C \end{aligned} \tag{3}$$

where $\sigma_{e\varepsilon}^2$ and σ_{nv}^2 denote the variances of monetary policy shock e and other shock n, respectively.

Due to the recursive zero restrictions, the variance of y_{1t} changes only due to monetary policy shock 1. Thus, we can identify Ψ_{11} up to a scale from the difference in the variance on policy event and control days ($\Psi_{11}^2\sigma_{1\varepsilon}^2$). Intuitively, the variance of y_{1t} on control days serves as a counterfactual for the volatility of financial market variables in the absence of a monetary policy shock.

We can identify the impact on y_{2t} from changes in the covariance:

$$\begin{aligned} \mathbb{COV}[y_{1t}, y_{2t}] &= \quad \Psi_{11}\Psi_{21}\sigma_{1\varepsilon}^2 + \textstyle\sum_{n=1}^N \Gamma_{1n}\Gamma_{2n}\sigma_{nv}^2 \quad \text{for } t \in P \\ \mathbb{COV}[y_{1t}, y_{2t}] &= \qquad\quad \textstyle\sum_{n=1}^N \Gamma_{1n}\Gamma_{2n}\sigma_{nv}^2 \qquad\quad \text{for } t \in C \end{aligned} \tag{4}$$

where $\Psi_{11}\Psi_{21}\sigma_{1\varepsilon}^2$ corresponds to the difference in the covariances between policy event and control days. Having identified Ψ_{11}, this difference allows us to identify Ψ_{21}.

Because only the first shock affects the first variable, we can identify Ψ_{i1} for $i = 1, \ldots, N$ using a standard heteroscedasticity-based identification scheme (Rigobon, 2003). Therefore, we can estimate the impulse response using an IV-estimator (Lewis, 2022b; Rigobon & Sack, 2004). The instrument, the first, as well as the second stage read:

$$\begin{aligned} Z_{1t} &= \left[\mathbf{1}(t \in P)\frac{T}{T_P} - \mathbf{1}(t \in C)\frac{T}{T_C}\right] y_{1t} \\ y_{1t} &= \alpha_1 + \beta_1 Z_{1t} + u_{1t} \\ y_{it} &= \alpha_i + \tilde{\Psi}_{i1}\hat{y}_{1t} + e_{it} \end{aligned} \tag{5}$$

where $\mathbf{1}(t \in X)$ denotes an indicator function that equals one if the condition in parentheses is true and zero otherwise, and T, T_P, and T_C are the number of total, policy event and control days, respectively. In addition, Z_{1t} and $\hat{y}_{1t} = \hat{\beta}_1 Z_{1t}$ denote the instrument, as well as the first-stage prediction based on OLS estimates. Finally, α_i, β_i, and $\tilde{\Psi}_{ij}$ are regression parameters and u_{1t} and e_{it} are regression residuals.

Four comments are in order. First, the instrument is uncorrelated with v_t, and therefore

e_{it}, because ε_{1t} occurs only during policy event periods (see e.g. Lewis, 2022b, for a detailed discussion). Second, the instrument is also uncorrelated with other monetary policy shocks because the variance of y_{1t} changes on event days only due to ε_{1t} (recursive zero restriction). Third, as we construct the instrument with y_{1t}, we assume that the first shock changes the variance of this variable on event days. As we will see below, we can construct an F-statistic to verify this. Finally, we identify the impulse responses only up to a scale because the impact on y_{1t} is normalized to unity, that is, $\tilde{\Psi}_{i1} = \Psi_{i1}/\Psi_{11}$.

We can then identify the causal effect of monetary policy shock 2 using the second equation of the model:

$$\begin{aligned} y_{2t} &= \Psi_{21}\varepsilon_{1t} + \Psi_{22}\varepsilon_{2t} + \Gamma_2 v_t \quad &&\text{for } t \in P \\ y_{2t} &= \Gamma_2 v_t &&\text{for } t \in C. \end{aligned} \tag{6}$$

Because Ψ is lower triangular, the variance of y_{2t} changes on policy event days due to the first and second monetary policy shock. If we fail to control for shock 1, the instrument will be correlated with ε_{1t}, and the error term. Therefore, the exclusion restriction would be violated. Controlling for monetary policy shock 1 is straightforward by separately controlling for y_{1t} on event and control days. This is because, on control days, y_{1t} depends on ε_{1t} but not on ε_{2t}. We can construct an additional instrument using the second variable and then use both instruments to estimate Ψ_{21}. The instrument, the first, as well as the second stage, then read:

$$\begin{aligned} Z_{2t} &= \left[\mathbf{1}(t \in P)\frac{T}{T_P} - \mathbf{1}(t \in C)\frac{T}{T_C}\right] y_{2t} \\ y_{1t} &= \alpha_1 + \beta_{11} Z_{1t} + \beta_{12} Z_{2t} + u_{1t} \\ y_{2t} &= \alpha_2 + \beta_{21} Z_{1t} + \beta_{22} Z_{2t} + u_{2t} \\ y_{it} &= \alpha_i + \tilde{\Psi}_{i2}\hat{y}_{2t} + \tilde{\Psi}_{i1}\hat{y}_{1t} + e_{it}. \end{aligned} \tag{7}$$

On event days, y_{2t} and Z_{2t} are correlated with shocks ε_{1t} and ε_{2t}. However, by including $\hat{y}_{1t}$ as a control, the instrument will not be correlated with the error term. Again, we identify Ψ_{i2} only up to a scale because the initial response on y_{2t} is normalized to unity, that is, $\tilde{\Psi}_{i2} = \Psi_{i2}/\Psi_{22}$.

More generally, we can recursively identify the impact matrix of E-dimensional monetary policy shocks using the following instruments, first and second stages:

$$
\begin{aligned}
Z_{et} &= \left[\mathbf{1}(t \in P)\frac{T}{T_P} - \mathbf{1}(t \in C)\frac{T}{T_C}\right] y_{et}, \;\; e = 1, \ldots, E \\
y_{et} &= \alpha_e + \sum_{j=1}^{E} \beta_{ej} Z_{jt} + u_{et}, \;\; e = 1, \ldots, E \\
y_{it} &= \alpha_i + \sum_{j=1}^{E} \tilde{\Psi}_{ij} \hat{y}_{jt} + e_{it}, \;\; i = 1, \ldots, N.
\end{aligned}
\tag{8}
$$

We can extend this framework to include additional control variables and estimate cumulative daily impulse responses. Details are given in Appendix A.

2.2 Identifying assumptions

The main identifying assumption is that policy events occur on pre-determined days (see Canetg & Kaufmann, 2022). For example, suppose the Federal Reserve is more likely to make decisions during economic distress. In that case, the variance of other shocks is different between policy event days and control days. Focusing on FOMC decisions, as well as planned speeches, fulfills this requirement. We will distinguish between scheduled and unscheduled FOMC decisions in a robustness test.

Furthermore, we assume that other shocks occur randomly across policy and control days. This assumption is violated if the FOMC schedules its policy meeting as a function of major economic data releases. For example, if FOMC meetings are usually scheduled after the release of quarterly GDP figures, there is a 'news' shock that will not affect the economy on policy event days. In addition, it may be that other central banks schedule their meetings briefly after the Federal Reserve to take into account policy surprises in their own decisions. Therefore, the assumption that the variance of other shocks is constant between policy event days and control days is violated. We account for this issue by excluding various other events from the control days across multiple robustness checks.

Finally, we impose recursive zero restrictions. These restrictions are unnecessary to identify the overall monetary policy shock, that is, the weighted average of all orthogonal dimensions. But, they serve to disentangle various orthogonal dimensions if they exist.[6] In our application, we order interest rates along the term structure, ordering a short-term interest rate first. The recursive zero restrictions imply that the first shock potentially affects all variables and has to increase the variance of the short-term interest rate. Therefore, it resembles the target surprise by Altavilla et al. (2019), which is a factor estimated on a high-frequency data set that loads only on short-term interest rates. Because of the zero restriction, our second shock has no immediate impact on the short-term interest rate but affects the medium-term interest rate. Therefore, it resembles the path surprise Altavilla et al. (2019) identified as being orthogonal to the target surprise. Finally, our term premium shock does not immediately impact short- or medium-term interest rates. But it has to affect the term spread. This resembles the QE shock by Altavilla et al. (2019), which is identified using high-frequency surprises that are orthogonal to the target and path surprises.

2.3 Weak instruments and number of monetary policy shocks

To test for weak instruments, we follow Lewis (2022b) and compute a heteroscadasticity-robust F-statistic for every instrument ($e = 1, \dots, E$):

$$F_e = \frac{\hat{\beta}_e^2 \left(\sum_{t=1}^{T} Z_{et}^2 \right)^2}{\sum_{t=1}^{T} Z_{et}^2 \hat{u}_{et}^2} \tag{9}$$

where $\hat{\beta}_e$ and $\hat{u}_{et}$ are the OLS estimates of the first-stage coefficient and residuals, respectively. Intuitively, the F-statistic increases in the absolute size of the first-stage regression coefficient. The instrument is stronger if the instrument is more highly correlated with the outcome variable. The correlation will be higher the more the variance changes during policy event days. Then, the F-statistic falls with a higher covariance between the instrument and the first-stage residuals. Intuitively, the instrument is weaker if it is more highly correlated with unobserved factors ('background noise'). As Z_{et} is generally correlated with u_{et}, an increase in the variance of u_{et} leads to an increase in the covariance between Z_{et} and u_{et}. Intuitively, if more of the variation in Z_{et} stems from background noise rather than the changes in the variance between policy event days and control days, the instrument will be weaker.

[6] Swanson (2021) uses similar assumptions to identify three-dimensional monetary policy shocks. First, he imposes that changes in forward guidance and LSAP do not affect the current federal funds rate. Second, he imposes the restriction that the LSAP shock is as small as possible in the pre-ELB period. Therefore, our assumptions are weaker since we do not assume his second restriction.

Interestingly, the F-statistic also indicates whether there is a relevant additional monetary policy shock dimension in the first place. Recall that we construct an additional instrument for equation e with variable y_{et}. Therefore, we assume that shock e changes the variance of this variable, conditional on shocks $1, \ldots, e-1$. Suppose there are E monetary policy shocks, but we estimate the first-stage regression for a nonexistent shock $e = E + 1$.[7] Then, the variance of $y_{E+1,t}$ increases during policy events only due to the shocks $1, \ldots, E$, for which we control by including the other instruments in the first-stage $Z_{jt}, j = 1, \ldots, E$. That is, conditional on the other shocks, the variance of $y_{E+1,t}$ does not increase on policy event days. Therefore, the OLS estimate on instrument $Z_{t,E+1}$ is zero, and $F_{E+1} = 0$ asymptotically.[8] This suggests that a positive F-statistic is a sufficient condition for the existence of a monetary policy shock.

2.4 Estimation of the monetary policy shock series

We adapt the method developed by Bu et al. (2021) to estimate three-dimensional monetary policy shock series from the term structure of interest rates. Bu et al. (2021) propose a two-step regression in the spirit of Fama and MacBeth (1973) to estimate a one-dimensional unobserved monetary policy shock, ε_t. First, they estimate the impact of a monetary policy shock on interest rate changes of maturities from 1 to 30 years via heteroscedasticity. Second, for every period with an FOMC decision, they perform a cross-sectional regression of the interest rate changes on the impact matrix. The OLS coefficients of these regressions are then proportional to the underlying unobserved monetary policy shocks.

Their approach can be readily extended to multiple monetary policy shocks. Suppose there are three orthogonal dimensions of monetary policy:

$$\varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}. \tag{10}$$

We construct an interest rate data set with the following ordering:

[7] See also Appendix B.

[8] Note, however, that a low F-statistic can be the result of a lot of background noise relative to the variance of an existing structural shock or of a sign of the absence of an additional shock.

$$y_t = [i_t^{3m},\ i_t^{2y},\ i_t^{10y-2y},\ i_t^{20y}]' \tag{11}$$

where the first three variables are required to impose the recursive zero restrictions, we can add further interest rate data to estimate the shocks. For ease of exposition, we only add one additional interest rate.[9]

The model, therefore, reads:

$$y_t = \begin{bmatrix} \Psi_{11} & 0 & 0 \\ \Psi_{21} & \Psi_{22} & 0 \\ \Psi_{31} & \Psi_{32} & \Psi_{33} \\ \Psi_{41} & \Psi_{42} & \Psi_{43} \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix} + \Gamma v_t \quad \text{for } t \in P. \tag{12}$$

However, we can estimate each column of Ψ only up to scale, where we assume:

$$\Psi = \tilde{\Psi} \begin{bmatrix} a & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & c \end{bmatrix} \tag{13}$$

where a, b, and c are constants.

Bu et al. (2021) suggest regressing the vector of dependent variables on the impact matrix for every event day. In our multi-dimensional setting, we have one impact matrix for every shock and, therefore, a multi-variate regression: The OLS estimator of

[9] In our application, we use the three and six-month interest rates and the one to thirty-year Treasury yields from the Gürkaynak et al. (2007) dataset to estimate the shocks.

y_t on $\tilde{\Psi}$ on day t can be written as:

$$\begin{aligned}
\hat{\varepsilon}_t &= [\tilde{\Psi}'\tilde{\Psi}]^{-1}\tilde{\Psi}' y_t \\
&= [\tilde{\Psi}'\tilde{\Psi}]^{-1}\tilde{\Psi}'\Psi\varepsilon_t + [\tilde{\Psi}'\tilde{\Psi}]^{-1}\tilde{\Psi}'\Gamma v_t \\
&= [\tilde{\Psi}'\tilde{\Psi}]^{-1}\tilde{\Psi}'\Psi\varepsilon_t + [\tilde{\Psi}'\tilde{\Psi}]^{-1}\tilde{\Psi}'\Gamma v_t \\
&= [\tilde{\Psi}'\tilde{\Psi}]^{-1}\tilde{\Psi}'\tilde{\Psi} \begin{bmatrix} a & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & c \end{bmatrix} \varepsilon_t + [\tilde{\Psi}'\tilde{\Psi}]^{-1}\tilde{\Psi}'\Gamma v_t.
\end{aligned} \tag{14}$$

OLS is an unbiased estimator if the term $[\tilde{\Psi}'\tilde{\Psi}]^{-1}\tilde{\Psi}'\Gamma v_t$ is zero in expectation. We can show that this is formally the case if $\mathbb{E}[\Gamma v_t|\tilde{\Psi}] = 0$, that is, we need an orthogonality assumption between $\tilde{\Psi}$ and Γv_t (see Appendix C). This implies that the cross-sectional variation in the responses of the dependent variables to the monetary policy shocks is unrelated to the variation in the responses to other shocks. Under this assumption, we have:

$$\mathbb{E}\begin{bmatrix} \hat{\varepsilon}_{1t} \\ \hat{\varepsilon}_{2t} \\ \hat{\varepsilon}_{3t} \end{bmatrix} = \mathbb{E}\begin{bmatrix} a\varepsilon_{1t} \\ b\varepsilon_{2t} \\ c\varepsilon_{3t} \end{bmatrix} \propto \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}. \tag{15}$$

That is, we can recover the underlying shocks up to a scale. If this assumption is violated, the shocks will suffer from an unobserved variables bias because we fail to control for variation in Γv_t. This introduces time-varying 'background noise' via the other shocks v_t (see Appendix C).

2.5 The structural VAR model

Having an estimate for the three dimensions of monetary policy shocks, it is of interest to see how these shocks affect macroeconomic variables on a lower frequency. To calculate the responses at a monthly frequency, we use the estimated shocks in an SVAR identified with external instruments (also known as proxy VARs) (Mertens & Ravn, 2013; Stock & Watson, 2018).

In a first step, we estimate a reduced-form monthly VAR with $n = 7$ macroeconomic variables:

$$Y_t = \alpha + B(L)Y_{t-1} + u_t \tag{16}$$

where Y_t is a vector of endogenous variables, $B(L)$ denotes the lag operator, and u_t is a vector of reduced-form residuals with covariance matrix $\mathbb{V}[u_t] = \Omega$. As is common in the literature, we use a specification with 12 monthly lags (Bauer & Swanson, 2023b; Gertler & Karadi, 2015; Ramey, 2016). We assume the relationship between the reduced-form residuals, u_t, and the structural shocks, ε_t, is linear

$$u_t = S\varepsilon_t \tag{17}$$

where S is the $n \times n$ structural impact matrix. Following common practice, we assume that the economy is governed by a sequence of uncorrelated structural shocks, ε_t, with $\mathbb{V}(\varepsilon_t) = I$. Without loss of generality, we assume that the first shock is a target shock, ε_{1t}, the second shock is a path shock, ε_{2t}, and the third shock is a term premium shock, ε_{3t}. Therefore, columns 1 through 3 of S specify the impact effects of different dimensions of monetary policy on u_t and Y_t. It follows from the variances of u_t and ε_t that

$$SS' = \Omega. \tag{18}$$

The goal is to identify the first three columns of S. However, infinitely many potential matrices S satisfy the equation (18). To estimate S, we need additional information or assumptions.

2.6 VAR identification using external instruments

We use the external instruments approach to estimate the effects of different dimensions of monetary policy. We use the monetary policy shocks as our instruments z_t, which are converted to a monthly series by summing the shocks on event days within each month.

The main assumption behind the external instruments approach is that the instruments are correlated with the structural shock of interest but uncorrelated with all other shocks. For example, this condition might be violated when the instrument for the target shock is not only correlated with the target shock but also with the term premium shock. Table 5 in the Appendix provides evidence that this might be the case. This correlation might result from a violated orthogonality condition when estimating the shocks (see Section 2.4). To account for this, we jointly identify the three dimensions of the monetary policy shock. The identifying restrictions are given by

$$\mathbb{E}\left[z_t \varepsilon_{1,t}'\right] = \Phi \tag{19}$$

$$\mathbb{E}\left[z_t \varepsilon_{2,t}'\right] = 0_{k\times(n-k)} \tag{20}$$

where Φ is a $k \times k$ matrix of full rank. $\varepsilon_{1,t}$ is the vector of k structural shocks to be identified, and $\varepsilon_{2,t}$ denotes all the other structural shocks. The relevance (19) and exogeneity (20) conditions together with the variances for u_t and ε_t imply

$$\mathbb{E}\left[z_t u_t'\right] = \mathbb{E}\left[z_t \varepsilon_t'\right] S' = \mathbb{E}\left[z_t \begin{pmatrix} \varepsilon_{1,t}' & \varepsilon_{2,t}' \end{pmatrix}\right] \begin{pmatrix} S_1' \\ S_2' \end{pmatrix} = (\Phi, 0) \begin{pmatrix} S_1' \\ S_2' \end{pmatrix} = \Phi S_1' \tag{21}$$

$$\mathbb{E}\left[z_t u_t'\right] \mathbb{E}\left[u_t u_t'\right]^{-1} \mathbb{E}\left[u_t z_t'\right] = \Phi S_1' \left(S S'\right)^{-1} S_1 \Phi' = \Phi S_1' (S')S^{-1} S_1 \Phi' = \Phi\Phi' \tag{22}$$

where $S^{-1}S_1 = \begin{pmatrix} I_k & 0_{(n-k)\times k} \end{pmatrix}'$ and S_1 is the first k columns of S. If $k = 1$, Φ is a scalar, and the identification is unique up to sign and scale. If $k > 1$, Φ has k^2 unique elements, while $\Phi\Phi'$ is symmetric with only $\frac{k(k+1)}{2}$ unique elements. Hence, the instrument moment restrictions are not sufficient. Therefore, we additionally impose the restriction that the path and the term premium shocks do not affect the three-month interest rate on impact. Moreover, the term premium shock does not affect the two-year Treasury yield on impact. These additional assumptions identify the three structural shocks. We provide more details on the joint identification of k structural shocks with k instruments in Appendix D.

3 Data

In what follows, we present the dependent and control variables used to estimate daily and monthly exchange rate responses, policy event days, and control days. We use daily data from 1988–2022.[10] The monthly variables span from January 1973 to February 2020. Note that in an SVAR identified with external instruments, the estimation and identification sample do not need to be congruent. Following Bauer and Swanson (2023b), we use the sample spanning January 1988 to December 2019 for identification. The exact data sources are listed in Appendix E.

[10]There are some missing values due to weekends and public holidays. We remove all these values and interpolate a few additional missings before transforming the data.

3.1 Dependent variables

We use exchange rate data recorded at noon EST from the Federal Reserve Board. Besides a nominal effective exchange rate, we also examine the USD exchange rate vis-à-vis the CHF, GBP, JPY, CAD, and EUR. Before the euro-changeover, we use the USD/DEM exchange rate.[11] All exchange rates are defined as one USD in terms of foreign currency. A decrease in the exchange rate is an appreciation of the USD. All exchange rates are included as log-changes, multiplied by 100, such that the cumulative impulse responses are measured in percent.

We use interest rates along the term structure to identify multiple dimensions of monetary policy shocks on daily frequency. Specifically, we use the three-month interest rate to represent the target shock and the two-year Treasury bill and a term spread (ten-year minus the two-year Treasury bill) to represent the path and term premium shocks, respectively. They are recorded at market close, typically 4 pm EST. We include them in first-differences so that the cumulative impulse responses are measured in percentage points.

Recall that the model reads

$$y_t = \sum_{l=1}^{L} \Phi_l y_{t-l} + \Psi \varepsilon_t + \Gamma v_t \quad \text{for } t \in P \tag{23}$$

where we include $L = 4$ lags of the dependent variables.

In the baseline, we set

$$y_t = [i_t^{3m},\ i_t^{2y},\ i_t^{10y-2y},\ \text{neer}_t]' \tag{24}$$

with

$$\Psi \varepsilon_t = \begin{bmatrix} \Psi_{11} & 0 & 0 \\ \Psi_{21} & \Psi_{22} & 0 \\ \Psi_{31} & \Psi_{32} & \Psi_{33} \\ \Psi_{41} & \Psi_{42} & \Psi_{43} \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix}. \tag{25}$$

The ordering implies that the target shock (ε_{1t}), which changes the variance of the

[11] The USD/DEM is transformed to a hypothetical USD/EUR using the official euro-changeover exchange rate.

three-month interest rate, affects on impact all variables.[12] The path shock (ε_{2t}), which changes the variance of the two-year rate (conditional on the target shock), does not affect the three-month rate on impact. The term premium shock (ε_{3t}), which changes the variance of the term spread (ten-year minus two-year rate), conditional on the target and path shocks, does not affect the three-month and two-year rate on impact. In addition, we include the nominal effective exchange rate as the outcome variable of main interest.

