Australian National University
Crawford School of Public Policy

CAMA

Centre for Applied Macroeconomic Analysis

UIP Holds Conditional on Monetary Policy Shocks

CAMA Working Paper 68/2026
August 2026

Naveed Javed
Reserve Bank of New Zealand

Nicolas Groshenny
GAINS, Le Mans Université
Centre for Applied Macroeconomic Analysis, ANU

Abstract

We estimate SVAR models for six advanced small open economies to evaluate the extent of deviations from uncovered interest parity following SOE and US monetary policy shocks. Since UIP implies that currency movements are driven by the expected path of the spread between the domestic and foreign short-term interest rates, our econometric strategy disciplines the dynamic response of the SOE-US policy rate differential to monetary disturbances. Specifically, our approach jointly identifies the systematic component of SOE and US monetary policy by combining block exogeneity and sign restrictions on policy parameters. We find that UIP broadly holds conditional on SOE and US monetary policy shocks irrespective of the observed exchange rate overshooting patterns.

Keywords

uncovered interest rate parity, monetary policy shocks, systematic component of monetary policy, forward discount puzzle, vector autoregressions, small open economies, block exogeneity

JEL Classification

C32, E52, F31, F41

Address for correspondence:

(E) cama.admin@anu.edu.au

ISSN 2206-0332

UIP holds conditional on monetary policy shocks*

Naveed Javed† Nicolas Groshenny‡

August 8, 2026

Abstract

We estimate SVAR models for six advanced small open economies to evaluate the extent of deviations from uncovered interest parity following SOE and US monetary policy shocks. Since UIP implies that currency movements are driven by the expected path of the spread between the domestic and foreign short-term interest rates, our econometric strategy disciplines the dynamic response of the SOE-US policy rate differential to monetary disturbances. Specifically, our approach jointly identifies the systematic component of SOE and US monetary policy by combining block exogeneity and sign restrictions on policy parameters. We find that UIP broadly holds conditional on SOE and US monetary policy shocks irrespective of the observed exchange rate overshooting patterns.

Keywords: Uncovered interest rate parity, Monetary policy shocks, Systematic component of monetary policy, Forward discount puzzle, Vector autoregressions, Small open economies, Block exogeneity.

JEL codes **C32**, **E52, F31, F41**.

*For discussions and comments, we thank Fabio Bagliano, Efrem Castelnuovo, Jamie Cross, Renée Fry-McKibbin, Francesco Furlanetto, James Graham, Eleonora Granziera, Punnoose Jacob, Mariano Kulish, Van Luu, Tommaso Monacelli, James Morley, Niall Peat, Matthew Read, Tim Robinson, David Stephan, Olav Syrstad, Anthony Terriau, Benjamin Wong as well as conference and seminar participants at LéP (Poitiers), WAMS Sydney 2022, ESAM Sydney 2023, CEM Melbourne 2023, ANZESG Wellington 2024, IMAC Rennes 2024, GDRE Money and Banking Rennes 2026.

†Reserve Bank of New Zealand, 2 The Terrace, Wellington 6140.
naveed.javed@rbnz.govt.nz (corresponding author).

‡GAINS, Le Mans Université and CAMA. nicolas.groshenny@univ-lemans.fr.

1 Introduction

To this day, UIP remains a fundamental building block in a wide range of open-economy macroeconomic frameworks featuring rational expectations and sticky prices, from the classic models of Dornbusch (1976) and Obstfeld and Rogoff (1995b) to modern Dynamic Stochastic General Equilibrium (DSGE) models of the New Open Economy Macroeconomics (NOEM) paradigm (Lane, 2001; Lubik and Schorfheide, 2006; Corsetti, 2008). Formally, the UIP condition can be expressed as:

$$r_t \approx r_t^* + \mathbb{E}_t\{s_{t+1}\} - s_t \ , \tag{1}$$

where r_t and r_t^* denote respectively the domestic and foreign riskless short-term nominal interest rates, s_t is the log of the nominal exchange rate (defined as the domestic price of the foreign currency) and $\mathbb{E}_t$ stands for the rational expectations operator conditional on information available at time t. UIP means that, under perfect capital mobility, the returns from investing in domestic or foreign one-period default-free bonds should roughly be equal once expressed in the same currency. Rearranging Equation (1) as follows:

$$\mathbb{E}_t\{s_{t+1}\} - s_t \approx r_t - r_t^* \ , \tag{2}$$

shows that, according to UIP, the *ex-ante* currency depreciation rate must generally equal the domestic to foreign short-term interest differential (Engel, 2014). UIP thus requires that a surprise tightening of domestic monetary policy triggers a specific response from the exchange rate to eliminate arbitrage opportunities. The benchmark framework of Dornbusch (1976) famously formalizes this mechanism and predicts that a contractionary domestic monetary shock causes the currency to overshoot instantaneously, i.e., an immediate discontinuous appreciation ($\Delta s_0 < 0$) followed by a gradual depreciation ($\mathbb{E}_0\{s_1\} > s_0$).[1]

Several empirical studies that estimate structural vector autoregressions (SVAR) report evidence of large and persistent deviations from UIP conditional on monetary policy shocks. This finding, known as the 'forward discount puzzle', is often coupled with the observation of delayed overshooting – a gradual exchange rate appreciation

[1] $\Delta s_0 = s_0 - \bar{s}$, where $\bar{s}$ is the steady-state log exchange rate, i.e., the value of the log exchange rate before the shock.

for over a year in response to a contractionary domestic monetary policy shock – in contrast to Dornbusch's overshooting.[2] The pervasiveness of the forward discount and delayed overshooting puzzles has motivated some DSGE modelers to alter the UIP condition in order to obtain a hump-shaped response of the exchange rate to a monetary policy shock (Adolfson et al., 2008).[3] Indeed, Faust and Rogers (2003) assert that "*the UIP element of the Dornbusch model is most problematic empirically*".

It is crucial, however, to keep in mind that Dornbusch's overshooting is not a general implication of UIP. Dornbusch's prediction hinges on two prerequisites: (i) The foreign policy rate is exogenous (or, at least, it does not react to the shock); (ii) Following the shock, the domestic policy rate reverts monotonously to its pre-shock level. In other words, the Dornbusch's overshooting narrative is incomplete and peculiar. Solving Equation (2) forward for s_t exposes deeper and more general implications of UIP:

$$s_t \approx -\sum_{j=0}^{\infty} \mathbb{E}_t(r_{t+j} - r^*_{t+j}) + \lim_{j\to\infty} \mathbb{E}_t\{s_{t+j+1}\}\ . \tag{3}$$

First, the exchange rate is fundamentally a forward-looking variable. Second, for UIP to hold, the impact response of the exchange rate to the domestic monetary shock must offset the cumulated sum of present and expected future interest differentials. Put differently, UIP ties currency movements to the *endogenous* dynamic paths of the domestic and foreign policy rates (Engel, 2014; Galí, 2020).

In this paper, we shed new light on the link between UIP deviations and exchange rate overshooting patterns (instantaneous or delayed) conditional on monetary disturbances by jointly identifying the domestic and the foreign monetary policy rule. Specifically, we contribute to the debate sparked by Scholl and Uhlig (2008). Their influential finding that "*the forward discount puzzle is robust even without delayed overshooting*" has recently been challenged by Rüth and Van der Veken (2023). While Scholl and Uhlig (2008) and Rüth and Van der Veken (2023) conduct SVAR-based evaluations of UIP conditional on US monetary policy shocks, we follow the approach of Bjørnland (2009) and Bjørnland and Halvorsen (2014) and estimate SVAR models

[2]See Eichenbaum and Evans (1995), Cushman and Zha (1997), Kim and Roubini (2000), Faust and Rogers (2003), Kim (2005), Scholl and Uhlig (2008) and Kim et al. (2017) among others.