We estimate a reduced-form VAR with $n = 7$ macroeconomic variables to calculate the responses at monthly frequency. As has become standard in monetary policy VARs following Gertler and Karadi (2015), we use the log of industrial production, the log of the consumer price index (CPI), and the Gilchrist and Zakrajšek (2012) excess bond premium. Additionally, we add the log of the nominal exchange rate index. We add the three-month interest rate to represent the target dimension of monetary policy. For the path component, we follow Swanson (2024) and add the two-year Treasury yield. Finally, we add a term spread (ten-year minus two-year Treasury yield) to represent the term premium dimension. Gertler and Karadi (2015) use the one-year instead of the two-year Treasury yield. However, the two-year rate was unconstrained during the ZLB, making it a better stance of the path component of monetary policy.[13] Following Bauer and Swanson (2023b) and Brennan et al. (2024) we use the end-of-month values for all interest rates. Our sample spans January 1973 to February 2020. We end the sample in February 2020 because we do not want to estimate a model with the large swings of industrial production during the Covid–19 pandemic. All variables except interest rates and the bond premium are expressed in logarithms multiplied by 100. Therefore, their responses are measured in percent, while the responses of the interest rates and the bond premium are in percentage points.

3.2 Events

As monetary policy events, we use the 323 FOMC announcement dates (announcements only) for the period 1988-2019 by Swanson and Jayawickrema (2023), extending them to include 2020–2022. We end up with 344 FOMC announcement dates, whereby 284 are regularly scheduled FOMC meetings.[14] The remaining 60 correspond to unscheduled

[12]In the baseline, we use the three-month rate instead of the Federal Funds Rate to identify the target shock because FOMC meetings do not occur every day. Therefore, target surprises are usually expected to change the interest rate for more than one day.

[13]The results are very similar whether we use the one- or two-year Treasury yield in our analysis.

[14]Note that the FOMC only started in 1994 to announce its decisions for the federal funds rate target after each FOMC meeting.

FOMC (intermeeting) conference calls.[15] In addition, we use dates of relevant speeches and testimony before Congress by the Chair and the Vice-Chair of the Federal Reserve. Recent work by Swanson (2023) and Swanson and Jayawickrema (2023) shows that these speeches are an important source of variation in U.S. monetary policy. In contrast to Swanson and Jayawickrema (2023) who read the newspaper the following day to judge whether the speech had implications for monetary policy, we use a more data-driven approach to identify relevant speeches.[16] We use a topic modeling approach, identifying transcripts that mainly concern monetary policy decisions.[17] We aim to exclude transcripts that refer mainly to the state of the economy or regulatory changes. Thereby, we aim to exclude potential information effects (see Nakamura & Steinsson, 2018). In total, we add 81 speeches to our event dataset.[18] As a robustness test, we also estimate monetary policy shock series over a longer sample starting in 1982. Between 1982 and 1988, we identified 17 more important speeches, 48 scheduled FOMC meetings, and 19 discount rate changes that we use as event days. Our baseline specification uses all other days as control. However, we test the robustness of the results by excluding days that may systematically increase the variance of control days relative to policy event days.

4 Empirical results

This section discusses the results. We start by showing how our three-dimensional monetary policy shock is related to the high-frequency surprises by Swanson (2021). Then, we discuss the exchange rate responses on a daily and monthly basis. Moreover, we show how sensitive daily and monthly results are to different modeling and data specifications.

4.1 The monetary policy shock series

How do lower-frequency non-financial variables respond to our novel target and path shocks? To answer these questions, we estimate the monetary policy shock series, extending the approach by Bu et al. (2021) to multiple dimensions and estimate impulse responses in an IV-SVAR framework at monthly frequency.

[15]Note that these numbers differ from Swanson and Jayawickrema (2023) because we use daily data and define events on a daily basis. In contrast, they sometimes have two events on one day. We refer to their paper for more details about the selection of event dates.

[16]Unfortunately, we can not compare the speeches we identified with the speeches by Swanson and Jayawickrema (2023) because their dataset is not available to the public at the time of writing this chapter.

[17]A detailed description of how relevant articles are identified can be found in Appendix F

[18]Two of them take place on the same date as a FOMC announcement.

Table 1 — Comparison to existing shocks

	Swanson FFR	Swanson Path	Swanson LSAP	Bu et al. (2021)
Target	1.534***	0.073	−0.382***	0.118***
	(0.285)	(0.203)	(0.127)	(0.003)
Path	0.631**	2.388***	0.342	0.178***
	(0.281)	(0.525)	(0.281)	(0.003)
Term premium	−0.982***	0.240	1.593***	-0.003
	(0.348)	(0.378)	(0.584)	(0.002)
Observations	241	241	241	215
R^2	0.352	0.331	0.287	0.986
Adjusted R^2	0.344	0.323	0.278	0.986

Notes: The table shows regressions of our estimated monetary policy shocks on the shocks provided by Swanson (2021) and Bu et al. (2021). Significance levels are given by $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. HAC robust standard errors are in parentheses.

To check whether the procedure produces reasonable shock series, we compare the estimated shocks to the three-dimensional high-frequency shocks by Swanson (2021). Figure 21 in the Appendix shows that the estimated target and path shocks are substantially correlated with Swanson's high-frequency counterparts. The correlation amounts to around 0.5.[19] In Table 1, we regress our shocks on Swanson's high-frequency shocks as well as the Bu et al. (2021) shocks. Our shock explains about one-third of the variation in Swanson's FFR, path, and LSAP shocks. Moreover, the corresponding coefficients are highly statistically significant. Moreover, our shocks explain 99.8 % of the variation in the Bu et al. (2021) shock, with all coefficients being statistically significant. Bu et al. (2021) show that their shock is not predictable by any other information available before the release of the FOMC announcement. This suggests that our shocks are not predictable as well. These results show that even if the methodology and the data compared to Swanson (2021) are different, the shocks are substantially correlated. This suggests that our shocks are reasonable and can be used to estimate the

[19]For robustness, we used alternative interest rate data published by the Federal Reserve Board instead of the estimates by Gürkaynak et al. (2007). The advantage is that we know that the time stamp is 4 pm. The disadvantage is that we have fewer maturities (3M, 6M, 1Y, 2Y, 3Y, 5Y, 7Y, 10Y, 20Y, 30Y). The correlation with the shocks by Swanson (2021) is even higher (see Figure 23 and Table 4 in the Appendix), while the correlation with the shocks by Bu et al. (2021), who use the same data as in our baseline, is lower. However, our results are robust to using either data source.

impact of monetary policy on macroeconomic variables at a lower frequency.

4.2 Daily effects on the exchange rate

Figure 1 shows the impulse responses to a target, path, and a term premium shock, respectively. The solid lines show the local projection estimates. In addition, the figure provides the F-statistics for each shock. The F-statistics for all three shocks are relatively large. Lewis (2022b) suggests, as a rule of thumb, that for $F > 23$ the bias due to weak instruments is sufficiently small. This condition is satisfied for all three dimensions. This suggests that monetary policy events comprise at least three orthogonal dimensions affecting short-, medium-, and long-term interest rates.

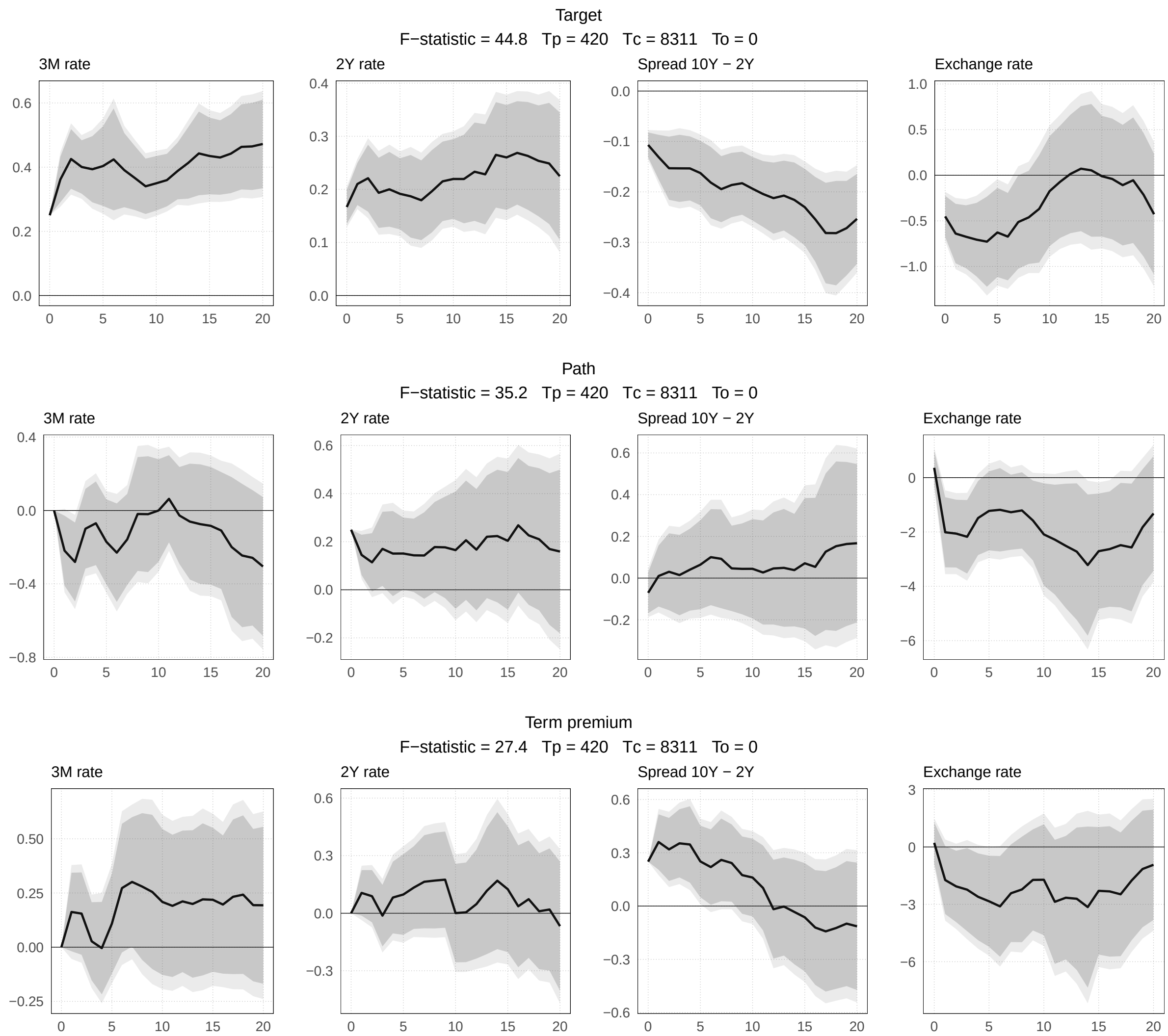
Turning to the impulse responses, a target shock tightening leads to a temporary appreciation of the USD, which vanishes after ten working days. The response is slightly delayed. However, the delay is not statistically significant. In addition, this may be partly related to the fact that exchange rates are recorded at noon, so it takes one working day until the full effect of the monetary policy shock is recorded in the data. Overall, there is no indication of a delayed overshooting puzzle.

A path shock tightening does not affect the 3M interest rate on impact due to the recursive zero restriction. As we would expect, the short-term interest rate is not significantly affected even after a few working days. However, we observe a rapid appreciation of the exchange rate. The exchange rate remains persistently stronger for the entire horizon we examine. However, the response is relatively imprecisely estimated. Finally, the term premium shock raises the term spread for up to ten working days while not significantly affecting the 3M or 2Y interest rates. The exchange rate also appreciates. Although the response is slightly delayed, it reaches the trough already after about five working days.

The delayed overshooting puzzle observed in monthly or quarterly VARs occurs at longer lags. We, therefore, estimate the exchange rate response to a target and path shock for up to 100 working days. Figure 2 shows that the exchange rate response is not statistically significantly different from zero at any horizon between 10 and 100 working days for the target shock.[20] Therefore, we do not find evidence in favor of delayed overshooting. However, we find a more persistent response for the path and term premium shocks. Given the large estimation uncertainty, other patterns are also possible, in line with Faust et al. (2003). The daily responses are not accurate enough

[20] The F-statistics are slightly different from the baseline because we adapt the sample to estimate the long-run responses with the same number of observations as the short-run responses.

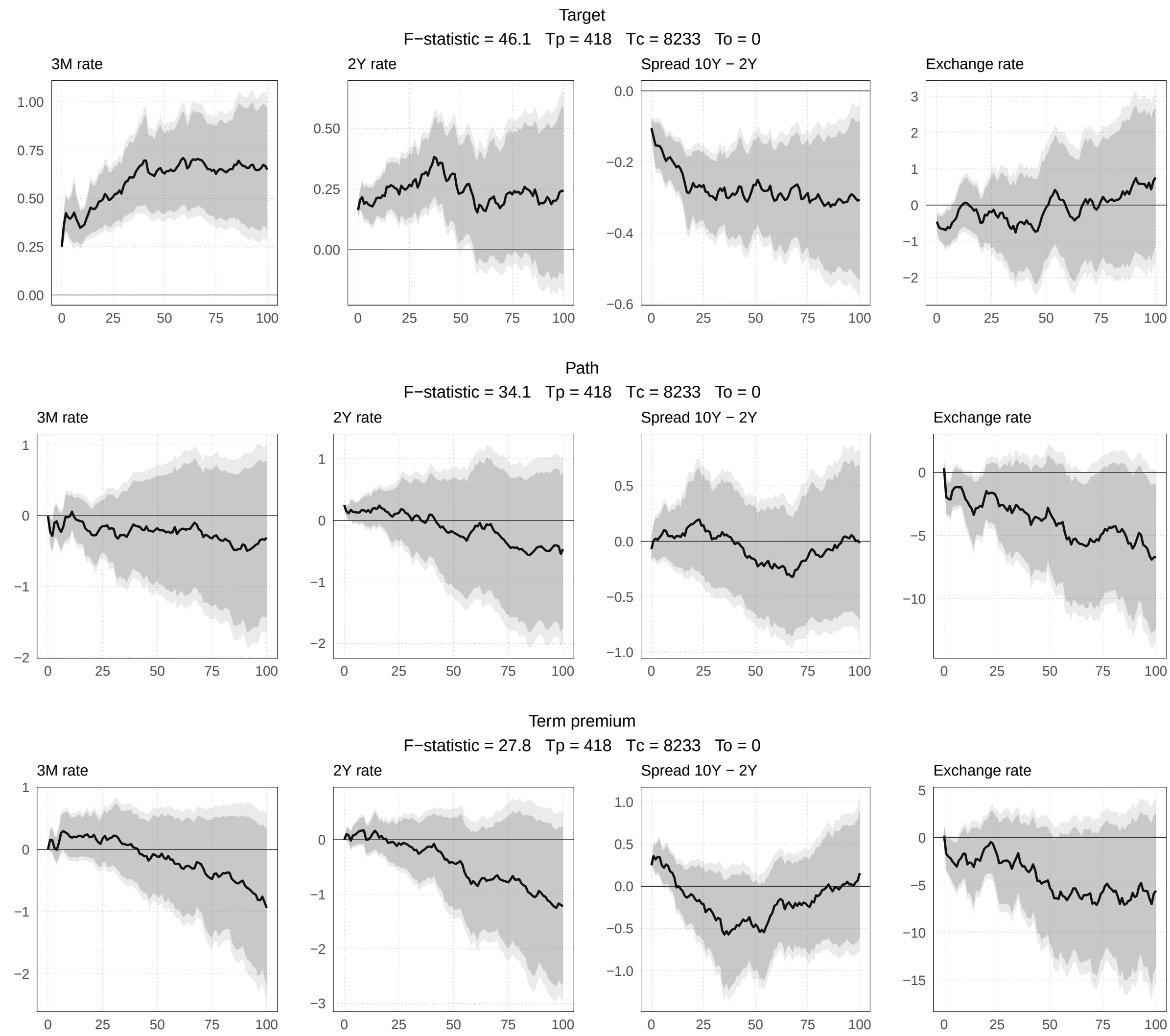
Figure 1 — Impulse responses to orthogonal monetary policy shocks



Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The horizontal axis is measured in working days (excluding weekends and holidays). All interest rate responses are measured in percentage points. The exchange rate response is measured in percent. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy event days, control days, and other days, respectively.

to provide evidence in favor or against delayed overshooting for the path and term premium shocks. In the next section, we will address the question in more detail when estimating monthly impulse responses in a SVAR.

Figure 2 — Long-run impulse responses to orthogonal monetary policy shocks



Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The horizontal axis is measured in working days (excluding weekends and holidays). All interest rate responses are measured in percentage points. The exchange rate response is measured in percent. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy event days, control days, and other days, respectively.

4.3 Monthly macroeconomic effects

Is the lack of delayed overshooting due to the daily frequency of our data? To answer this question, we estimate the responses of the nominal exchange rate and other macroeconomic variables on monthly frequency using a SVAR identified with external instruments.

Table 2 — First-stage regressions

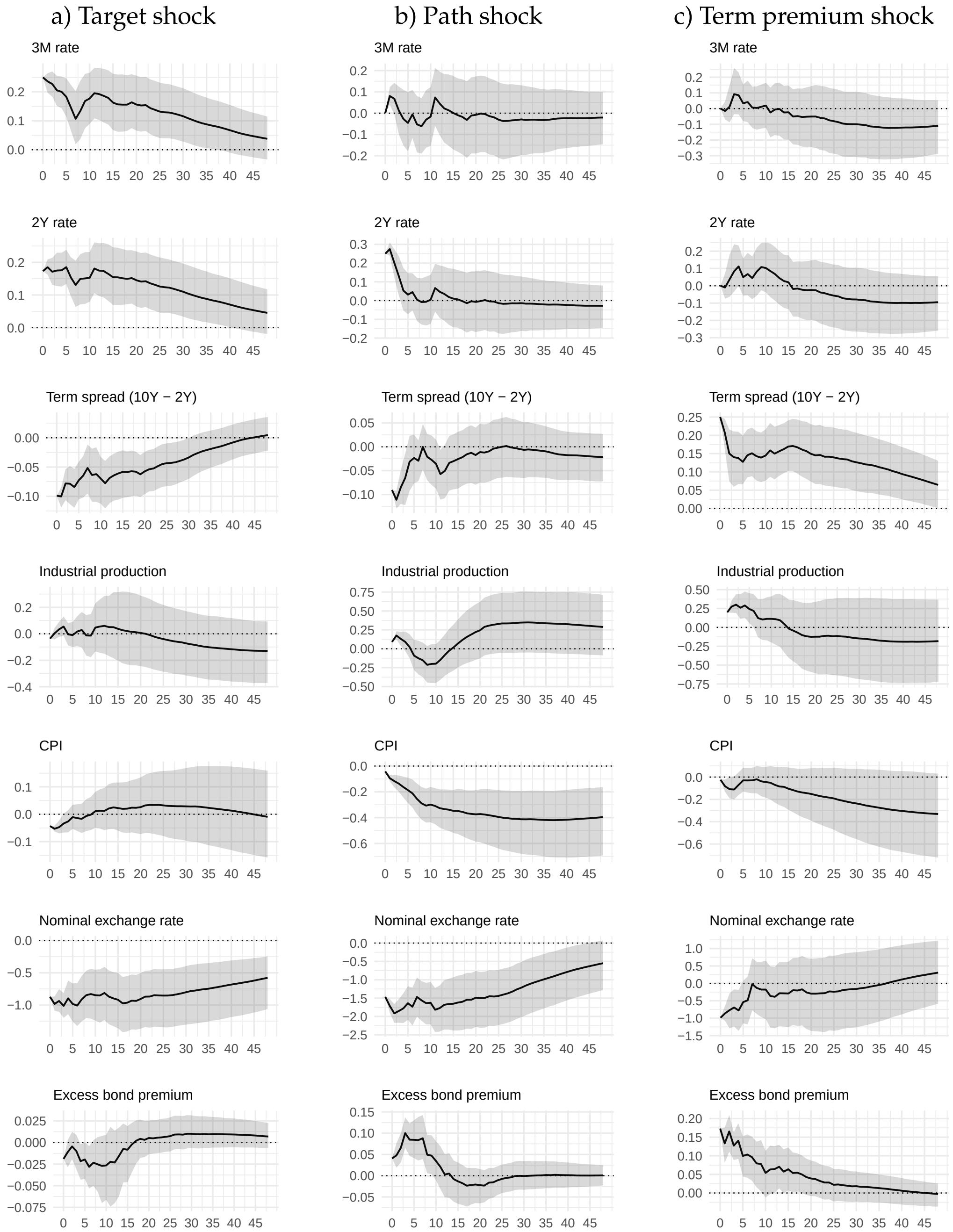
	Burri and Kaufmann			Swanson (2021)			Bu et al. (2021)
	Target	Path	Term premium	FFR	Path	LSAP	
F-stat	12.05	4.35	15.43	7.29	2.32	7.30	0.21
R^2	0.09	0.03	0.11	0.06	0.02	0.06	0
Obs.	384	384	384	336	336	336	312

Notes: The table shows the results of the first-stage regressions of the corresponding interest rate residual (3M, 2Y, 10Y - 2Y) on the three external instruments in the column header. The one-dimensional Bu et al. (2021) shock is regressed on the two-year Treasury bill residual. F-statistics above 10 indicate strong instruments.

The core assumption behind the method of external instruments is that the instruments are correlated with the structural shocks to be identified yet uncorrelated with any other structural shocks. Because the true value of the monetary policy shocks is unobserved, these conditions must be justified economically. Our shocks capture news about monetary policy transmitted via FOMC announcements and speeches by FOMC officials. Therefore, our series is expected to meet the relevance condition economically, though there is a concern that the instrument may be only weakly relevant. In this case, standard inference may fail to produce reliable results. An important statistic to check for the strength of the instrument is the F-statistic in the first-stage regression of the corresponding interest rate residual from the VAR on the instruments (Montiel Olea et al., 2021). To be confident that a weak instrument problem is not present, Montiel Olea et al. (2021) use a rule of thumb of $F > 10$. Table 2 shows the results of the first-stage regressions of the corresponding interest rate residual on the three external instruments. The F-statistics are above 10 for the target and term premium shocks, suggesting that the instruments are strong. However, the F-statistic is below 10 for the path shock. This suggests that the path shock is not precisely estimated. Therefore, we should interpret the results of the path shock with caution. For comparison, we also show the F-statistics for the Swanson (2021) and Bu et al. (2021) shocks. The F-statistics are well below 10, suggesting that the instruments are potentially weak.

The exogeneity condition is more difficult to justify. Recent research findings put into question that this condition holds for commonly used high-frequency monetary policy shocks by showing that they are predictable by information available to the public before the FOMC announcements (See, e.g. Bauer & Swanson, 2023a, 2023b;

Figure 3 — Macroeconomic effects of monetary policy



Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The identification period spans from 1988 – 2019. The horizontal axis is measured in months. All interest rate and bond premium responses are measured in percentage points. All other responses are measured in percent. 90% confidence intervals are based on a moving block bootstrap with 10,000 replications.

Miranda-Agrippino & Ricco, 2021). However, our shock series, derived from the methodology outlined in Bu et al. (2021), explains 98.6% of the variation in the shock identified by Bu et al. (2021). This shock has been demonstrated to be unpredictable by any information available prior to the FOMC announcement. Consequently, this suggests that the exogeneity condition may indeed be satisfied.