[3]See also Adolfson et al. (2007a), Christiano et al. (2011), Grabek and Klos (2013) and Hoffmann et al. (2021) among others.

for six advanced SOEs featuring floating exchange rates and Inflation Targeting: Australia, Canada, New Zealand, Norway, Sweden, and the United Kingdom. In contrast to the existing literature, we evaluate the extent of UIP deviations conditional on both domestic (SOE) and foreign (US) monetary policy shocks.

Our main finding reveals that UIP holds pretty well across all SOE-US pairs examined, regardless of the observed idiosyncratic exchange rate overshooting patterns. Specifically, we do not observe large and persistent deviations from UIP conditional on either SOE or US monetary shocks: at most horizons, the response of the depreciation rate approximately offsets the interest rate differential. Our result contrasts sharply with Faust and Rogers (2003) and Scholl and Uhlig (2008), while it aligns with the evidence reported by Bjørnland (2009) for SOE shocks, and Rüth (2020) and Rüth and Van der Veken (2023) for US shocks.

Our econometric strategy is uniquely designed for examining the validity of UIP conditional on monetary shocks. Firstly, since UIP implies that currency movements are driven by the expected path of the spread between the domestic and foreign short-term interest rates, our approach aims to discipline the dynamic response of the SOE-US policy rate differential to monetary shocks by jointly identifying the systematic component of SOE and US monetary policy. Specifically, our identification scheme combines block exogeneity (Cushman and Zha, 1997) with a small set of agnostic sign restrictions imposed on the parameters of the SOE and US monetary policy rules (Arias et al., 2019).

Secondly, our approach jointly identifies SOE and US monetary shocks, allowing us to investigate whether the extent of UIP deviations differs according to the origin of the monetary impulse.[4] As a matter of fact, there is a stark asymmetry between the Federal Reserve and any SOE central bank: to put it plainly, we live in a 'dollar world' (Gourinchas, 2021) and US monetary policy is the main driver of global funding costs (Miranda-Agrippino and Rey, 2020). Our approach therefore recognizes that a SOE

[4] Several papers focus on US monetary shocks (Eichenbaum and Evans, 1995; Faust and Rogers, 2003; Scholl and Uhlig, 2008; Kim et al., 2017; Rüth, 2020; Castelnuovo et al., 2022; Rüth and Van der Veken, 2023). Others study the impacts of non-US monetary shocks (Cushman and Zha, 1997; Kim and Roubini, 2000; Bjørnland, 2009; Bjørnland and Halvorsen, 2014; Kim and Lim, 2018; Terrell et al., 2026). Earlier papers consider relative money shocks without taking a stance on the origin of disturbances (Clarida and Gali, 1994; Rogers, 1999).

central bank may react to shifts in US monetary policy but not vice versa, with the consequence that the dynamic effects of SOE and US monetary shocks on the interest differential may be quite different. Once again, this is a key point since UIP binds exchange rate movements to the expected SOE-US policy-spread path.[5]

Thirdly, our strategy allows for an *instantaneous* interaction between the bilateral exchange rate and the policy rates.[6] This is important as several authors argue that delayed overshooting may be an artifact of overly restrictive recursive identification schemes that preclude simultaneous interaction among financial and money-market variables.[7]

The next section places the contribution of our paper against the backdrop of the related literature. Section 3 describes the data, the identification scheme and the Bayesian estimation. Sections 4 presents our main result while Section 5 contains robustness checks. Section 6 concludes.

2 Related literature

Our paper intersects with two strands of the SVAR literature examining the exchange rate effects of monetary policy shocks. The first strand focuses on the effects of US shocks while the second strand analyzes the consequences of SOE shocks. Starting with the first strand, Eichenbaum and Evans (1995) work with a recursive identification scheme and find that a contractionary US monetary policy shock leads to large and protracted UIP deviations accompanied by a persistent appreciation of both the real and nominal exchange rates.[8] Faust and Rogers (2003) and Scholl and Uhlig (2008)

[5]Cushman and Zha (1997) show that in the SOE setting, explicitly accounting for endogenous policy reactions is essential for UIP to hold. In the same vein, McCallum (1994) demonstrates that serious UIP violations occur in regressions that ignore endogenous monetary policy reactions to interest rates and exchange rates.