We now turn to the findings from the SVAR model, which was identified with external instruments. Figure 3 illustrates the impulse responses to identified three-dimensional monetary policy shocks, standardized to cause a 0.25 basis points increase in the corresponding interest rate. The solid black lines represent the point estimates, while the shaded regions indicate 90 percent confidence intervals, which are derived from 10,000 bootstrap replications.[21]

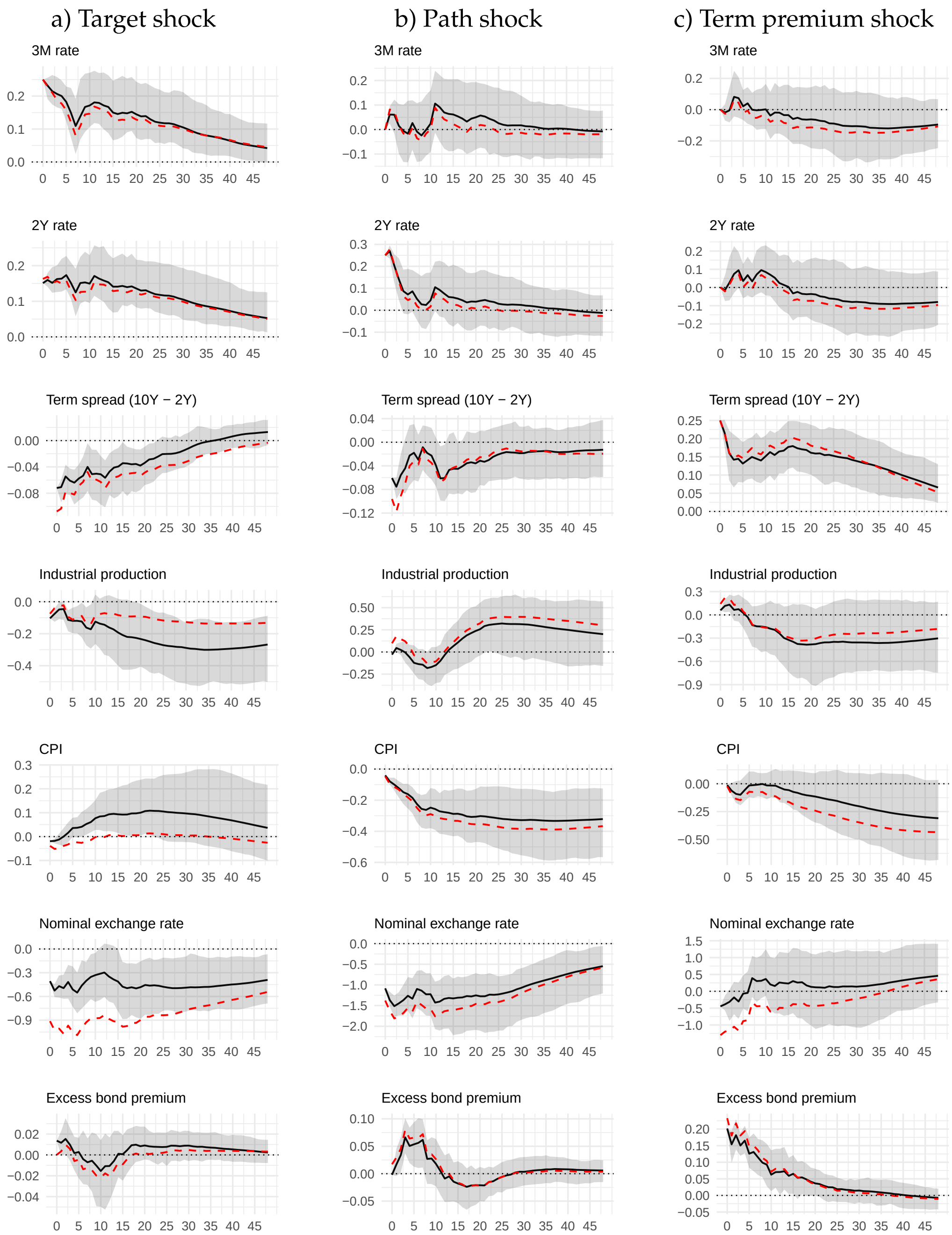
The responses to the target shock are depicted in panel a) of Figure 3. By construction, the three-month interest rate increases by 0.25 percentage points on impact and then gradually declines. The same holds for the two-year Treasury yield with a slightly lower increase on impact. The term spread decreases by 0.1 percentage points on impact and then gradually increases. The exchange rate significantly appreciates by about one percent on impact and then slowly depreciates. Industrial production is hardly affected. The CPI drops slightly on impact, by about 0.05 percent, then increases gradually. The response turns insignificant after about three months. The excess bond premium decreases on impact, becoming statistically insignificant as it increases again.

Panel b) of Figure 3 shows the responses to the path shock. By construction, the three-month interest rate is not affected on impact, and the two-year Treasury yield increases by 0.25 percentage points on impact. It then gradually decreases. The responses of the term spread, industrial production, and the exchange rate are similar to the target shock. The CPI drops slightly on impact and then declines around 0.4 percent over the following years. The excess bond premium increases around five basis points on impact, increases a further five basis points over a few months, and then declines back.

Finally, panel c) of Figure 3 shows the responses to the term premium shock. The three-month interest rate and the the two-year Treasury yield are not affected on impact.

[21] For calculating the confidence intervals, a moving block bootstrap technique is employed as suggested by Jentsch and Lunsford (2019, 2021). This approach yields confidence intervals that are asymptotically accurate under relatively mild α-mixing conditions. The length of each block is fixed at 24, and to address the difference between estimation and identification samples, any missing values in the instruments are set to zero (see, e.g. Känzig, 2021).

Figure 4 — Macroeconomic effects of monetary policy using long identification sample



Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The red dashed lines indicate our baseline responses. The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The identification period spans from 1982 – 2019. The horizontal axis is measured in months. All interest rate and bond premium responses are measured in percentage points. All other responses are measured in percent. 90% confidence intervals are based on a moving block bootstrap with 10,000 replications.

By construction, the term spread increases by 0.25 percentage points on impact and then gradually declines. Industrial production increases by 0.25 percent on impact and progressively reverts to steady-state, rendering the response insignificant after about six months. The exchange rate appreciates by about one percent on impact, then depreciates towards steady-state within a year. The CPI drops slightly on impact and then decreases further gradually. However, the response is not significantly different from zero. The excess bond premium increases on impact and then gradually decreases.

The impulse responses to these three monetary policy shocks are generally consistent with the predictions of standard macroeconomic models. We do not find evidence for a delayed overshooting of the exchange rate. Nevertheless, some estimates are not statistically significant. Moreover, the excess bond premium response to the target shock and the industrial production response to the path shock are puzzling. In a recent paper, Swanson (2024) also finds similar puzzling responses, particularly for industrial production, the CPI, and the bond spread, to what he calls FFR, forward guidance, and LSAP shocks. He argues this is due to the "Fed response to news bias" channel. This means that the Fed often tightens monetary policy when there is positive economic and financial news. This action moves economic variables in the opposite direction of what is expected from real monetary policy shocks, potentially leading to attenuation bias of the impulse responses. This channel may also explain the puzzling responses we find.

Because we are not using high-frequency data to construct our shocks, we can estimate them going back even further than 1988. We identify another 92 event days between 1982 and 1988 and use them to estimate the monetary policy shock series. Figure 4 shows the impulse responses using this longer identification sample. The responses are qualitatively similar to our baseline, with F-statistics of comparable magnitude. Therefore, the results are not driven by the sample period. This contrasts the finding of Kim et al. (2017), who finds that the exchange rate overshooting is an artifact of the 80s. Figure 22 in the Appendix shows that the shocks over the longer and shorter samples are highly correlated.

4.4 Robustness

We conducted a range of robustness tests reported in Appendix G.

Robustness of daily responses We examined the response of bilateral exchange rates. For all three shocks, the USD appreciates bilaterally against a variety of other currencies (CHF, JPY, GBP, EUR, CAD). As bilateral exchange rates are more volatile, estimation uncertainty is larger. Therefore, although the point estimates sometimes deviate from the response of the trade-weighted exchange rate, the differences are not statistically different from zero.

The main results carry over when excluding major data releases. The number of observations falls for two reasons. We exclude $T_o = 1,240$ data release dates from the sample. As a consequence, the F-statistics fall slightly. Still, for the path and term premium shocks, it fulfills the rule of thumb by Lewis (2022b). In addition, the responses of the exchange rate remain qualitatively similar.

We may expect that the volatility of changes in financial market variables differs according to the day of the week. For example, the exchange rate change on Monday (compared to Friday) may be different because news is released over the weekend. We therefore restrict the control days to Tuesday and Wednesday, the days of the week where 78% of all FOMC decisions take place. The F-statistics of the path shock indeed increases. However, the responses of the exchange rate remain qualitatively unchanged.

Bauer and Swanson (2023b) suggest that speeches comprise relevant information about monetary policy. However, our results are not driven by the relevant speeches we included as policy events. The impulse responses are estimated on a sample excluding speeches ($T_o = 79$). The impulse responses and the F-statistics remain qualitatively unchanged.

We also exclude a series of periods associated with increased financial market volatility ($T_o = 938$). The number of observations falls substantially, leading to higher estimation uncertainty. However, the F-statistics are still reasonably high, and the point estimate of the exchange rate response is qualitatively similar to the baseline.

Recent research has shown that minutes released by the FOMC affect financial markets (Swanson & Jayawickrema, 2023). We exclude $T_o = 261$ such days from the sample. The results remain virtually unchanged.

We also exclude unscheduled FOMC decisions from the sample. Note that this removes $T_o = 59$ events, which occur predominantly before 1994. Before then, policy meetings were not announced in advance (Swanson & Jayawickrema, 2023). The F-statistics fall for all three shocks. In particular, the responses to the target shock are not well identified anymore, and the exchange rate response is statistically insignificant. This suggests that with better central bank communication, target surprises lost importance, but path and term premium surprises gained importance.

Other central banks may respond to US monetary policy surprises, which also affect the exchange rate. We, therefore, exclude monetary policy announcements by the ECB (starting in 1999) and the Bank of England (starting in 1997). In total, this removes $T_o = 440$ observations. The results remain virtually unchanged.

We hypothesize that the importance of various shocks varied over time. The path and term premium shocks were probably particularly relevant at the effective lower bound (ELB).[22] Indeed, when estimating the model on an effective lower bound sample, the F-statistic for the target shock drops to 0, suggesting that no target monetary policy shock exists during this episode. Meanwhile, the exchange rate responses remain qualitatively similar for the path and term premium shocks. However, as the sample is much smaller, the F-statistics are lower, and the estimation uncertainty is higher. We also estimated a specification with data starting in 1982. Note that the event periods before 1988 are defined as days with policy rate changes. However, the F-statistics fall for all three shocks, suggesting that the background noise with unannounced policy changes during this early sample period was much higher and, therefore, the instruments very weak.

Finally, we estimated specifications by removing all controls, adding more lags of the dependent variables, and adding additional controls (stock price index, commodity price index, news sentiment index, corporate bond spread). The results are hardly affected.

Robustness of monthly responses To check whether our puzzling responses on monthly frequency are driven by the "Fed response to news bias" channel, following Jarociński and Karadi (2020) and Miranda-Agrippino and Nenova (2022), we censor our monetary policy shocks to zero whenever they move in the same direction as stock prices.[23] These periods may be affected by either a "Fed response to news bias" or an information effect (Nakamura & Steinsson, 2018). For example, suppose the Federal Reserve provides a more optimistic view of the state of the economy. In that case, stock prices may rise while markets are surprised by the monetary policy tightening. Figure 16 in the Appendix shows that the puzzles are eliminated when censoring the shocks. The response of the excess bond premium to the target shock is now positive, and the response of industrial production to the path shock is now negative and statistically significant. The other responses remain qualitatively similar, although somewhat less attenuated. This

[22] We define the ELB period from December 16, 2008, to December 16, 2015, as well as from March 16, 2020, to March 17, 2022.

[23] This procedure is also known as the poor man's sign restrictions.

suggests that the "Fed response to news bias" might be present, even if Bu et al. (2021) find that their method estimates shocks that are not predictable.

Another robustness check addresses the concern that the target shock is quite volatile during the ELB period when, by definition, no such shocks should exist. We, therefore, censored the target shock to zero whenever the federal funds rate was at the effective lower bound. The results in Figure 17 in the Appendix are almost identical to the baseline.

Is there evidence for the delayed overshooting puzzle using existing monetary policy shocks? To address this question, we estimate the impulse responses to the Swanson (2021) and Bu et al. (2021) shocks. The results are shown in Figure 18 and 19 in the Appendix. The path shock of Swanson (2021) generates a puzzling increase in industrial production. The LSAP shock generates puzzling responses regarding the sign of the CPI, the exchange rate, and the excess bond premium. However, these responses should be taken with a grain of salt, as the first-stage F-Statistics are well below 10. The Bu et al. (2021) shock generates responses in line with macroeconomic models. However, the first-stage F-statistic is very low, suggesting that the instrument is weak. Thus, even with existing monetary policy shocks, there is no evidence for a well-identified delayed overshooting puzzle.

Finally, we identify the three shocks using our shocks and the Swanson (2021) shocks as instruments. Thus the model is overidentified. These different types of shocks might complement each other and provide more precise estimates. However, the first-stage F-statistics are below ten and lie somewhere in between our baseline and the Swanson (2021) F-statistics (See Table 2). The results are shown in Figure 20 in the Appendix. The responses constitute a mix of the responses to the individual shocks, being closer to our baseline responses.

5 Concluding remarks

In this paper, we propose to combine a heteroscedasticity-based identification scheme with recursive zero restrictions to identify multiple orthogonal monetary policy shocks along the term structure of interest rates. We then show how to estimate daily dynamic causal effects by modifying the IV approach by Rigobon and Sack (2004).

Applying this identification scheme, we contribute to the ongoing debate in the literature about the effects and the timing of monetary policy shocks on the exchange rate.

So far, there is little evidence in the literature on whether different monetary policy actions, such as changes in the interest rate target, forward guidance, or large-scale asset purchases, affect the exchange rate differently.

The results show that all three dimensions have the expected effect on the exchange rate. A monetary policy tightening appreciates the exchange rate immediately. There is no evidence to support the presence of delayed exchange rate overshooting. This finding holds true for all three identified monetary policy dimensions. Moreover, we do not find evidence that different policy actions affect the exchange rate in different directions. Differences appear mainly in the persistence of the exchange rate effects. However, the responses on horizons that are longer than two weeks suffer from large estimation uncertainty.

To estimate the effects on lower frequency and on other macroeconomic variables, we extend the methodology developed by Bu et al. (2021) to estimate multiple dimensions of monetary policy shocks. Using the shocks in an SVAR identified via external instruments, we find persistent responses of the exchange rate. However, we do not find evidence for an exchange rate overshooting or that different policy actions affect the exchange rate in different directions. This holds when we estimate the model with data including the 1980s and extend our shock series back to 1982. Therefore, this suggests that the delayed overshooting puzzle is an artifact of the identification scheme rather than the estimation period (Kim et al., 2017). This also has implications for the calibration of theoretical models of exchange rate dynamics based on portfolio-adjustment costs (see e.g. Bacchetta & Van Wincoop, 2021).

Further, we find that our shocks are substantially correlated with the multi-dimensional high-frequency surprises by Swanson (2021), even though we use a different method based on daily data. This suggests that our procedure is a valid alternative for countries and periods where high-frequency data is missing or the exact time-stamp of monetary policy announcements is unknown.

Because this approach is not reliant on high-frequency data and the exact timing of events, a promising avenue for future research could be to apply it to other fields where identifying causal relationships is challenging. For example, similar to Bianchi et al. (2024), it could be used to estimate the effects of news shocks on financial markets. Moreover, it could be used to estimate the effects of monetary policy in a historical context, provided that daily data exist.

References

Altavilla, C., Brugnolini, L., Gürkaynak, R. S., Motto, R., & Ragusa, G. (2019). Measuring euro area monetary policy. *Journal of Monetary Economics*, *108*, 162–179. https://doi.org/10.1016/j.jmoneco.2019.08.016

Bacchetta, P., & Van Wincoop, E. (2021). Puzzling exchange rate dynamics and delayed portfolio adjustment. *Journal of International Economics*, *131*, 103460. https://doi.org/10.1016/j.jinteco.2021.103460

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593–1636. https://doi.org/10.1093/qje/qjw024

Bauer, M. D., & Swanson, E. T. (2023a). An alternative explanation for the "fed information effect". *American Economic Review*, *113*(3), 664–700. https://doi.org/10.1257/aer.20201220

Bauer, M. D., & Swanson, E. T. (2023b). A reassessment of monetary policy surprises and high-frequency identification. *NBER Macroeconomics Annual*, *37*, 87–155. https://doi.org/10.1086/723574

Benigno, G. (2004). Real exchange rate persistence and monetary policy rules. *Journal of Monetary Economics*, *51*(3), 473–502. https://doi.org/10.1016/j.jmoneco.2003.06.001

Bianchi, F., Ludvigson, S., & Ma, S. (2024). What hundreds of economic news events say about belief overreaction in the stock market. *NBER Working Paper No. 32301*. https://doi.org/10.3386/w32301

Bjørnland, H. C. (2009). Monetary policy and exchange rate overshooting: Dornbusch was right after all. *Journal of International Economics*, *79*(1), 64–77. https://doi.org/10.1016/j.jinteco.2009.06.003

Blei, D. M., & Lafferty, J. D. (2007). A correlated topic model of science. *The Annals of Applied Statistics*, *1*(1), 17–35. https://doi.org/10.1214/07-AOAS114

Braun, R., Miranda-Agrippino, S., & Saha, S. (2023). Measuring monetary policy in the UK: The UK monetary policy event-study database. *Bank of England Working Paper No. 1050*. https://doi.org/10.2139/ssrn.4698305

Brennan, C. M., Jacobson, M. M., Matthes, C., & Walker, T. B. (2024). Monetary policy shocks: Data or methods? *Finance and Economics Discussion Series 2024-011*, (2024). https://doi.org/https://doi.org/10.17016/FEDS.2024.011

Bu, C., Rogers, J., & Wu, W. (2021). A unified measure of fed monetary policy shocks. *Journal of Monetary Economics*, *118*, 331–349. https://doi.org/10.1016/j.jmoneco.2020.11.002

Canetg, F., & Kaufmann, D. (2022). Overnight rate and signalling effects of central bank bills. *European Economic Review*, *143*, 104060. https://doi.org/10.1016/j.euroecorev.2022.104060

Ciminelli, G., Rogers, J., & Wu, W. (2022). The effects of u.s. monetary policy on international mutual fund investment. *Journal of International Money and Finance*, *127*, 102676. https://doi.org/10.1016/j.jimonfin.2022.102676

Dornbusch, R. (1976). Expectations and exchange rate dynamics. *Journal of Political Economy*, *84*(6), 1161–1176. https://doi.org/10.1086/260506

Eichenbaum, M., & Evans, C. L. (1995). Some empirical evidence on the effects of shocks to monetary policy on exchange rates. *The Quarterly Journal of Economics*, *110*(4), 975–1009. https://doi.org/10.2307/2946646

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, *81*(3), 607–636. https://doi.org/10.1086/260061

Faust, J., & Rogers, J. H. (2003). Monetary policy's role in exchange rate behavior. *Journal of Monetary Economics*, *50*(7), 1403–1424. https://doi.org/10.1016/j.jmoneco.2003.08.003

Faust, J., Rogers, J. H., Swanson, E., & Wright, J. H. (2003). Identifying the effects of monetary policy shocks on exchange rates using high frequency data. *Journal of the European Economic Association*, *Vol. 1*, pp. 1031–1057.

Gertler, M., & Karadi, P. (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, *7*(1), 44–76. https://doi.org/10.1257/mac.20130329

Gilchrist, S., & Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American Economic Review*, *102*(4), 1692–1720. https://doi.org/10.1257/aer.102.4.1692

Gürkaynak, R. S., Sack, B., & Swanson, E. T. (2005). Do actions speak louder than words? the response of asset prices to monetary policy actions and statements. *International Journal of Central Banking*, *1*(1), 39.

Gürkaynak, R. S., Sack, B., & Wright, J. H. (2007). The u.s. treasury yield curve: 1961 to the present. *Journal of Monetary Economics*, *54*(8), 2291–2304. https://doi.org/10.1016/j.jmoneco.2007.06.029

Jarociński, M., & Karadi, P. (2020). Deconstructing monetary policy surprises— the role of information shocks. *American Economic Journal: Macroeconomics*, *12*(2), 1–43. https://doi.org/10.1257/mac.20180090

Jentsch, C., & Lunsford, K. G. (2019). The dynamic effects of personal and corporate income tax changes in the united states: Comment. *American Economic Review*, *109*(7), 2655–2678. https://doi.org/10.1257/aer.20162011

Jentsch, C., & Lunsford, K. G. (2021). Asymptotically valid bootstrap inference for proxy SVARs. *Journal of Business & Economic Statistics*, 1–16. https://doi.org/10.1080/07350015.2021.1990770

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, *95*(1), 161–182. https://doi.org/10.1257/0002828053828518

Känzig, D. R. (2021). The macroeconomic effects of oil supply news: Evidence from OPEC announcements. *American Economic Review*, *111*(4), 1092–1125. https://doi.org/10.1257/aer.20190964

Kearn, J., & Manners, P. (2006). The impact of monetary policy on the exchange rate: A study using intraday data. *International Journal of Central Banking*, *2*(4).

Kim, S.-H., Moon, S., & Velasco, C. (2017). Delayed overshooting: Is it an '80s puzzle? *Journal of Political Economy*, *125*(5), 1570–1598. https://doi.org/10.1086/693372

Kuttner, K. N. (2001). Monetary policy surprises and interest rates: Evidence from the fed funds futures market. *Journal of Monetary Economics*, *47*(3), 523–544. https://doi.org/10.1016/S0304-3932(01)00055-1

Lakdawala, A. (2019). Decomposing the effects of monetary policy using an external instruments SVAR. *Journal of Applied Econometrics*, *34*(6), 934–950. https://doi.org/10.1002/jae.2721

Lewis, D. J. (2022a). Announcement-specific decompositions of unconventional monetary policy shocks & their macroeconomic effects. *Staff Report, No. 891, Federal Reserve Bank of New York*.

Lewis, D. J. (2022b). Robust inference in models identified via heteroskedasticity. *The Review of Economics and Statistics*, *104*(3), 510–524. https://doi.org/10.1162/rest_a_00963

Mertens, K., & Ravn, M. O. (2013). The dynamic effects of personal and corporate income tax changes in the united states. *American Economic Review*, *103*(4), 1212–1247. https://doi.org/10.1257/aer.103.4.1212

Miranda-Agrippino, S., & Nenova, T. (2022). A tale of two global monetary policies. *Journal of International Economics*, *136*, 103606. https://doi.org/10.1016/j.jinteco.2022.103606

Miranda-Agrippino, S., & Rey, H. (2022). The global financial cycle. In G. Gopinath, E. Helpman, & K. Rogoff (Eds.), *Handbook of international economics: International macroeconomics, volume 6* (pp. 1–43). Elsevier. https://doi.org/https://doi.org/10.1016/bs.hesint.2022.02.008

Miranda-Agrippino, S., & Ricco, G. (2021). The transmission of monetary policy shocks. *American Economic Journal: Macroeconomics*, *13*(3), 74–107. https://doi.org/10.1257/mac.20180124

Montiel Olea, J. L., Stock, J. H., & Watson, M. W. (2021). Inference in structural vector autoregressions identified with an external instrument. *Journal of Econometrics*, *225*(1), 74–87. https://doi.org/10.1016/j.jeconom.2020.05.014

Müller, G. J., Wolf, M., & Hettig, T. (2023). Delayed overshooting: The case for information rigidities. *American Economic Journal: Macroeconomics*, *forthcoming*.

Nakamura, E., & Steinsson, J. (2018). High-frequency identification of monetary non-neutrality: The information effect*. *The Quarterly Journal of Economics*, *133*(3), 1283–1330. https://doi.org/10.1093/qje/qjy004

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, *55*(3), 703. https://doi.org/10.2307/1913610

Ramey, V. (2016). Macroeconomic shocks and their propagation. *Handbook of macroeconomics* (pp. 71–162). Elsevier. https://doi.org/10.1016/bs.hesmac.2016.03.003

Rigobon, R. (2003). Identification through heteroskedasticity. *Review of Economics and Statistics*, *85*(4), 777–792. https://doi.org/10.1162/003465303772815727

Rigobon, R., & Sack, B. (2004). The impact of monetary policy on asset prices. *Journal of Monetary Economics*, *51*(8), 1553–1575. https://doi.org/10.1016/j.jmoneco.2004.02.004

Roberts, M. E., Stewart, B. M., & Airoldi, E. M. (2016). A model of text for experimentation in the social sciences. *Journal of the American Statistical Association*, *111*(515), 988–1003. https://doi.org/10.1080/01621459.2016.1141684

Roberts, M. E., Stewart, B. M., & Tingley, D. (2019). Stm: An r package for structural topic models. *Journal of Statistical Software*, *91*(2). https://doi.org/10.18637/jss.v091.i02

Rogoff, K. (2002). Dornbusch's overshooting model after twenty-five years: International monetary fund's second annual research conference mundell-fleming lecture. *IMF Staff Papers*, *49*, 1–34. https://doi.org/10.2307/3872469

Schlaak, T., Rieth, M., & Podstawski, M. (2023). Monetary policy, external instruments, and heteroskedasticity. *Quantitative Economics*, *14*(1), 161–200. https://doi.org/10.3982/QE1511

Schmitt-Grohé, S., & Uribe, M. (2022). The effects of permanent monetary shocks on exchange rates and uncovered interest rate differentials. *Journal of International Economics*, *135*, 103560. https://doi.org/10.1016/j.jinteco.2021.103560

Scholl, A., & Uhlig, H. (2008). New evidence on the puzzles: Results from agnostic identification on monetary policy and exchange rates. *Journal of International Economics*, *76*(1), 1–13. https://doi.org/10.1016/j.jinteco.2008.02.005

Stock, J. H., & Watson, M. W. (2018). Identification and estimation of dynamic causal effects in macroeconomics using external instruments. *The Economic Journal*, *128*(610), 917–948. https://doi.org/10.1111/ecoj.12593

Swanson, E. T. (2021). Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics*, *118*, 32–53. https://doi.org/10.1016/j.jmoneco.2020.09.003

Swanson, E. T. (2023). The importance of fed chair speeches as a monetary policy tool. *mimeo*.

Swanson, E. T. (2024). The macroeconomic effects of the federal reserve's conventional and unconventional monetary policies. *mimeo*.

Swanson, E. T., & Jayawickrema, V. (2023). Speeches by the fed chair are more important than FOMC announcements: An improved high-frequency measure of u.s. monetary policy shocks. *mimeo*.

Wright, J. H. (2012). What does monetary policy do to long-term interest rates at the zero lower bound? *The Economic Journal*, *122*(564), F447–F466. https://doi.org/10.1111/j.1468-0297.2012.02556.x

A Extension daily model

We may extend this framework to include observed control variables, such as lags of the dependent variables, in the information set. Let the model comprise M control variables:

$$\begin{aligned} y_t &= \sum_{l=1}^{L} \Phi_l x_{t-l} + \Psi \varepsilon_t + \Gamma v_t && \text{for } t \in P \\ y_t &= \sum_{l=1}^{L} \Phi_l x_{t-l} + \Gamma v_t && \text{for } t \in C \end{aligned} \tag{26}$$

where Φ_l are $N \times M$ matrices of coefficients for every lag $l = 1, \ldots, L$. Then, we add x_{t-l}, for $l = 1, \ldots, L$ as additional regressors in the IV estimation. The construction of the instrument remains unchanged.[24]

Following Jordà (2005), we can also estimate dynamic effects by iterating the dependent variable forward:

$$\begin{aligned} y_{t+h} &= \sum_{l=1}^{L} \Phi_l^{(h)} x_{t-l} + \sum_{n=0}^{h} \Psi^{(h-n)} \varepsilon_{t+n} + \Gamma^{(h-n)} v_{t+n} && \text{for } t \in P \\ y_{t+h} &= \sum_{l=1}^{L} \Phi_l^{(h)} x_{t-l} + \sum_{n=0}^{h} \Gamma^{(h-n)} v_{t+n} && \text{for } t \in C \end{aligned} \tag{27}$$

where $\Psi^{(h)}$ and $\Gamma^{(h)}$ are the impulse response functions after h periods and $\Phi_l^{(h)}$ are coefficients on the control variables, which differ for every horizon h.[25]

The error term in the IV estimation includes future monetary policy and other shocks. As the instruments are only affected by current shocks, not by future shocks, the exclusion restriction is still valid.[26] We can therefore use the same first-stage and then replace the dependent variable in the second stage with y_{t+h} to estimate the impulse response after h periods. For the same reason, we can estimate cumulative responses by using $\sum_{n=0}^{h} y_{t+h}$ as the dependent variable with the same instrument.

B Simulation study

We conducted a simulation study to show that we can recover the impulse responses of a multi-dimensional monetary policy shock with our IV estimator. We simulate 5'000 observations for $N = 3$ variables using VAR with $P = 2$ lags. There are $R = 3$ i.i.d.

[24] If $x_{t-l} = y_{t-l}$ and $L = 1$ we have the structure of a VAR of order 1.

[25] For example, if the data generating process is a VAR(1) we have that $y_{t+h} = \Phi^h y_{t-1} + \sum_{n=0}^{h} \Phi^{h-n} \Psi \varepsilon_{t+n} + \Phi^{h-n} \Gamma v_{t+n}$, with $\Psi^{(h)} \equiv \Phi^h \Psi$ and $\Gamma^{(h)} \equiv \Phi^h \Gamma$.

[26] However, the error term is autocorrelated, such that it is important to use a HAC-consistent variance estimator (see Newey & West, 1987)

structural shocks that occur on all periods and $E = 2$ i.i.d. structural shocks that occur every 3rd period only. Both impact matrices are lower triangular. The specific values of the impact matrices and VAR coefficients are drawn randomly subject to the constraint that the VAR is stationary.

Figure 1 shows that we can estimate the impulse responses of the three variables to the two shocks that occur only every 3rd period using the recursive heteroskedasticity-based IV estimator. The impact effect is accurately estimated, while there are larger deviations and wider confidence intervals at longer horizons. Looking at the estimated responses for the third dimension, which does actually not exist, we see that the confidence intervals are wide and include zero. In addition, the F-statistic is lower than 23, the rule-of-thumb by Lewis (2022b).

C Estimation of shocks via OLS

According to Bu et al. (2021) we can estimate the underlying shocks via an OLS regression of the cross-sectional variation of the interest rates across the term structure and the impact matrix. Let our estimated $\tilde{\Psi}$ be proportional to the true impact matrix: $\tilde{\Psi}A = \Psi$, where A is a diagonal matrix. The OLS estimator for a given time period t reads:

$$\hat{\varepsilon}_t = (\tilde{\Psi}'\tilde{\Psi})^{-1}\tilde{\Psi}'y_t. \tag{28}$$

On policy event days, the interest rates are affected by monetary policy shocks and other shocks: $y_t = \Psi\varepsilon_t + \Gamma v_t$. Therefore

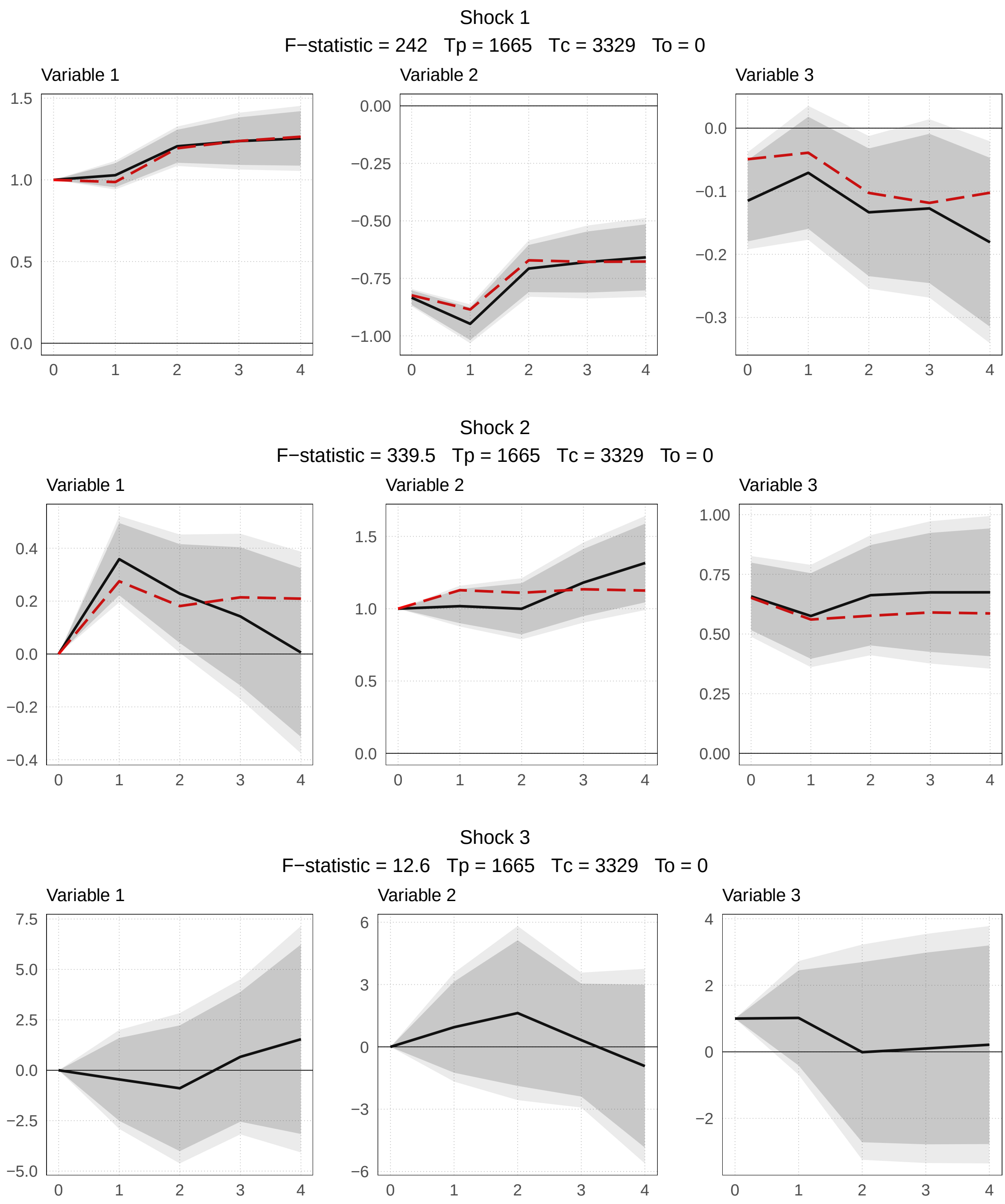
$$\hat{\varepsilon}_t = (\tilde{\Psi}'\tilde{\Psi})^{-1}\tilde{\Psi}'\Psi\varepsilon_t + (\tilde{\Psi}'\tilde{\Psi})^{-1}\tilde{\Psi}'\Gamma v_t. \tag{29}$$

Using the fact that $\tilde{\Psi}$ is proportional to Ψ yields

$$\hat{\varepsilon}_t = A\varepsilon_t + (\tilde{\Psi}'\tilde{\Psi})^{-1}\tilde{\Psi}'\Gamma v_t. \tag{30}$$

Note that if $(\tilde{\Psi}'\tilde{\Psi})^{-1}\tilde{\Psi}'\Gamma$ is different from zero, we will introduce background noise

Figure 1 — Impulse responses simulated data $E = 2$



Notes: Cumulative impulse responses two-dimensional shock occurring every third period estimated using local projections. The red dashed lines give the true impulse responses. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy event days, control days, and other days, respectively.

because the other structural shocks v_t will lead to time-variation in the estimated monetary policy shocks. Therefore, we need an orthogonality assumption. Let us assume that:

$$\mathbb{E}[\Gamma v_t|\tilde{\Psi}] = 0 \tag{31}$$

which corresponds to the classical OLS assumption that the error term is uncorrelated with the regressors. Using the law of total expectation we then obtain:

$$\mathbb{E}[\hat{\varepsilon}_t] = A\varepsilon_t + \mathbb{E}\left[\left(\tilde{\Psi}'\tilde{\Psi}\right)^{-1}\tilde{\Psi}'\mathbb{E}[\Gamma v_t|\tilde{\Psi}]\right] = A\varepsilon_t. \tag{32}$$

Therefore, OLS yields an unbiased estimate of the underlying shocks (up to a scale) if the sensitivity of the interest rates across the term structure to other structural shocks is unrelated to the sensitivity across the term structure to the monetary policy shocks ($\mathbb{E}[\Gamma v_t|\tilde{\Psi}] = 0$).

D External instrument identification with k shocks and k instruments

In this Appendix, we provide more details on the joint identification strategy of the $k = 3$ monetary policy shocks in a SVAR with k instruments (See also Känzig, 2021; Lakdawala, 2019; Mertens & Ravn, 2013, for other applications). Specifically, we allow the instruments to be correlated not only with one structural shock but impose additional restrictions on their impact effects.

We start by organizing the structural shocks as $\varepsilon_t = \begin{pmatrix}\varepsilon'_{1,t} & \varepsilon'_{2,t}\end{pmatrix}'$, where $\varepsilon_{1,t}$ represents a $k \times 1$ vector of the structural shocks we aim to identify, and $\varepsilon_{2,t}$ denotes a $(n-k)\times 1$ vector encompassing the remaining structural shocks. Similarly, we express u_t as $\begin{pmatrix}u'_{1,t} & u'_{2,t}\end{pmatrix}'$. The identification of these shocks relies on moment restrictions for the instrument as follows:

$$\mathbb{E}\left[z_t\varepsilon'_{1,t}\right] = \Phi_{k\times k} \tag{33}$$
$$\mathbb{E}\left[z_t\varepsilon'_{2,t}\right] = 0_{k\times(n-k)} \tag{34}$$

where Φ is of full rank. The covariance restrictions are expressed by the equation:

$$SS' = \Omega. \tag{35}$$

In the next step, we partition S as

$$S^{n\times n} = \left(S_1^{n\times k}, S_2^{n\times(n-k)}\right) = \begin{pmatrix} S_{11}^{k\times k} & S_{12}^{k\times(n-k)} \\ S_{21}^{(n-k)\times k} & S_{22}^{(n-k)\times(n-k)} \end{pmatrix}. \tag{36}$$

The instrument moment conditions together with $u_t = S\varepsilon_t$ imply

$$\Sigma_{zu'} = \mathbb{E}\left[z_t u_t'\right] = \mathbb{E}\left[z_t \varepsilon_t'\right] S' = \mathbb{E}\left[z_t \begin{pmatrix} \varepsilon_{1,t}' & \varepsilon_{2,t}' \end{pmatrix}\right] \begin{pmatrix} S_1' \\ S_2' \end{pmatrix} = (\Phi, 0) \begin{pmatrix} S_1' \\ S_2' \end{pmatrix} = \Phi S_1'. \tag{37}$$

Together with the variances of u_t and ε_t, this yields

$$\mathbb{E}\left[z_t u_t'\right] \mathbb{E}\left[u_t u_t'\right]^{-1} \mathbb{E}\left[u_t z_t'\right] = \Phi S_1' \left(SS'\right)^{-1} S_1 \Phi' = \Phi S_1'(S')S^{-1} S_1 \Phi' = \Phi\Phi' \tag{38}$$

where $S^{-1}S_1 = \begin{pmatrix} I_k & 0_{(n-k)\times k} \end{pmatrix}'$. If $k = 1$, Φ is a scalar and the identification is unique up to sign and scale. If $k > 1$, Φ has k^2 unique elements, while $\Phi\Phi'$ is symmetric with only $\frac{k(k+1)}{2}$ unique elements. Hence, S_1 is only identified up to a rotation.

Another way to show this is by partitioning $\Sigma_{zu'} = \begin{pmatrix} \Sigma_{zu_1'} & \Sigma_{zu_2'} \end{pmatrix}$ or equivalently

$$\Phi S_{11}' = \Sigma_{zu_1'} \tag{39}$$

$$\Phi S_{21}' = \Sigma_{zu_2'}. \tag{40}$$

Combining the two yields

$$S_{21} S_{11}^{-1} = \left(\Sigma_{zu_1'}^{-1} \Sigma_{zu_2'}\right)'. \tag{41}$$

This corresponds to the 2SLS estimator in a regression of $u_{2,t}$ on $u_{1,t}$ using z_t as an instrument for $u_{1,t}$.

The covariance restrictions yield

$$
\begin{aligned}
SS' &= \Omega \qquad (42)\\
\begin{pmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{pmatrix} \begin{pmatrix} S'_{11} & S'_{21} \\ S'_{12} & S'_{22} \end{pmatrix} &= \begin{pmatrix} S_{11}S'_{11} + S_{12}S'_{12} & S_{11}S'_{21} + S_{12}S'_{22} \\ S_{21}S'_{11} + S_{22}S'_{12} & S_{21}S'_{21} + S_{22}S'_{22} \end{pmatrix} = \begin{pmatrix} \Omega_{11} & \Omega_{12} \\ \Omega_{21} & \Omega_{22} \end{pmatrix}.
\end{aligned}
$$

Since Ω is a covariance matrix, it is symmetric, i.e., $\Omega'_{12} = \Omega_{21}$. Thus, this system yields three equations:

$$S_{11}S'_{11} + S_{12}S'_{12} = \Omega_{11} \qquad (43)$$

$$S_{11}S'_{21} + S_{12}S'_{22} = \Omega_{12} \qquad (44)$$

$$S_{21}S'_{21} + S_{22}S'_{22} = \Omega_{22}. \qquad (45)$$

To identify S up to a rotation, it is sufficient to find $S_{11}S'_{11}$, $S_{22}S'_{22}$, $S_{21}S_{11}^{-1}$ and $S_{12}S_{22}^{-1}$. This is because one can write

$$S = \begin{pmatrix} L_1 & S_{12}S_{22}^{-1}L_2 \\ S_{21}S_{11}^{-1}L_1 & L_2 \end{pmatrix} \qquad (46)$$

where $L_1 = \text{chol}(S_{11}S'_{11})$ and $L_2 = \text{chol}(S_{22}S'_{22})$. This still satisfies $SS' = \Omega$. Thus, it proves useful to rewrite these equations in terms of $S_{11}S'_{11}$, $S_{22}S'_{22}$, $S_{21}S_{11}^{-1}$ and $S_{12}S_{22}^{-1}$:

$$S_{11}S'_{11} + S_{12}S_{22}^{-1}S_{22}S'_{22}(S'_{22})^{-1}S'_{12} = \Omega_{11} \qquad (47)$$

$$S_{11}S'_{11}S_{11}^{-1}S'_{21} + S_{12}S_{22}^{-1}S_{12}S'_{22} = \Omega_{12} \qquad (48)$$

$$S_{21}S_{11}^{-1}S_{21}S'_{21}S_{11}^{-1}S'_{21} + S_{22}S'_{22} = \Omega_{22}. \qquad (49)$$

Note that $S_{21}S_{11}^{-1}$ is identified by the instrument conditions. Thus, this is a system of 3 matrix equations in 3 unknown matrices. The solutions are given by

$$S_{12}S'_{12} = \left(\Omega_{21} - S_{21}S_{11}^{-1}\Omega_{11}\right)' \zeta^{-1} \left(\Omega_{21} - S_{21}S_{11}^{-1}\Omega_{11}\right) \tag{50}$$

$$\zeta = \left(\Omega_{22} + S_{21}S_{11}^{-1}\Omega_{11}(S'_{11})^{-1}S'_{21} - S_{21}S_{11}^{-1}\Omega_{12} - \Omega_{21}(S'_{11})^{-1}S'_{21}\right) \tag{51}$$

$$S_{11}S'_{11} = \Omega_{11} - S_{12}S'_{12} \tag{52}$$

$$S_{22}S'_{22} = \Omega_{22} - S_{21}S_{11}^{-1}S_{11}S'_{11}(S'_{11})^{-1}S'_{21} \tag{53}$$

$$S_{12}S_{22}^{-1} = \left(\Omega_{12} - S_{11}S'_{11}(S'_{11})^{-1}S'_{21}\right)\left(S_{22}S'_{22}\right)^{-1} \tag{54}$$

which is sufficient to evaluate S.

However, this only identifies S up to a rotation. The parameter space can be characterized by

$$SR = \begin{pmatrix} L_1 & S_{12}S_{22}^{-1}L_2 \\ S_{21}S_{11}^{-1}L_1 & L_2 \end{pmatrix} \begin{pmatrix} R_k & 0 \\ 0 & R_{n-k} \end{pmatrix} = \begin{pmatrix} L_1R_k & S_{12}S_{22}^{-1}L_2R_{n-k} \\ S_{21}S_{11}^{-1}L_1R_k & L_2R_{n-k} \end{pmatrix} \tag{55}$$

where R is an orthonormal rotation matrix. Our focus is on pinpointing the first k shocks, which entails selecting an appropriate R_k rotation submatrix for S_1's identification. Setting $R_k = I_k$ is deemed a suitable choice for the scenario under consideration. This presupposes that the VAR orders the three-month interest rate first, followed by the two-year Treasury yield, and then the ten-year Treasury yield. Given that L_1 is a lower triangular matrix, it implies the assumption that initially, the path and term premium shocks have no immediate effect on the three-month interest rate. Furthermore, it assumes that the term premium shock does not immediately impact the two-year Treasury yield. These additional assumptions identify the three structural shocks.