[6]We consider *bilateral* SOE/US real exchange rates, departing from the real effective exchange rates (REER) employed by Bjørnland (2009). Working with bilateral exchange rates (instead of trade-weighted indices) allows us to implement a clean and transparent test of UIP, mapping directly each SOE/US exchange rate to its corresponding SOE-US short-term interest differential. Put differently, we do not construct a synthetic foreign interest rate for each SOE. Eichenbaum and Evans (1995), Faust and Rogers (2003) and Scholl and Uhlig (2008) also use bilateral exchange rates.

[7]See Faust and Rogers (2003), Bjørnland (2009) and Rüth (2020). For a different point of view, see Kim (2005) and Landry (2009).

[8]The observed similarities between the responses of the real and nominal exchange rates in the short-to-medium run may be explained by the presence of nominal rigidities.

tackle the rigidity of recursive identification schemes by employing sign restrictions on the impulse responses of selected variables.[9] Both studies document that monetary shocks lead to long and sizeable departures from UIP, albeit disagreeing on the robustness of delayed overshooting. Faust and Rogers (2003) argue that delayed overshooting is a fragile result, whereas Scholl and Uhlig (2008) report evidence in favor of delayed overshooting. Scholl and Uhlig (2008) also investigate whether the forward discount puzzle could be a twin appearance of delayed overshooting. Using an identification scheme that rules out delayed overshooting by construction, they conclude that the forward discount puzzle is robust even without delayed overshooting. Recent papers refine these findings by exploring subsample periods and more sophisticated identification strategies. Working with the identification scheme of Scholl and Uhlig (2008), Kim et al. (2017) report evidence of delayed overshooting and UIP deviations during the Volcker era, while instantaneous overshooting and UIP seem to hold in the post-Volcker period. Rüth (2020) estimates a proxy-SVAR model and finds evidence consistent with instantaneous overshooting and UIP, even for the Volcker era. Castelnuovo et al. (2022) extend the analysis of Kim et al. (2017) by adding sign restrictions on policy coefficients and find robust evidence of instantaneous overshooting across different sample periods. Rüth and Van der Veken (2023) focus on the pre-GFC period and implement an identification scheme featuring sign restrictions on both impulse responses and structural parameters, combined with narrative sign restrictions. They report evidence of delayed overshooting while finding little empirical support for the forward discount puzzle. Müller et al. (2024) study the response of the bilateral US-UK exchange rate to US monetary policy shocks. They find that delayed overshooting may coexist with insignificant deviations from UIP. Using a direct measure of market participants' expectations about the future level of the exchange rate, they show that delayed overshooting is not due to a failure of UIP, but rather reflects the sluggish adjustment of investors' expectations. Braig et al. (2024) utilize the DSGE model of Adolfson et al. (2007b) as data-generating process and demonstrate that imposing sign restrictions on policy coefficients in SVARs is key to resolve the delayed-overshooting and forward-discount puzzles.[10]

[9] Faust and Rogers (2003) impose most of their sign restrictions on impact only. In contrast, Scholl and Uhlig (2008) impose most of their sign restrictions for a full year following the shock.

[10] See also Yang et al. (2024).

Turning to the second strand of the literature, which investigates the effects of SOE monetary policy shocks, Cushman and Zha (1997) and Kim and Roubini (2000) impose block exogeneity to disentangle domestic shocks from global influences. Both studies document moderate and transitory departures from UIP and exchange rate dynamics that roughly align with instantaneous overshooting. Bjørnland (2009) estimate SVAR models for four SOEs. Her identification scheme allows simultaneous interaction between the policy rate and the exchange rate while imposing long-run neutrality on the real exchange rate. Her findings corroborate instantaneous overshooting and UIP. Terrell et al. (2026) extend the work of Bjørnland (2009) by estimating a time-varying SVAR with stochastic volatility. They obtain evidence in line with Bjørnland (2009).[11] Kim and Lim (2018) consider four SOEs and impose sign restrictions on IRFs. They find little evidence of UIP deviations and document a short delay in overshooting for some SOEs.[12]

From a methodological perspective, our contribution lies in integrating block exogeneity (Cushman and Zha, 1997) with agnostic sign restrictions on policy coefficients (Arias et al., 2019) to jointly identify the systematic component of US and SOE monetary policy. In terms of substantive results, by explicitly modeling the SOE central bank's reaction function to US monetary policy shifts, our framework demonstrates that diverse exchange rate overshooting patterns remain fundamentally consistent with the UIP condition.