E Data

Table 1 — Time series

Category	Source	Variants	Time stamp	Comments
Treasury bill yields	Board of Governors	3M, 6M, 1Y, 2Y, 3Y, 5Y, 7Y, 10Y, 20Y, 30Y	4pm EST	www.federalreserve.gov/releases/h15/
Treasury bill yields	Gürkaynak et al. (2007)	1Y to 30Y		https://www.federalreserve.gov/data/nominal-yield-curve.htm
Federal Funds Rate	Board of Governors		Close	www.federalreserve.gov/releases/h15/
Exchange rates	Board of Governors	NEER, USD/CHF, USD/JPY, USD/GBP, USD/EUR	Noon EST	www.federalreserve.gov/releases/h10/. For the nominal effective exchange rate, we linked the discountinued series with FRED identifier DTWEXM with DTWEXAFEGS. For the USD/EUR exchange rate, we linked the USD/DEM with the USD/EUR exchange rate using the official changeover exchange rate from www.eu-info.de/euro-waehrungsunion/5007/5222/5170/.
Stock prices	TradingView	S&P 500	4pm EST	de.tradingview.com/symbols/SPX/
Bond spreads	Moody's	AAA, BAA		fred.stlouisfed.org/series/DAAA fred.stlouisfed.org/series/DBAA. We computed the spreads as the difference to the 10Y government bond yield.
Economic Policy Uncertainty	Baker et al. (2016)			fred.stlouisfed.org/series/USEPUINDXD
Commodity price index	Dow Jones, Bloomberg			
Industrial production	FRED		Monthly	FRED variable key: INDPRO
CPI	FRED		Monthly	FRED variable key: CPIAUCSL
Excess bond premium	Gilchrist and Zakrajšek (2012)		Monthly	

Table 2 — Events

Category	Source	Comments
FOMC announcements	1982 to 1987: https://www.federalreserve.gov/monetarypolicy/fomc_historical_year.htm, 1988 to 2019: Swanson and Jayawickrema (2023), from 2020: https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm	
Discount rate changes	Monetary Policy and Open Market Operations 1982 - 1989, FRBNY Quarterly Review, 1983 - 1990, https://www.newyorkfed.org/research/quarterly_review/75th.html	Collected for 1982 - 1989
Speeches and Congressional Testimony	To 1996: https://alfred.stlouisfed.org/, from 1997: https://www.federalreserve.gov/newsevents/speeches.htm	
FOMC minutes	https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm	Available from 1988
ECB decisions	Altavilla et al. (2019)	Available from 1999
BoE decisions	Braun et al. (2023)	Available from 1997
CPI releases	https://www.bls.gov/bls/news-release/cpi.htm, https://alfred.stlouisfed.org/	
PPI releases	https://www.bls.gov/bls/news-release/ppi.htm	Available from 1994
Employment situation releases	https://www.bls.gov/bls/news-release/empsit.htm	Available from 1994
Employment cost releases	https://www.bls.gov/bls/news-release/eci.htm	
GDP releases	https://www.bea.gov/index.php/news/archive?field_related_product_target_id=All&created_1=All&title=gross%20domestic%20product&page=0	Includes first, second and third estimates. Available from 1996
Industrial production releases	https://www.federalreserve.gov/releases/g17/release_dates.htm	

Notes: Prior to 1994, the FOMC did not explicitly announce its target for the federal funds rate, but implemented changes in its target via open market operations. These open market operations were conducted at 11:30am the next morning (see Swanson & Jayawickrema, 2023). Therefore, we use the next day after a regularly scheduled FOMC meeting as event day from 1982 - 1987.

F Identification of relevant speeches

Swanson (2023) and Swanson and Jayawickrema (2023) show that speeches and Congressional testimony (henceforward just speeches) of the Chair and the Vice-Chair of the Federal Reserve Board are an important source of variation in U.S. monetary policy. Therefore, we augment the event dataset with carefully selected speeches. In contrast to Swanson and Jayawickrema (2023) who read the newspaper the next morning to judge whether the speech had implications for monetary policy, we use a more data-driven approach to identify relevant speeches.

To identify speeches of the Chair and the Vice-Chair of the Federal Reserve, we apply a Correlated Topic Model (CTM).[27] Specifically, we downloaded all speeches by officials of the Federal Reserve from 1996 onwards from the website of the Federal Reserve.[28] Speeches before 1996 are collected from ALFRED. [29] We then identify and link together words that often appear together (e.g., interest rate or Federal Reserve) by calculating bigrams (contiguous sequences of two words). Finally, after cleaning the corpus from stopwords, numbers, and punctuation, we apply the CTM.

The CTM was initially developed by Blei and Lafferty (2007). Here, we use the algorithm described in Roberts et al. (2016), Roberts et al. (2019). Specifically, we estimate a Structural Topic Model (STM), which reduces to a fast implementation of the CTM if estimated without covariates.[30] The CTM is a statistical model used to analyze large sets of documents. It assumes that each document in the collection is made up of a mixture of different topics, and each topic is a probability distribution over the words in the vocabulary. It is superior in this context to other topic modeling approaches, such as Latent Dirichlet Allocation (LDA), because it explicitly models the correlations between the topics, which may be important for understanding the underlying structure of the data. For classifying speeches of Federal Reserve officials, there may be certain topics that are frequently discussed together (such as inflation and monetary policy) or that have a strong influence on each other.

In the following, we use the notation as in Roberts et al. (2016). We denote the documents

[27] We follow Swanson and Jayawickrema (2023) and focus on the most influential members of the FOMC: the Federal Reserve Board Chair and the Federal Reserve Board Vice Chair. However, to estimate the topic model we use all speeches given by Federal Reserve Board Governors. Thus, the resulting topics are rendered more interpretable by providing the algorithm with additional data.

[28] https://www.federalreserve.gov/newsevents/speeches.htm

[29] https://alfred.stlouisfed.org/

[30] See Roberts et al. (2016), Roberts et al. (2019) for more details on the STM.

using the index $d \in \{1, \ldots, D\}$ and the words (or positions within the documents) using the index $n \in \{1, \ldots, N\}$. Each word in a document, represented as $w_{d,n}$, is an instance of distinct words drawn from a vocabulary that is indexed by $v \in \{1, \ldots, V\}$. Additionally, the model assumes the selection of a certain number of topics, K, which are indexed by $k \in \{1, \ldots, K\}$.

The CTM is a generative model assuming that each document d, given the number of topics K and observed words $w_{d,n}$, is generated in the following way:

$$\eta_d \sim \mathcal{N}_{K-1}(\mu, \Sigma) \tag{56}$$

$$\theta_{d,k} = \frac{\exp(\eta_{d,k})}{\sum_{i=1}^{K} \exp(\eta_{d,i})} \tag{57}$$

where η_d is the latent topic proportion vector for document d, transformed to the simplex via a logistic function to get θ_d. $\eta_{d,K}$ is fixed to zero to identify the model. μ is the mean vector, and Σ is the covariance matrix (capturing topic correlations) of the topic proportion. Given the topic proportion vector, θ_d, for each word, indexed by n, within document d, a topic indicator is sampled from

$$z_{d,n} \sim \text{Multinomial}_K(\theta_d) \tag{58}$$

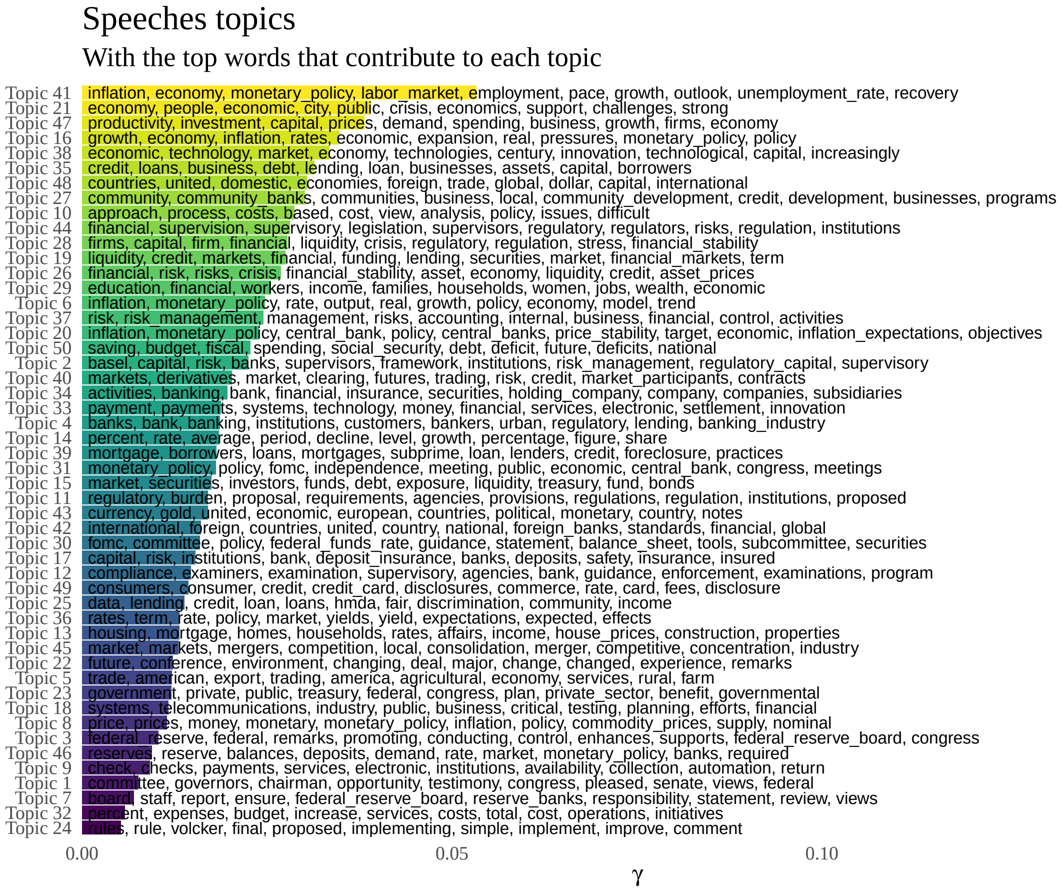
whose positive component indicates the topic associated with that particular position. Conditional on such a topic indicator, a word is sampled from

$$w_{d,n} \sim \text{Multinomial}_V(\beta_{z_{d,n}}) \tag{59}$$

where V is the size of the vocabulary and β is the $K \times V$ matrix representing the distributions of terms in the vocabulary corresponding to the K topics.

The objects of interest in a CTM include the distributions of topics within documents (θ_d), the distributions of words across topics (β), the topic assignments for each word ($z_{d,n}$), and the parameters (μ, Σ) of the logistic normal distribution. Estimating these components allows for a comprehensive understanding of the thematic structure present in a text corpus. However, inference in a CTM is challenging due to the non-conjugate nature of the logistic normal and multinomial distributions. Here, an approximate variational EM algorithm using a Laplace approximation developed by Roberts et al. (2016) is used. We refer to their paper for more details on the estimation procedure.

Figure 2 — Topic prevalence with the top words that contribute to topics

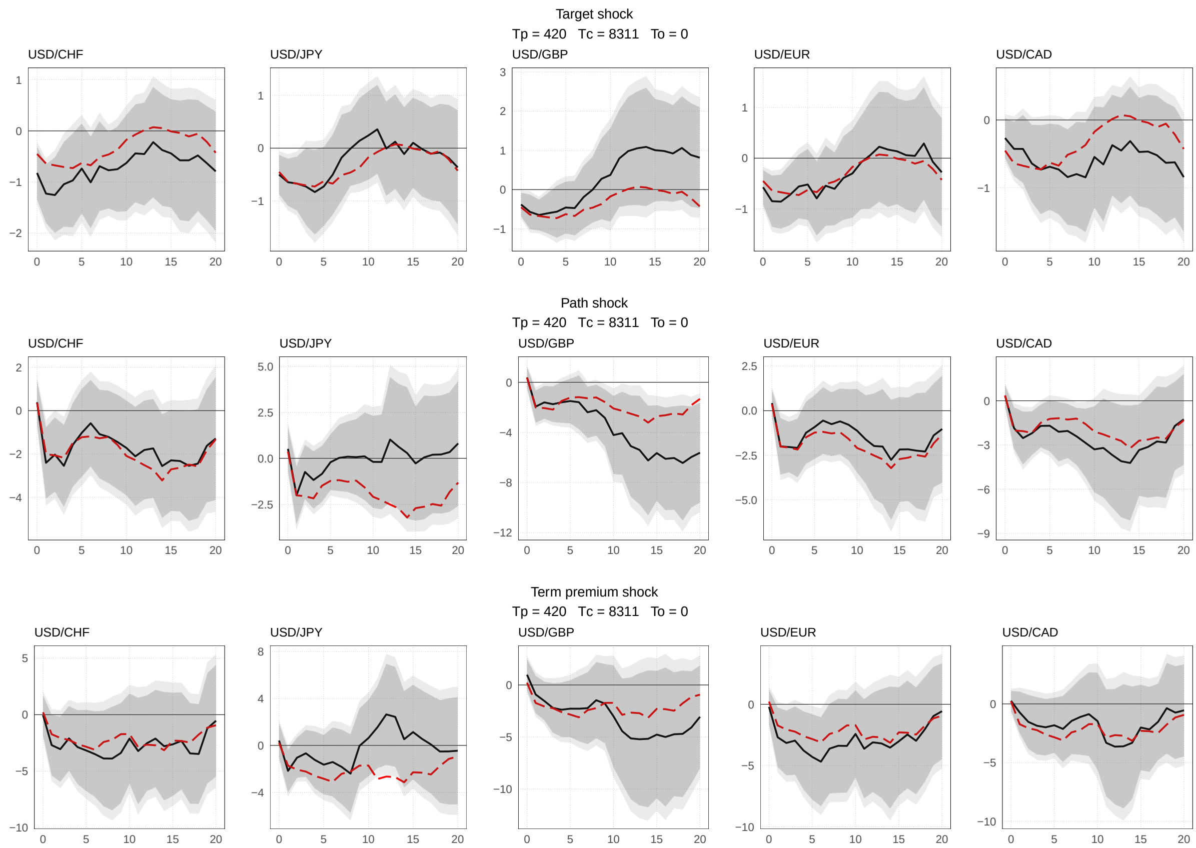


We use the default values of the algorithm developed by Roberts et al. (2019) and set the number of topics to $K = 50$. Figure 2 illustrates the identified topics in terms of their frequency of occurrence within the text corpus and the words that most accurately describe them. From a human standpoint, the top words are perceived as coherent and meaningful, resulting in the interpretability of the topics. Therefore, we use the top words to identify the topics associated with monetary policy. We explicitly choose only those topics that are directly related to monetary policy. In doing so, we can avoid possible concerns regarding information effects (see Nakamura & Steinsson, 2018). According to our judgment, the following six topics hold the greatest relevance for monetary policy: 6, 20, 30, 31, 36, 46. Accordingly, we identify and include 81 speeches in the event dataset.

G Robustness tests

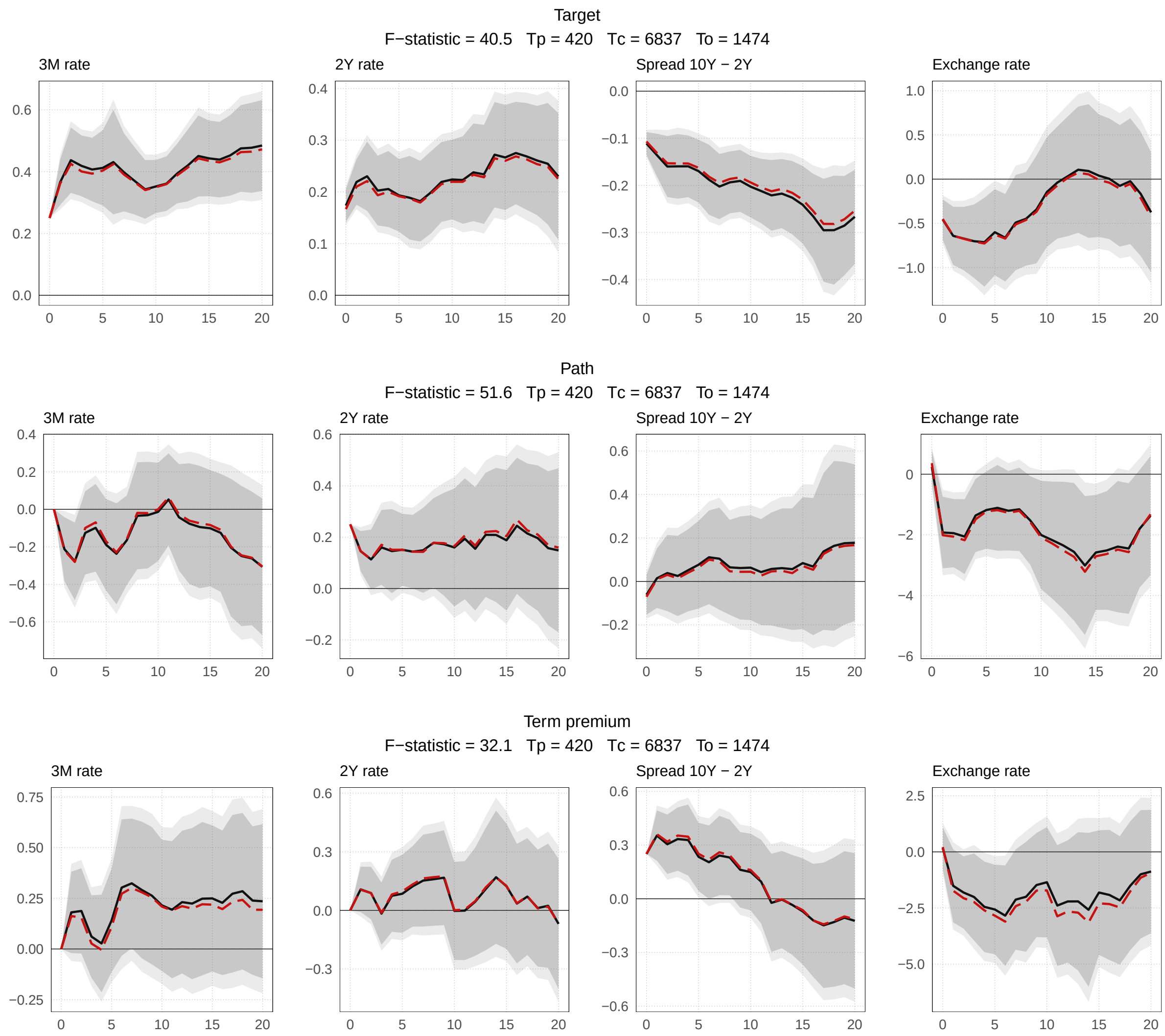
G.1 Daily responses

Figure 3 — Bilateral exchange rates



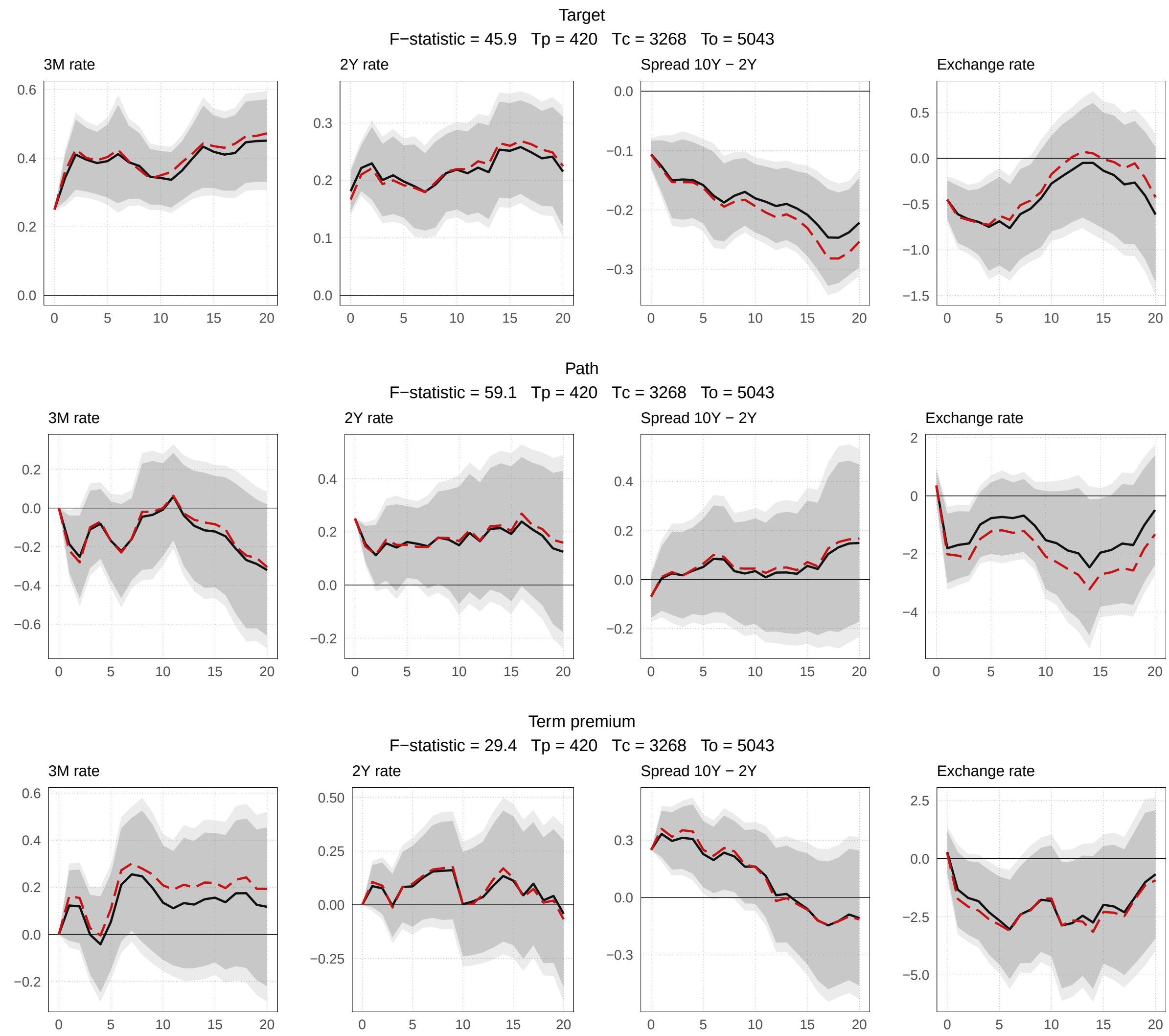
Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The model is estimated for every bilateral exchange rate. The horizontal axis is measured in working days (excluding weekends and holidays). The exchange rate response is measured in percent. Red dashed lines give the baseline response of the trade-weighted exchange rate. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy event days, control days, and other days, respectively.

Figure 4 — Excluding data releases



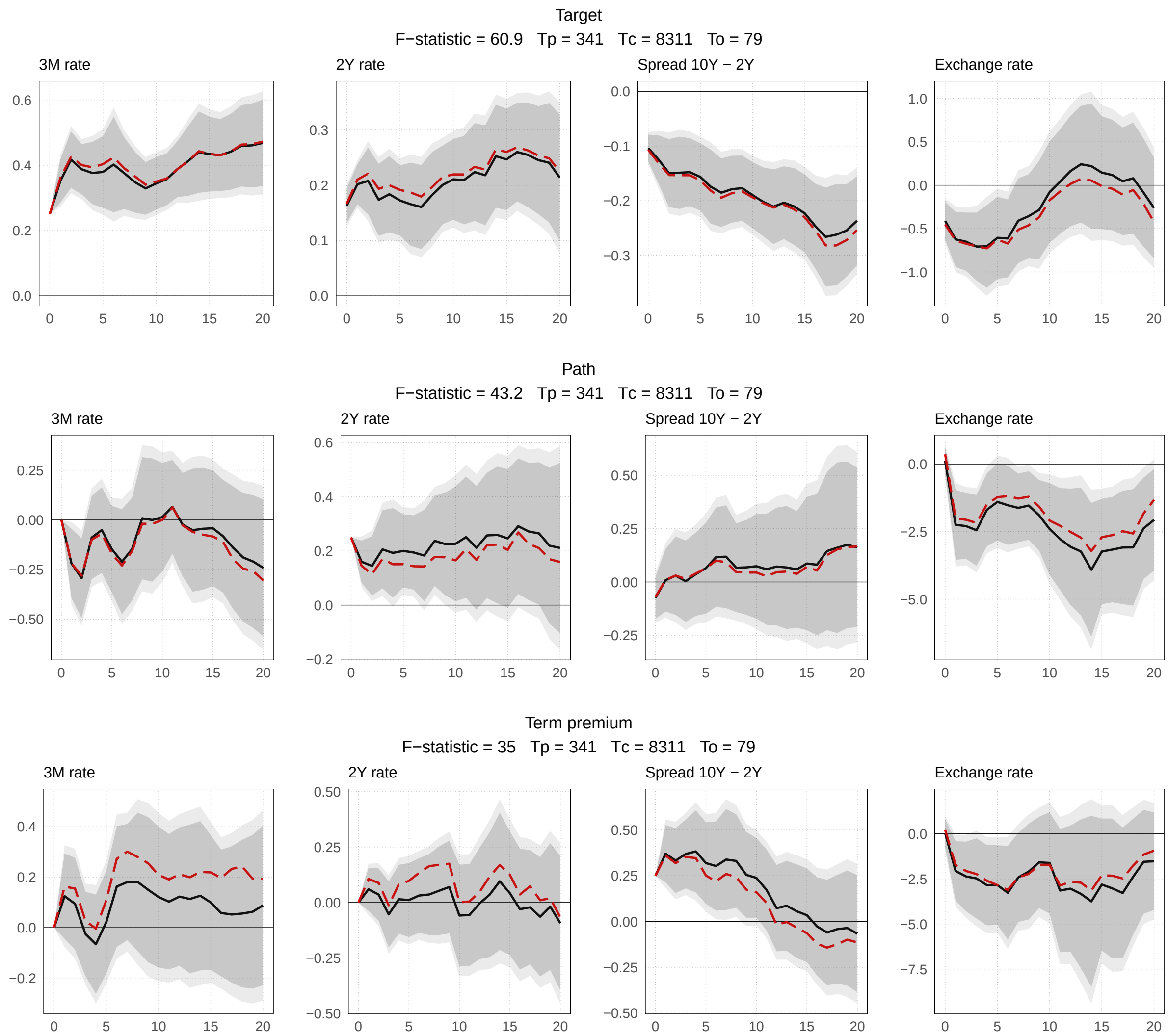
Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The model is estimated on a sample excluding important data releases. The horizontal axis is measured in working days (excluding weekends and holidays). All interest rate responses are measured in percentage points. The exchange rate response is measured in percent. The red dashed lines give the responses in the baseline model. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy event days, control days, and other days, respectively.

Figure 5 — Tuesday and Wednesday as control days



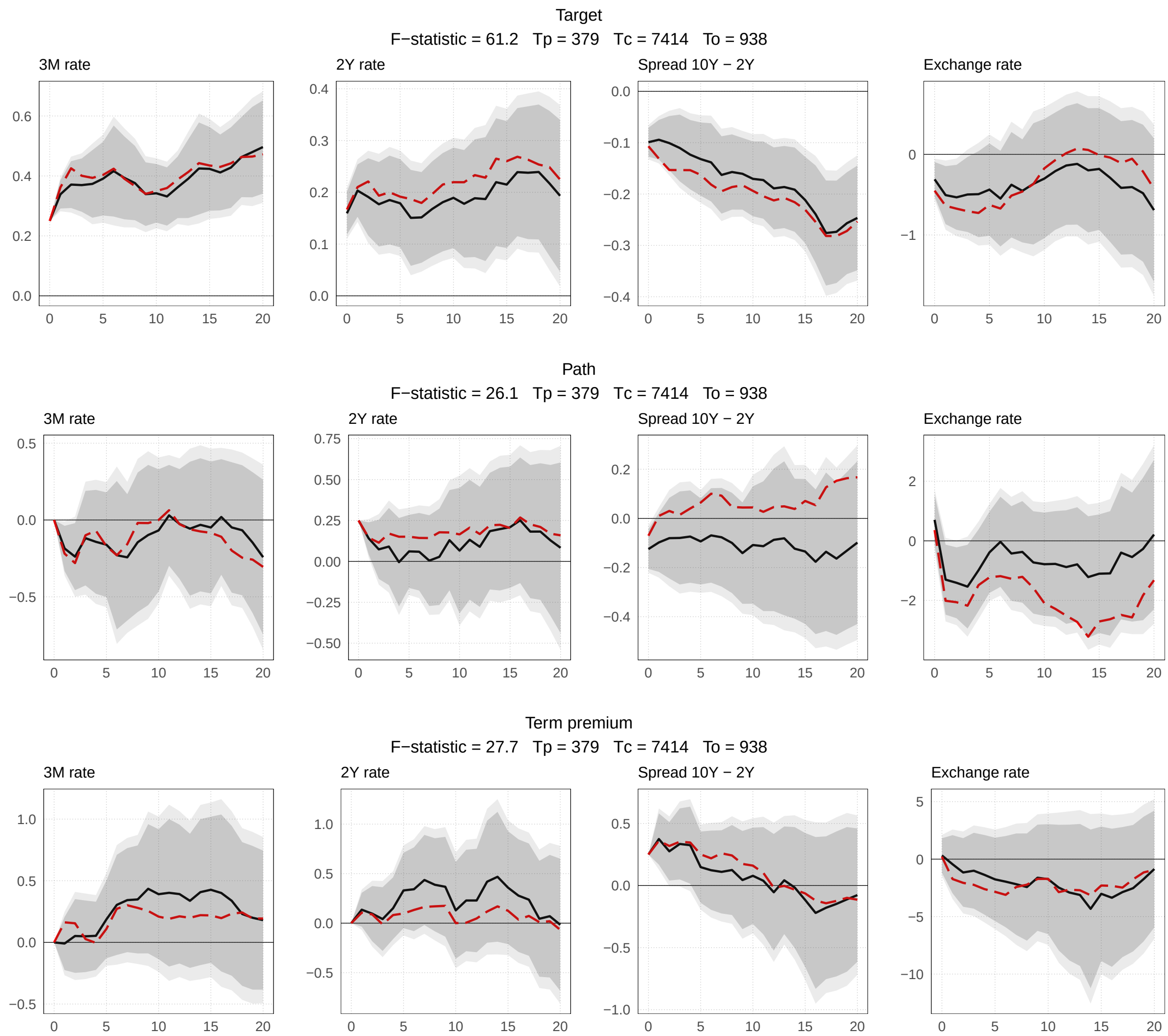
Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The horizontal axis is measured in working days (excluding weekends and holidays). The model is estimated on a sample using only Tuesdays and Wednesdays as control days. All interest rate responses are measured in percentage points. The exchange rate response is measured in percent. The red dashed lines give the responses in the baseline model. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy event days, control days, and other days, respectively.

Figure 6 — Excluding speeches



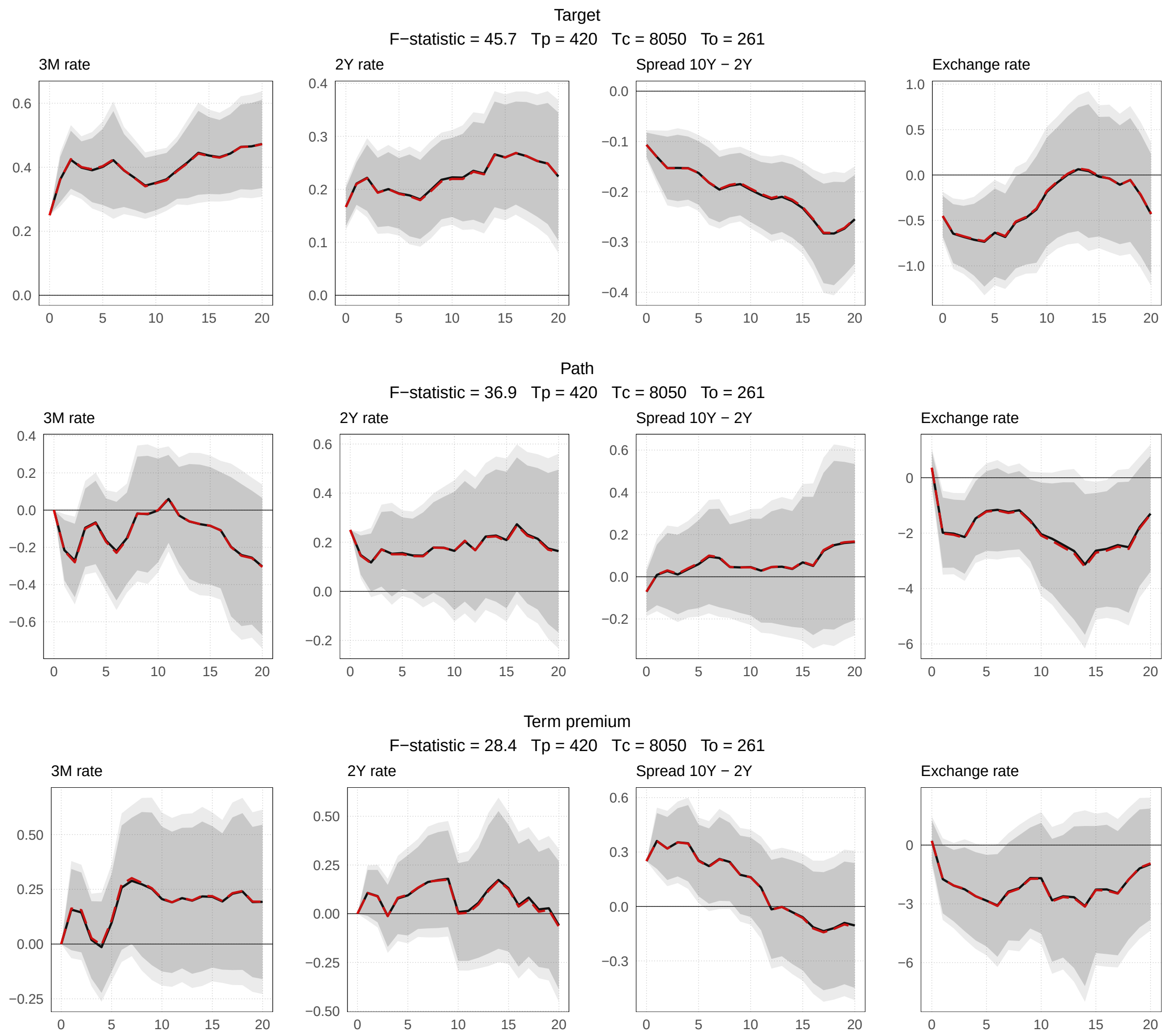
Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The model is estimated on a sample excluding speeches. The horizontal axis is measured in working days (excluding weekends and holidays). All interest rate responses are measured in percentage points. The exchange rate response is measured in percent. The red dashed lines give the responses in the baseline model. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy yevent da, control, and other days, respectively.

Figure 7 — Excluding volatile crisis periods



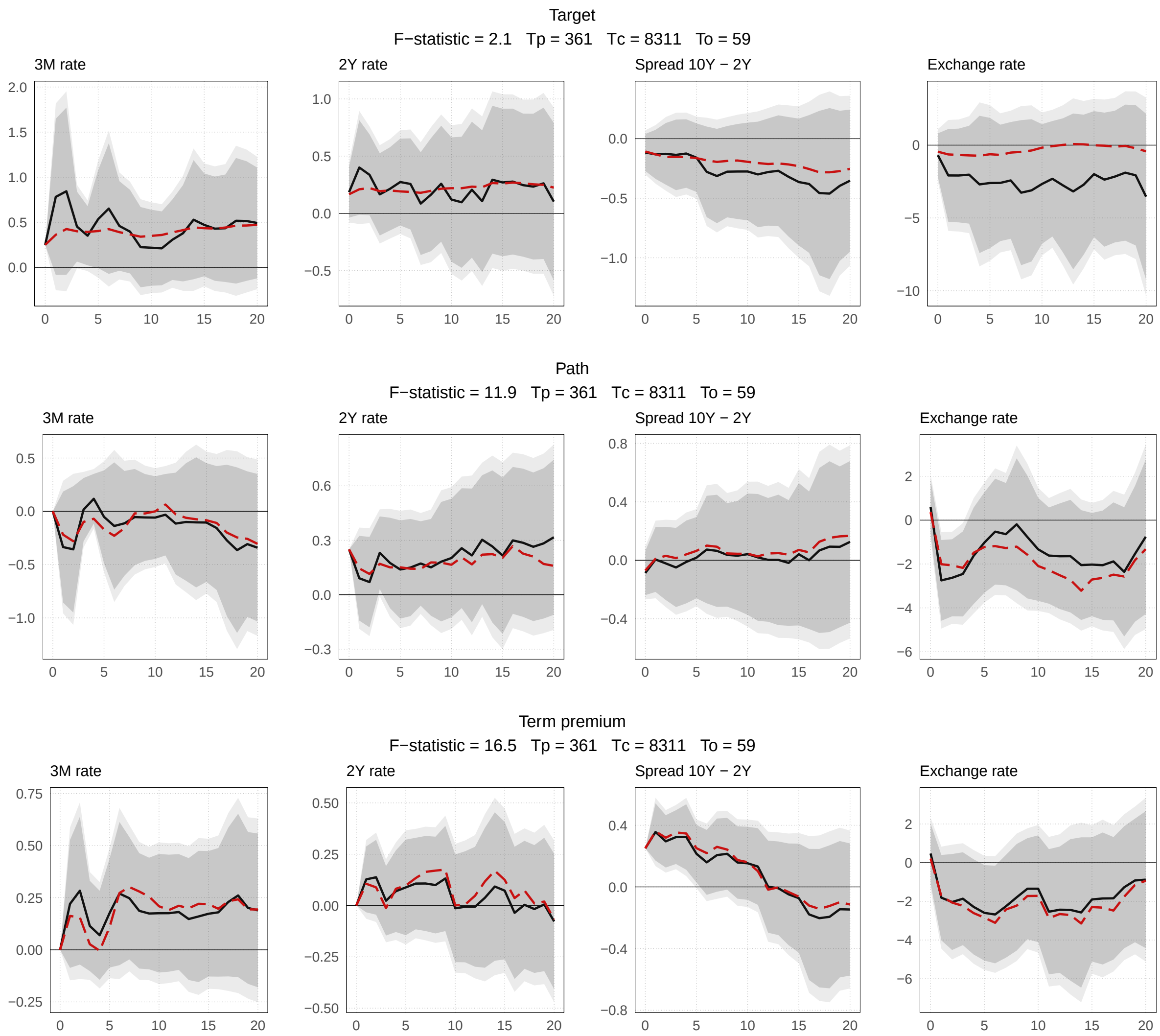
Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The model is estimated on a sample excluding volatile crisis periods. The horizontal axis is measured in working days (excluding weekends and holidays). All interest rate responses are measured in percentage points. The exchange rate response is measured in percent. The red dashed lines give the responses in the baseline model. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy event days, control days, and other days, respectively.

Figure 8 — Excluding FOMC minutes releases



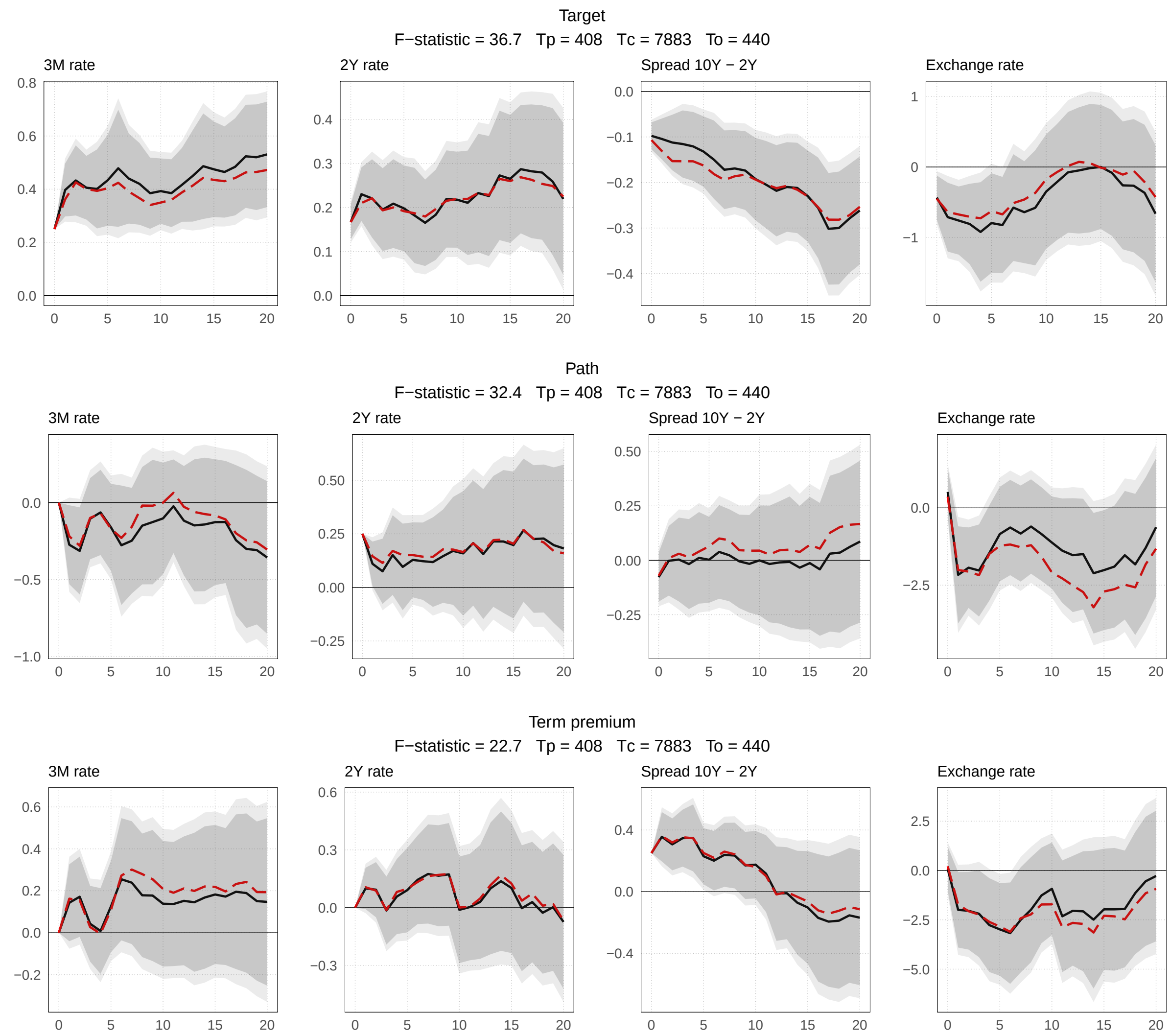
Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The model is estimated on a sample excluding days with releases of FOMC minutes. The horizontal axis is measured in working days (excluding weekends and holidays). All interest rate responses are measured in percentage points. The exchange rate response is measured in percent. The red dashed lines give the responses in the baseline model. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy event days, control days, and other days, respectively.

Figure 9 — Excluding unscheduled policy events



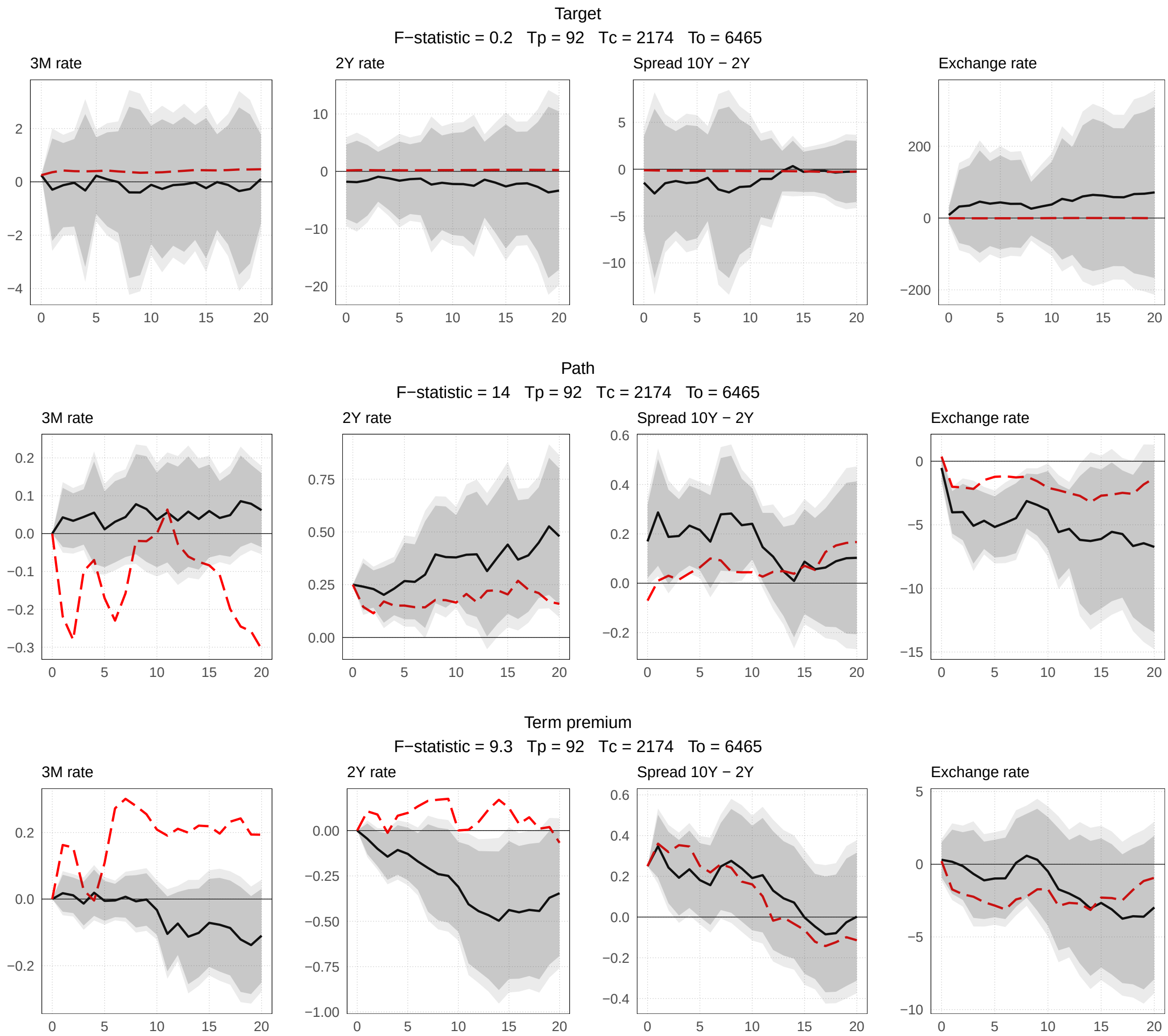
Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The model is estimated on a sample excluding unscheduled FOMC decisions. The horizontal axis is measured in working days (excluding unscheduled policy events). All interest rate responses are measured in percentage points. The exchange rate response is measured in percent. The red dashed lines give the responses in the baseline model. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy event days, control days, and other days, respectively.