3 Econometric strategy

3.1 Data

We consider the following six advanced SOEs: Australia, Canada, New Zealand, Norway, Sweden and the UK. We use quarterly observations from 1992:Q1 to 2019:Q4. The starting date corresponds roughly to the adoption of Inflation Targeting by the six SOEs (Kim and Lim, 2018). The end date marks the onset of the COVID-19

[11] Bjørnland and Halvorsen (2014) consider six SOEs and impose a combination of sign and exclusion restrictions on IRFs. They find no evidence of delayed overshooting. They do not report results for UIP.

[12] See also Jääskelä and Jennings (2011), Read (2023) and Fisher and Huh (2023) for related studies focusing on Australia.

pandemic.[13] Following Cushman and Zha (1997), we organize the variables into two blocks, a domestic one and a foreign one. The domestic block represents the SOE, while the foreign block stands for the US economy. The domestic block includes real GDP (y), inflation (π) measured as the annualized quarterly rate of change in the consumer price index, the policy rate (r) proxied by the 3-month interbank rate, and the bilateral SOE/US real exchange rate (e). For Sweden and the UK, we use the shadow rate series constructed respectively by De Rezende and Ristiniemi (2023) and Wu and Xia (2016). The foreign block consists of four variables: US real GDP (y^*), US inflation (π^*), Moody's Baa corporate credit spread (cs^*), and the US shadow rate (r^*) constructed by Wu and Xia (2016). All variables are expressed in log levels except the credit spread, inflation rates and policy rates, which are expressed in percentage points.[14]

3.2 Model

Our structural VAR model is given by:

$$\mathbf{y_t'A_0} = \sum_{l=1}^{p} \mathbf{y}_{t-l}'\mathbf{A}_l + \mathbf{c}' + \epsilon_{\mathbf{t}}' \ , \qquad \text{for } 1 \leq \mathbf{t} \leq \mathbf{T} \tag{4}$$

where $\mathbf{y_t'} = \begin{bmatrix}\mathbf{y_{1t}'} & \mathbf{y_{2t}'}\end{bmatrix}$, $\mathbf{y_{1t}'} = [y_t^*, \pi_t^*, cs_t^*, r_t^*]$ and $\mathbf{y_{2t}'} = [y_t, \pi_t, r_t, e_t]$. $\mathbf{y_{1t}}$ is a $(n_1 \times 1)$ vector of US variables and $\mathbf{y_{2t}}$ is a $(n_2 \times 1)$ vector of SOE variables, with $n = n_1 + n_2$ denoting the total number of variables. Similarly, the vector of structural shocks ϵ_t is divided into two blocks, $\epsilon_t' = \begin{bmatrix}\epsilon_{1t}' & \epsilon_{2t}'\end{bmatrix}$. $\mathbf{A_i}$, for $0 \leq i \leq p$, are $(n \times n)$ matrices of structural parameters, with $\mathbf{A_0}$ invertible. $\mathbf{c}$ is a $(n \times 1)$ vector of constants, p is the lag length, and $\mathbf{T}$ is the sample size. Conditional on past information and initial conditions $\mathbf{y}_0, ..., \mathbf{y}_{1-p}$, the vector ϵ_t is Gaussian with mean zero and covariance matrix $\mathbb{I}_n$. Following Rubio-Ramirez et al. (2010), we can write the SVAR in compact form:

$$\mathbf{y_t'A_0} = \mathbf{x_t'A_+} + \epsilon_t' \ , \tag{5}$$

where $\mathbf{x_t'} = [\mathbf{y_{t-1}'} \dots \mathbf{y_{t-p}'} \ \ 1]$. $\mathbf{A_0}$ and $\mathbf{A_+} = [\mathbf{A_1'} \dots \mathbf{A_p'} \ \ \mathbf{c}']$ are matrices of structural parameters. Post-multiplying Equation (5) by $\mathbf{A_0^{-1}}$, we obtain the reduced-form VAR

[13] See Kim et al. (2017), Kim and Lim (2018) and Castelnuovo et al. (2022) for empirical investigations of the delayed overshooting puzzle that emphasize the importance of estimating the SVAR model over a stable monetary policy regime.