Figure 10 — Excluding ECB and BoE decisions



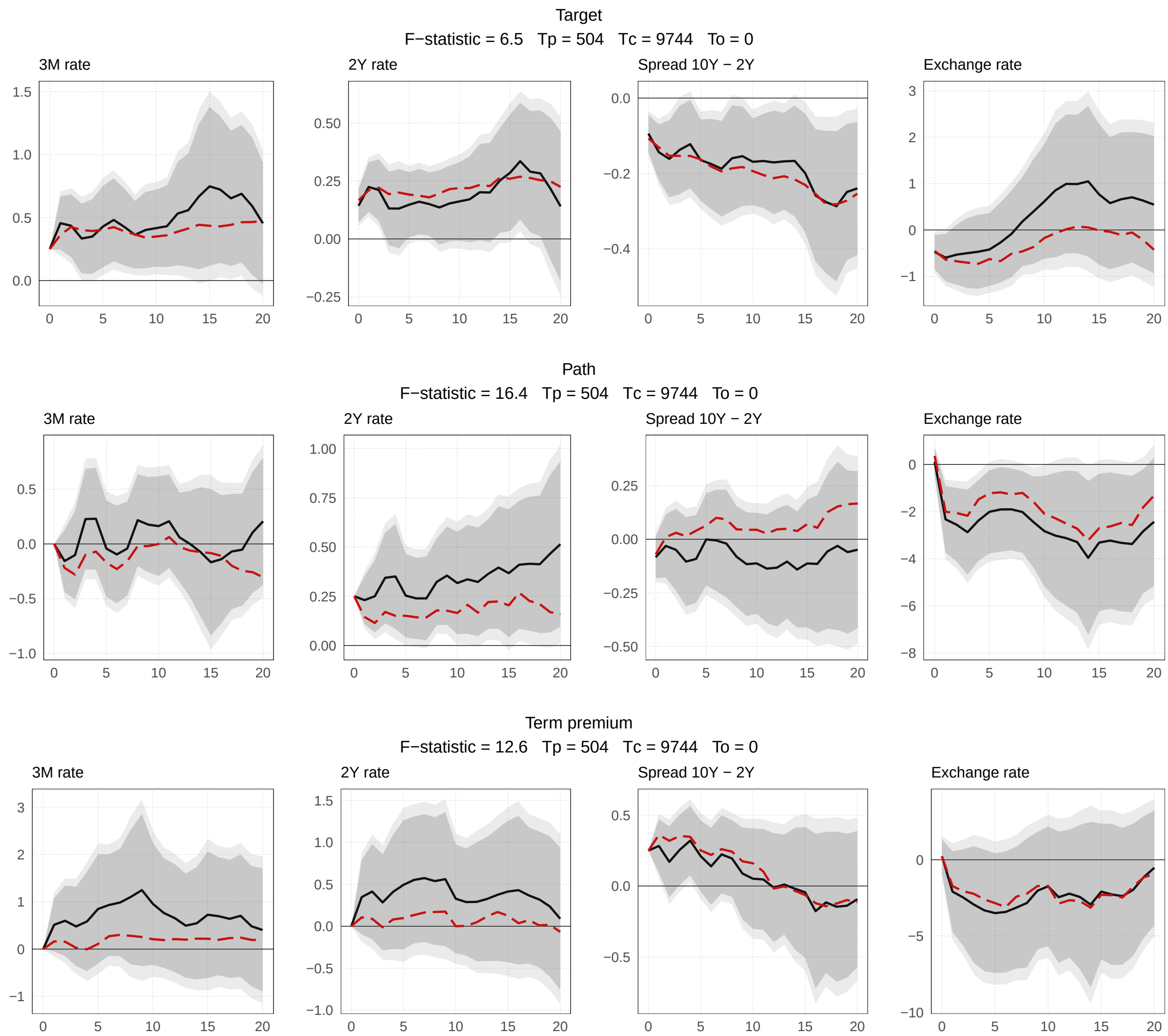
Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The model is estimated on a sample excluding days with decisions by the ECB and the Bank of England. The horizontal axis is measured in working days (excluding weekends and holidays). All interest rate responses are measured in percentage points. The exchange rate response is measured in percent. The red dashed lines give the responses in the baseline model. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy event days, control days, and other days, respectively.

Figure 11 — At the effective lower bound



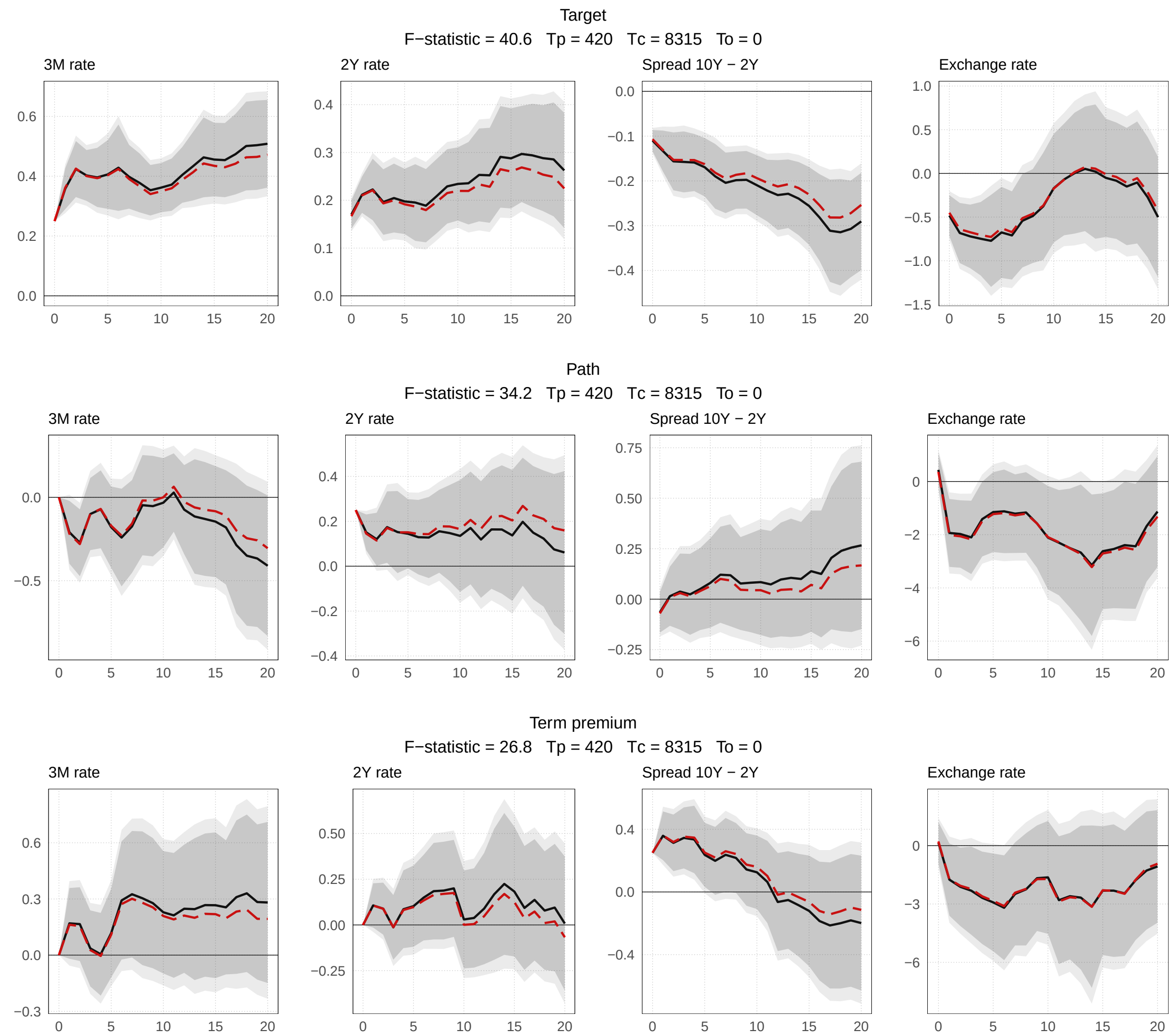
Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The model is estimated on a sample restricted to the effective lower bound period. The horizontal axis is measured in working days (excluding weekends and holidays). All interest rate responses are measured in percentage points. The exchange rate response is measured in percent. The red dashed lines give the responses in the baseline model. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy event days, control days, and other days, respectively.

Figure 12 — Long sample (1982–2022)



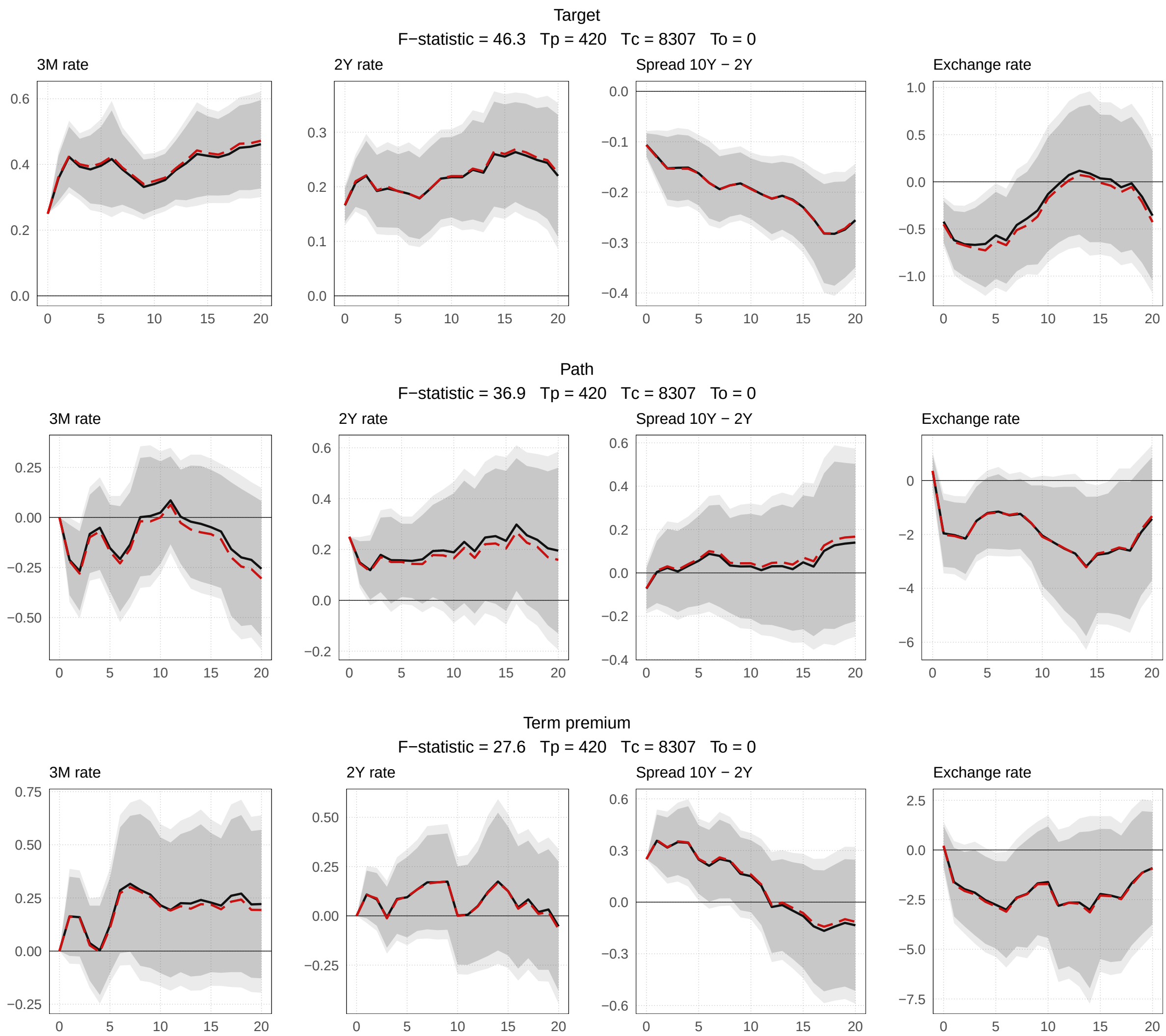
Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The model is estimated on a long sample from 1982–2022. The horizontal axis is measured in working days (excluding weekends and holidays). All interest rate responses are measured in percentage points. The exchange rate response is measured in percent. The red dashed lines give the responses in the baseline model. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy event days, control days, and other days, respectively.

Figure 13 — No controls



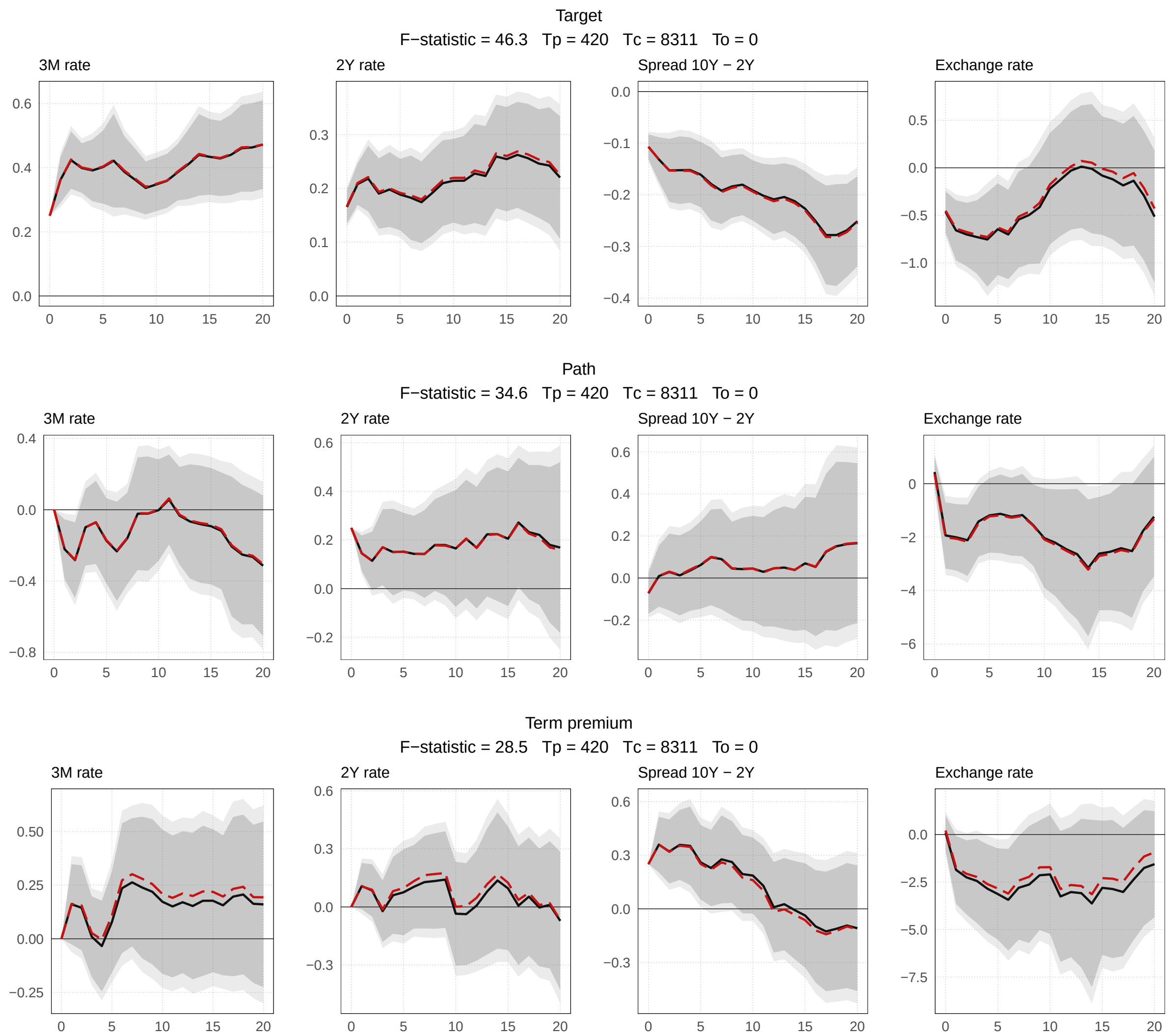
Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The model is estimated without controls. The horizontal axis is measured in working days (excluding weekends and holidays). All interest rate responses are measured in percentage points. The exchange rate response is measured in percent. The red dashed lines give the responses in the baseline model. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy event days, control days, and other days, respectively.

Figure 14 — Additional lags ($P = 8$)



Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The model includes additional lags of the dependent variables ($P = 8$). The horizontal axis is measured in working days (excluding weekends and holidays). All interest rate responses are measured in percentage points. The exchange rate response is measured in percent. The red dashed lines give the responses in the baseline model. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy event days, control days, and other days, respectively.

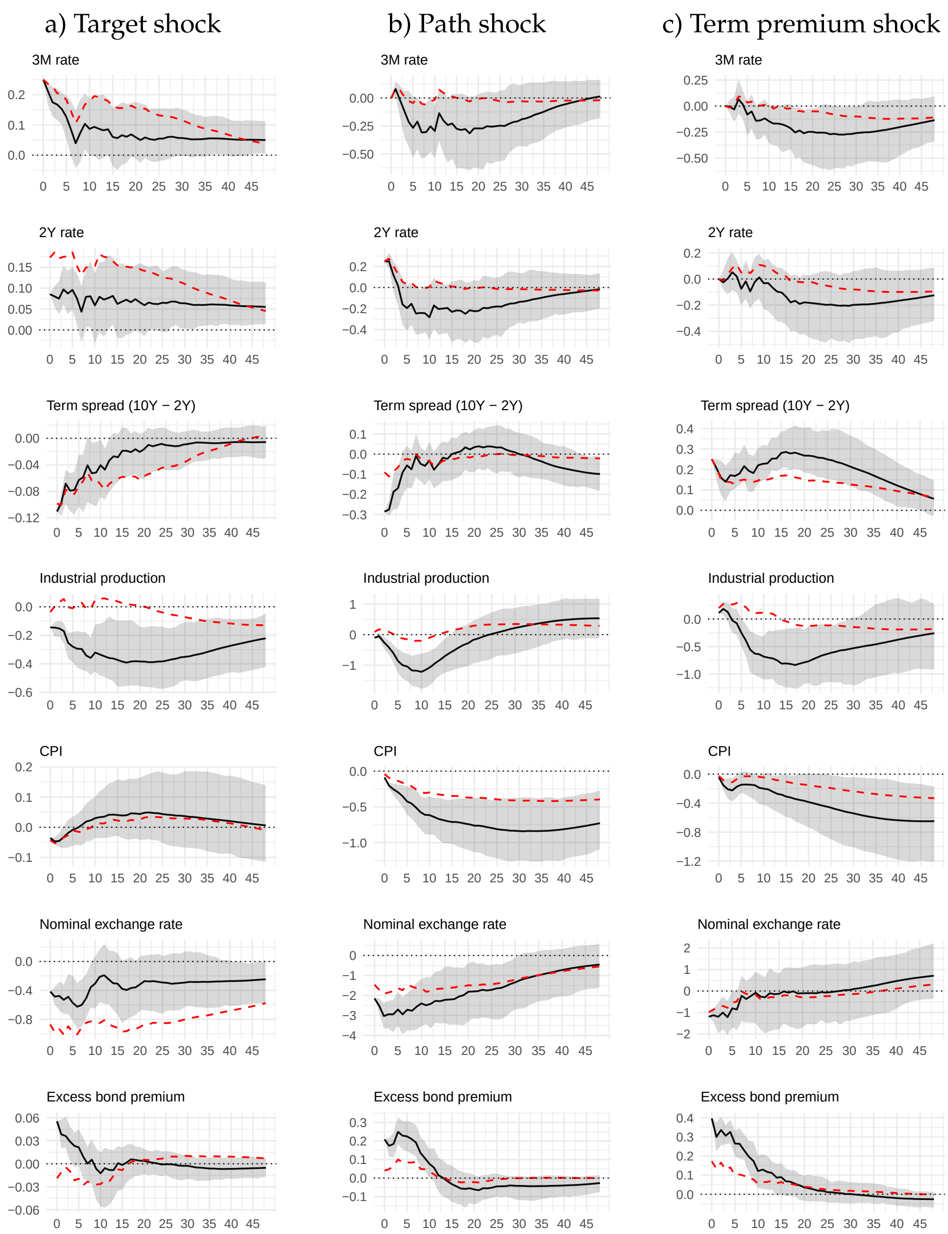
Figure 15 — Additional controls



Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The model is estimated with additional controls (stock price index, commodity price index, corporate bond spread, news sentiment index). The horizontal axis is measured in working days (excluding weekends and holidays). All interest rate responses are measured in percentage points. The exchange rate response is measured in percent. The red dashed lines give the responses in the baseline model. 90% and 95% confidence intervals are based on HAC-robust standard errors. T_p, T_c, T_o denote the number of policy event days, control days, and other days, respectively.

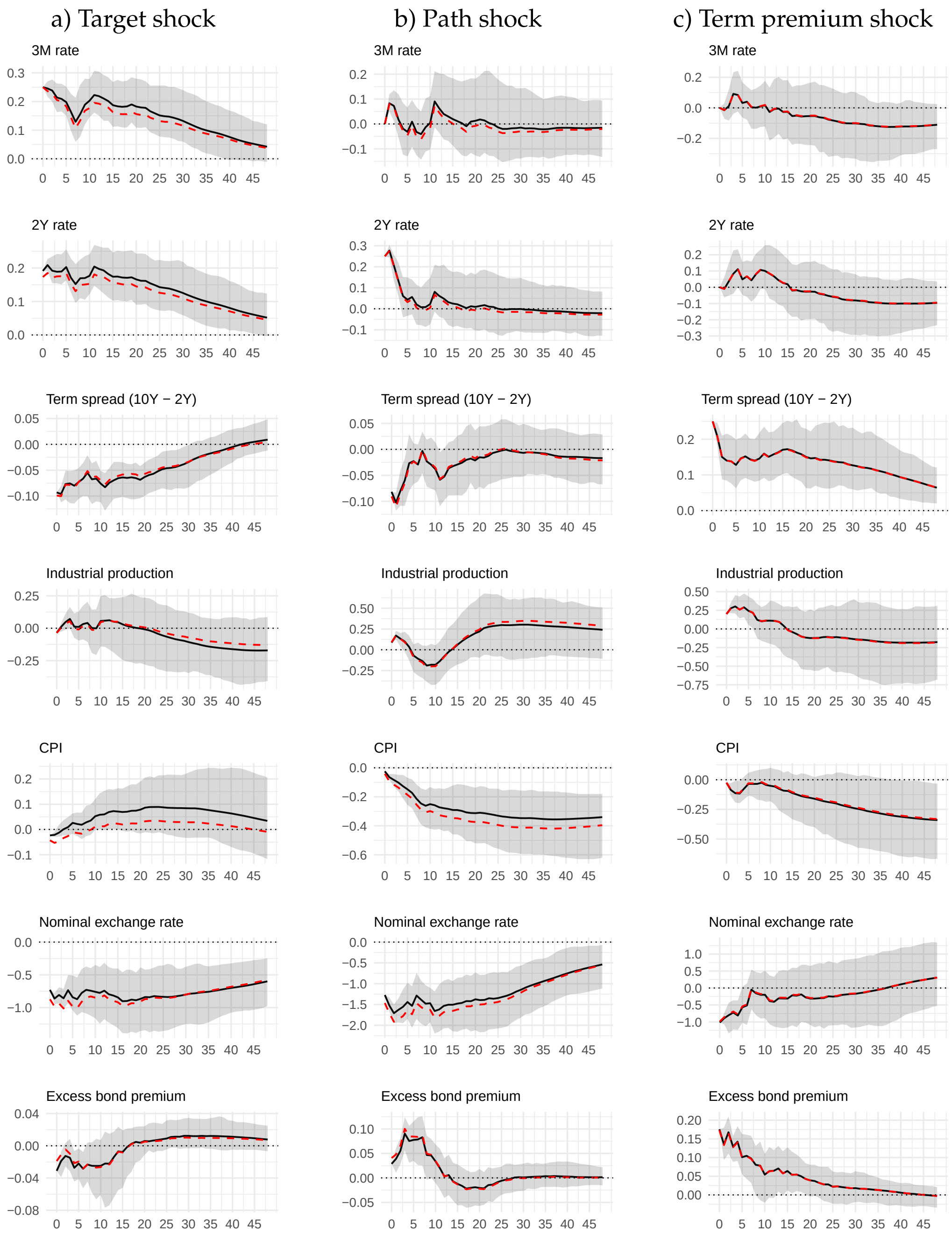
G.2 Monthly responses

Figure 16 — With poor man's sign restrictions



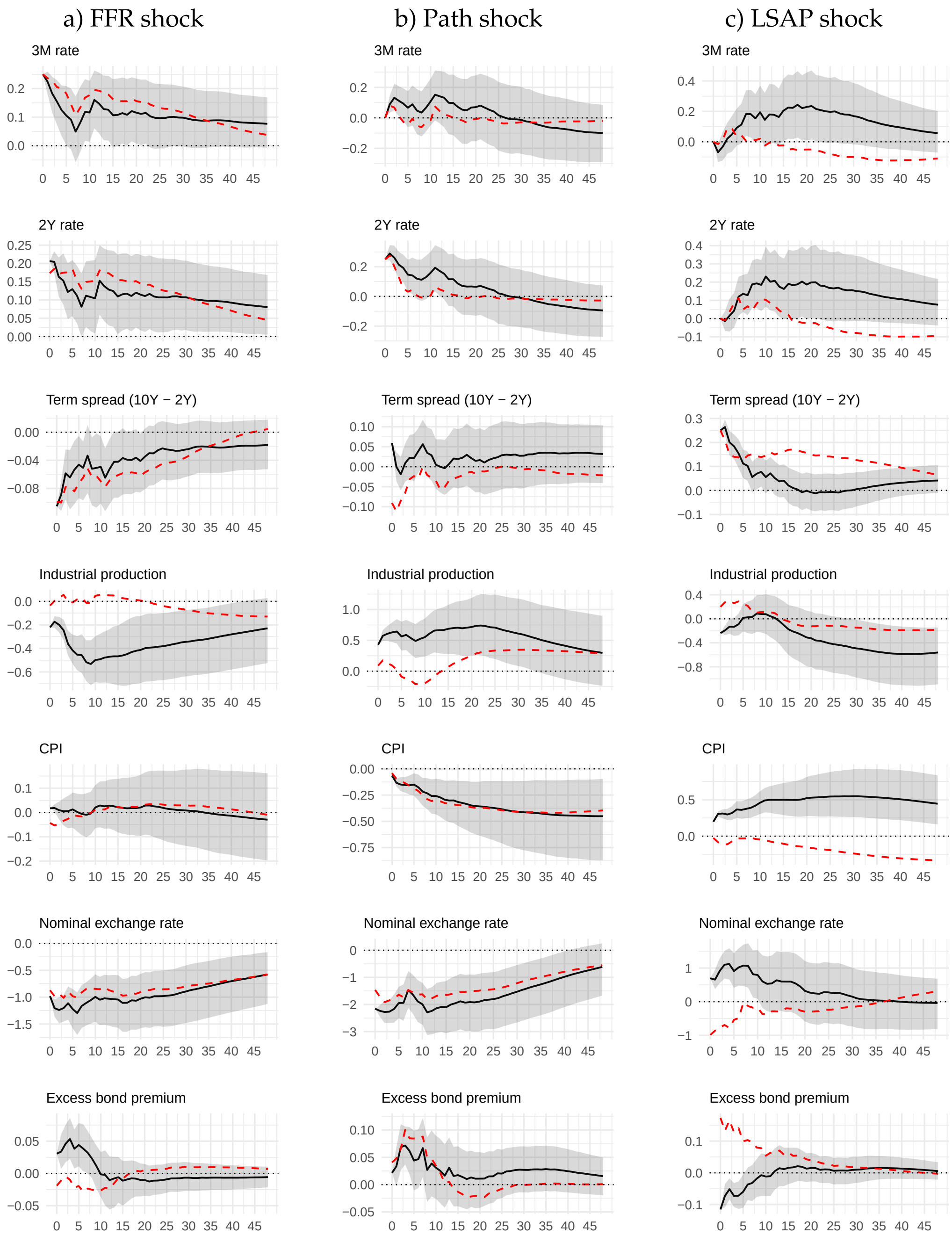
Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The red dashed lines indicate our baseline responses. The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. Shocks that move in the same direction as stock prices are set to zero (see Jarociński & Karadi, 2020). The horizontal axis is measured in months. All interest rate and bond premium responses are measured in percentage points. All other responses are measured in percent. 90% confidence intervals are based on a moving block bootstrap with 10,000 replications.

Figure 17 — Setting the target to zero at the effective lower bound



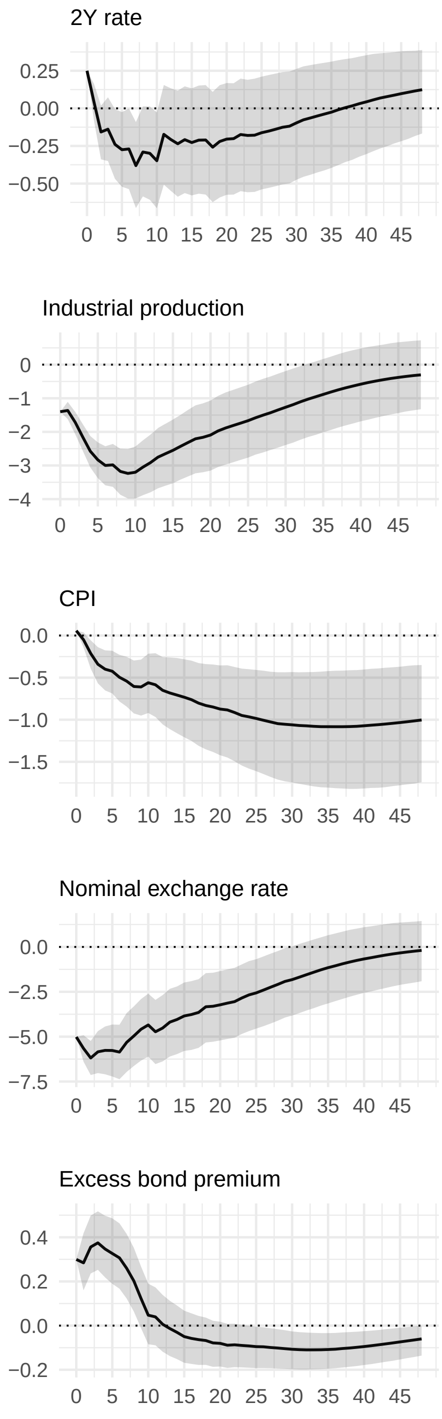
Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The red dashed lines indicate our baseline responses. The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The target shock is set to zero at the effective lower bound. The horizontal axis is measured in months. All interest rate and bond premium responses are measured in percentage points. All other responses are measured in percent. 90% confidence intervals are based on a moving block bootstrap with 10,000 replications.

Figure 18 — Using the shocks of Swanson (2021) as external instruments



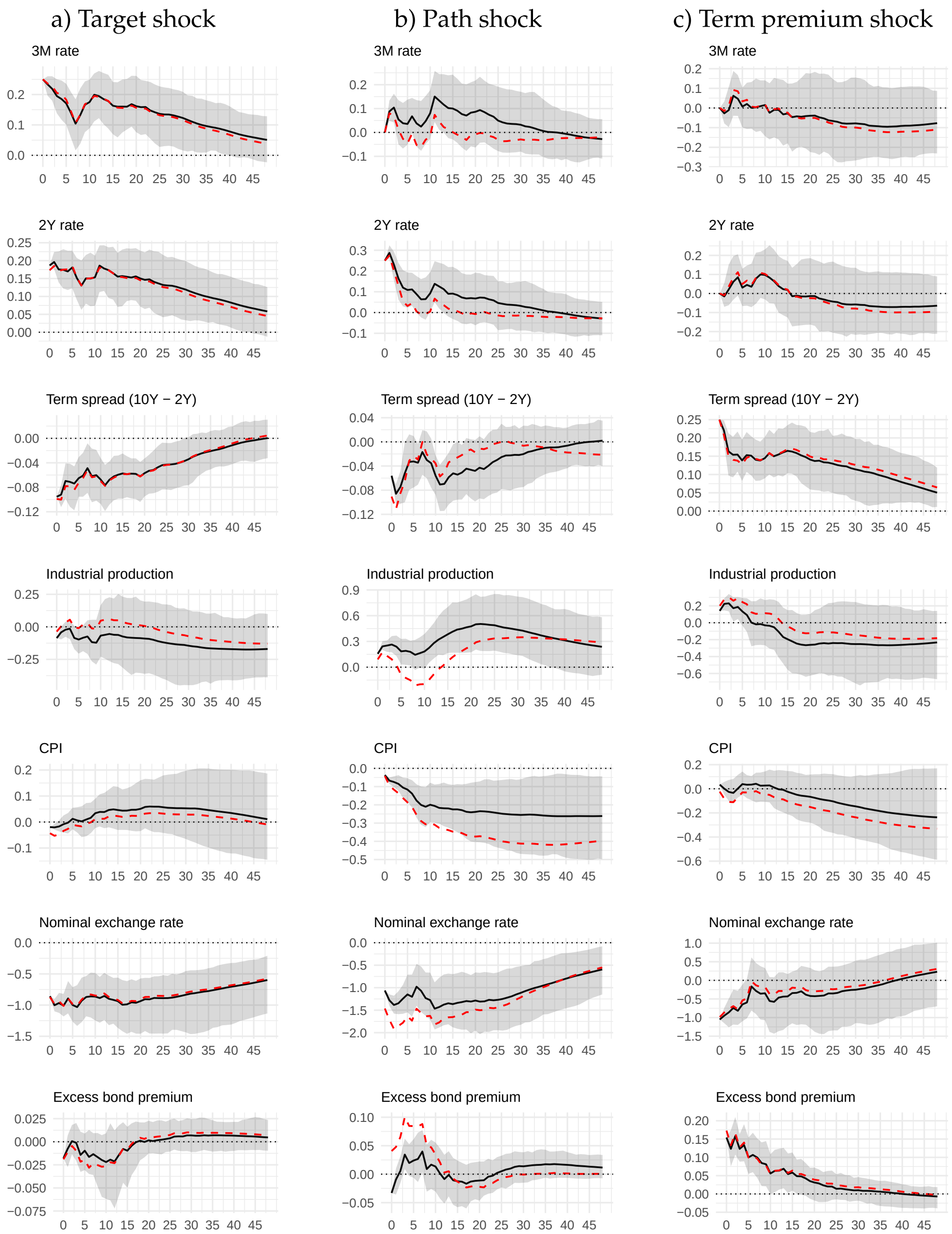
Notes: Impulse responses to monetary policy shocks identified by Swanson (2021). The red dashed lines indicate our baseline responses. The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The horizontal axis is measured in months. All interest rate and bond premium responses are measured in percentage points. All other responses are measured in percent. 90% confidence intervals are based on a moving block bootstrap with 10,000 replications.

Figure 19 — Using the shocks of Bu et al. (2021) as external instruments



Notes: Impulse responses to monetary policy shocks identified by Bu et al. (2021). The responses are normalized to a 25 bp increase in the 2Y rate. The horizontal axis is measured in months. All interest rate and bond premium responses are measured in percentage points. All other responses are measured in percent. 90% confidence intervals are based on a moving block bootstrap with 10,000 replications.

Figure 20 — Using our shocks together with the Swanson (2021) shocks as external instruments



Notes: Impulse responses to monetary policy shocks (target, path, and term premium). The red dashed lines indicate our baseline responses. The responses are normalized to a 25 bp increase in the 3M rate, 2Y rate, and 10Y - 2Y spread, respectively. The model uses our baseline shocks and the shocks by Swanson (2021) as external instruments. It is, therefore, overidentified. The horizontal axis is measured in months. All interest rate and bond premium responses are measured in percentage points. All other responses are measured in percent. 90% confidence intervals are based on a moving block bootstrap with 10,000 replications.

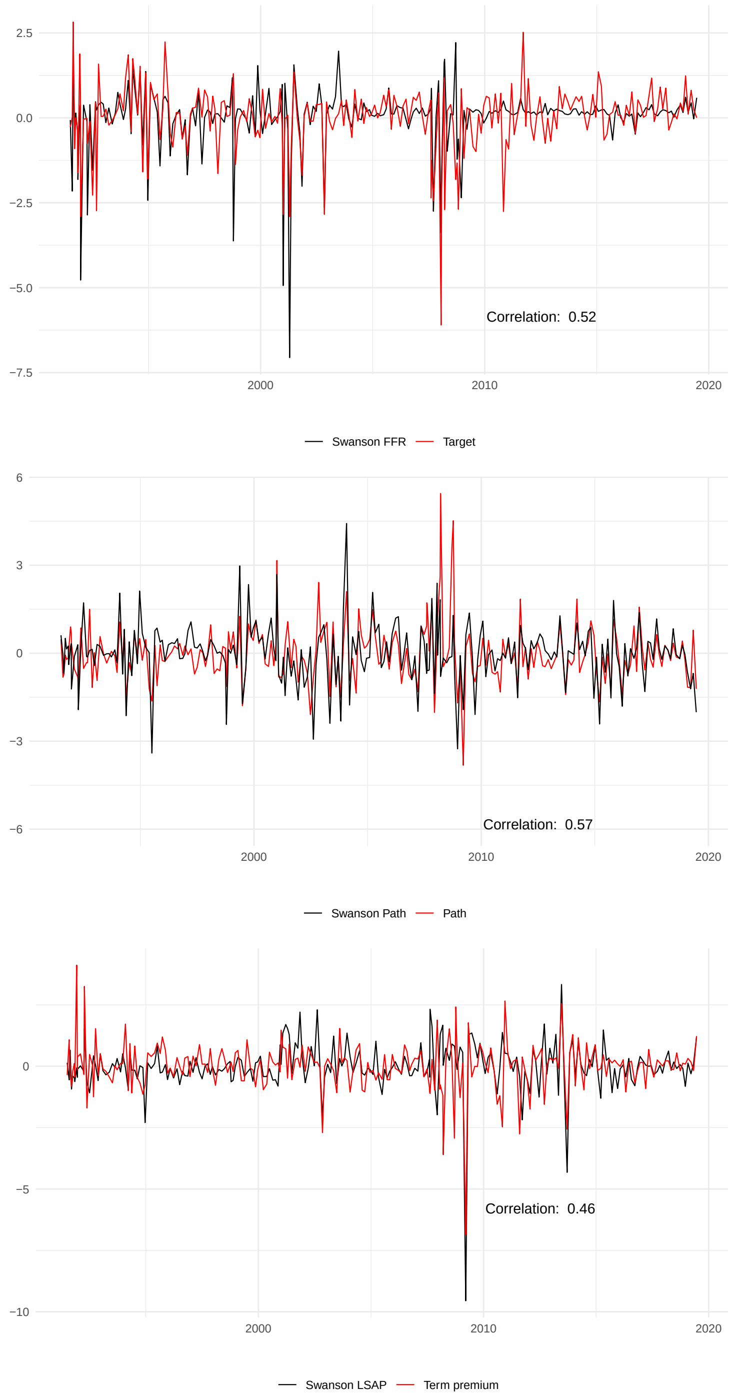
H Supplementary material

Table 3 — Comparison to existing shocks aggregated to monthly frequency

	Swanson FFR	Swanson Path	Swanson LSAP	Bu et al. (2021)
Target	0.955^{***}	0.042	-0.293^{***}	0.052^{***}
	(0.312)	(0.184)	(0.098)	(0.019)
Path	0.448	1.739^{***}	0.478^{*}	0.104^{***}
	(0.304)	(0.358)	(0.260)	(0.017)
Term premium	-1.049^{**}	0.372	1.259^{**}	0.005
	(0.413)	(0.327)	(0.583)	(0.020)
Observations	336	336	336	312
R^2	0.252	0.250	0.250	0.551
Adjusted R^2	0.245	0.243	0.244	0.546

Notes: The table shows regressions of our estimated monetary policy shocks on the shocks provided by Swanson (2021) and Bu et al. (2021). Before estimating the regressions, the shocks have been aggregated to monthly by summing them up within the same month. Significance levels are given by *p<0.1; **p<0.05; ***p<0.01. HAC robust standard errors are in parentheses.

Figure 21 — Heteroscedasticity-based compared to high-frequency shocks



Notes: These graphs compare our estimated three-dimensional monetary policy shock series to the high-frequency series by Swanson (2021) on FOMC announcement dates from July 1991 to June 2019. For readability, the series have been normalized to have a mean of zero and a standard deviation of one.

Figure 22 — Heteroscedasticity-based shocks over long and short sample

Notes: These graphs compare our estimated three-dimensional daily monetary policy shock series once estimated on a sample from 1982 to 2019 and once on a sample from 1988 to 2019. For readability, the series have been normalized to have a mean of zero and a standard deviation of one.

Figure 23 — Heteroscedasticity-based shocks with alternative interest rate data

Notes: These graphs compare our three-dimensional monetary policy shock series to the high-frequency series by Swanson (2021) on FOMC announcement dates from July 1991 to June 2019. The estimates are based on alternative interest rate data from the Federal Reserve Board. For readability, the series have been normalized to have a mean of zero and a standard deviation of one.

Table 4 — Comparison to existing shocks using alternative interest rate data

	Swanson FFR	Swanson Path	Swanson LSAP	Bu et al. (2021)
Target	1.852***	0.316	−0.273*	0.150***
	(0.313)	(0.307)	(0.146)	(0.014)
Path	0.567**	2.334***	0.297	0.148***
	(0.245)	(0.417)	(0.208)	(0.010)
Term premium	−0.630*	0.745**	2.070***	0.003
	(0.382)	(0.331)	(0.593)	(0.011)
Observations	241	241	241	215
R^2	0.385	0.376	0.360	0.788
Adjusted R^2	0.378	0.368	0.352	0.785

Notes: The table shows regressions of our estimated monetary policy shocks using alternative interest rate data by the Federal Reserve Board on the shocks provided by Swanson (2021) and Bu et al. (2021). Significance levels are given by *p<0.1; **p<0.05; ***p<0.01. HAC robust standard errors are in parentheses.

Table 5 — Correlation matrix of monetary policy shocks

	Target	Path	Term premium	FFR	Path	LSAP	BRW
Target	1.00						
Path	-0.23	1.00					
Term premium	0.21	-0.11	1.00				
Swanson FFR	0.52	0.03	-0.10	1.00			
Swanson Path	-0.12	0.57	0.03	-0.00	1.00		
Swanson LSAP	-0.14	0.18	0.46	-0.00	0.00	1.00	
BRW	0.42	0.73	0.06	0.33	0.49	0.03	1.00

Notes: The table shows the correlation matrix of the monetary policy shocks. For comparison, we also add the shocks by Swanson (2021) and Bu et al. (2021).

Table 6 — Correlation matrix of monetary policy shocks censoring target shock at effective lower bound

	Target	Path	Term premium	FFR	Path	LSAP	BRW
Target	1.00						
Path	-0.27	1.00					
Term premium	0.28	-0.11	1.00				
Swanson FFR	0.58	0.03	-0.10	1.00			
Swanson Path	-0.14	0.57	0.03	-0.00	1.00		
Swanson LSAP	-0.09	0.18	0.46	-0.00	0.00	1.00	
BRW	0.28	0.73	0.06	0.33	0.49	0.03	1.00

Notes: The table shows the correlation matrix of the monetary policy shocks. For comparison, we also add the shocks by Swanson (2021) and Bu et al. (2021). The target shock is set to zero at the effective lower bound.