[14] Appendix A provides further details on the dataset.

model:

$$\mathbf{y_t'} = \mathbf{x_t'}\mathbf{B} + u_t' \ , \tag{6}$$

where $\mathbf{B} = \mathbf{A}_+\mathbf{A_0}^{-1}, u_t' = \epsilon_t'\mathbf{A_0}^{-1}$ and $\mathbf{E}[u_t u_t'] = \mathbf{\Sigma} = (\mathbf{A_0}\mathbf{A_0'})^{-1}$. $\mathbf{B}$ is the matrix of reduced-form coefficients and $\mathbf{\Sigma}$ is the variance-covariance matrix of the reduced-form residuals. We set the lag order $p = 2$. All results are based on 1 million draws from the posterior distributions.[15]

3.3 Identification

Our approach jointly identifies the SOE and US monetary policy shocks by bringing together sign restrictions on policy parameters (Arias et al., 2019) and block exogeneity (Cushman and Zha, 1997).

Sign restrictions on policy parameters aim to identify monetary policy shocks by characterizing the systematic component of monetary policy (Leeper et al., 1996). This method, which hinges on a few qualitative and fairly uncontroversial restrictions, only achieves set-identification and may thus be subject to the so-called 'masquerading shocks' problem (Wolf, 2020; Fry and Pagan, 2011). To alleviate this issue, our identification strategy imposes sign restrictions on both US and SOE policy parameters, and further adds block exogeneity.

Block exogeneity is the cornerstone of SOE modeling. It is based on the assumption that, while SOEs are influenced by foreign factors, they do not exert any reciprocal impact on the Rest of the World. In our setting, implementing block exogeneity sharpens the identification of US and SOE monetary policy shocks through a set of plausible non-recursive zero restrictions. In particular, block exogeneity precludes any effects (contemporaneous or lagging) of the exchange rate on US monetary policy – a reasonable restriction given that we focus on bilateral SOE/US exchange rates which are arguably of little relevance from the Federal Reserve's point of view.

Crucial to our purpose, our unique identification strategy allows simultaneous interaction between the exchange rate and the SOE policy rate, and leaves the response of the exchange rate to SOE and US monetary shocks unrestricted at all horizons (Faust

[15] Appendix B gives a detailed description of our econometric strategy.

and Rogers, 2003; Bjørnland, 2009). We first describe the implementation of block exogeneity. Then, we discuss the sign restrictions on US and SOE monetary policy coefficients.

3.3.1 Block exogeneity

We adapt the Bayesian estimation methods of Arias et al. (2019) to incorporate block exogeneity (Cushman and Zha, 1997). Given the partition of $\mathbf{y_t'} = \begin{bmatrix}\mathbf{y_{1t}'} & \mathbf{y_{2t}'}\end{bmatrix}$, the matrix of contemporaneous relationships, $\mathbf{A_0}$, has the following structure:

$$\mathbf{A_0} = \begin{bmatrix} A_{0,11} & A_{0,12} \\ A_{0,21} & A_{0,22} \end{bmatrix},$$

where $A_{0,11}$ is $(n_1 \times n_1)$, $A_{0,12}$ is $(n_1 \times n_2)$, $A_{0,21}$ is $(n_2 \times n_1)$, $A_{0,22}$ is $(n_2 \times n_2)$. To ensure that SOE variables in $\mathbf{y_{2t}}$ do not influence US variables in $\mathbf{y_{1t}}$ contemporaneously, we apply zero-restrictions on the block $A_{0,21}$:

$$\mathbf{A_0} = \begin{bmatrix} A_{0,11} & A_{0,12} \\ 0 & A_{0,22} \end{bmatrix}.$$

Following Cushman and Zha (1997), we should also prevent SOE variables from influencing US variables in a dynamic fashion by imposing a block of zero-restrictions on each lag matrix $\mathbf{A}_l$, $1 \leq l \leq p$, in Equation (4), so that:

$$\mathbf{A}_l = \begin{bmatrix} A_{11,l} & A_{12,l} \\ A_{21,l} & A_{22,l} \end{bmatrix} = \begin{bmatrix} A_{11,l} & A_{12,l} \\ 0 & A_{22,l} \end{bmatrix},$$

where $A_{11,l}$ is $(n_1 \times n_1)$, $A_{12,l}$ is $(n_1 \times n_2)$, $A_{21,l}$ is $(n_2 \times n_1)$, $A_{22,l}$ is $(n_2 \times n_2)$. However, the procedure of Arias et al. (2019) only allows us to impose a maximum of $(n-k)$ zero restrictions per equation, where $k = 1, ..., n$ denotes the position of the k^{th} equation in the system. Hence, we cannot impose $A_{21,l} = \mathbf{0}$. We get around this problem by formulating a variant of the Minnesota prior on the reduced-form VAR, where the parameters governing the influence of lagged SOE variables on US variables are assigned informative priors tightly concentrated around zero.

Furthermore, Arias et al. (2019) specify Natural Conjugate Normal Inverse Wishart ($\mathcal{NIW}$) priors for the reduced-form parameters. Natural Conjugate priors are ill-fitted for our purpose as they feature a Kronecker structure for the variance-covariance matrix of the reduced-form parameters which implies that every equation must feature the same set of explanatory variables – making a block-exogenous configuration impractical (Dieppe et al., 2016; Koop et al., 2010). Fortunately, the Bayesian techniques developed by Arias et al. (2018) work with any prior distribution. We thus employ Independent $\mathcal{NIW}$ priors to implement the block-exogenous structure of the model. Our Independent $\mathcal{NIW}$ priors for $\beta = vec(\mathbf{B})$, the vector of reduced-form coefficients, and $\mathbf{\Sigma}$, the residual variance-covariance matrix are given by:

$$\beta \sim \mathcal{N}(\beta_0, \Omega_0) \tag{7}$$

$$\mathbf{\Sigma} \sim \mathcal{IW}(S_0, \alpha_0). \tag{8}$$

We center the distribution of every first-order auto-regressive coefficient at 1, and 0 otherwise, as in standard Minnesota priors. The variance-covariance matrix Ω_0 contains the usual hyper-parameters that control the tightness of the distributions of reduced-form coefficients, with an additional hyper-parameter to implement block exogeneity on lagged matrices (Dieppe et al., 2016).[16]

3.3.2 Sign restrictions on monetary policy parameters

Arias et al. (2019) impose sign and exclusion restrictions on the coefficients of the Federal Reserve's interest-rate rule. We adapt their methodology to a SOE context in two ways. First, we impose a block-exogenous structure on the SVAR model. Second, we simultaneously identify the respective interest-rate rules of the Federal Reserve and SOE central bank. Like in Arias et al. (2019), our identification focuses on the contemporaneous structural parameters. For the sake of exposition, let us abstract from constant terms and lags, and let us expand $\mathbf{y_t}$, $\mathbf{A_0}$ and ϵ_t to write the structural model of Equation (4) as follows:

$$\begin{bmatrix} y_t^* \; \pi_t^* \; cs_t^* \; r_t^* \; y_t \; \pi_t \; r_t \; e_t \end{bmatrix} \begin{bmatrix} a_{0,11} & a_{0,12} & a_{0,13} & a_{0,14} & a_{0,15} \cdots a_{0,18} \\ a_{0,21} & a_{0,22} & a_{0,23} & a_{0,24} & a_{0,25} \cdots a_{0,28} \\ a_{0,31} & a_{0,32} & a_{0,33} & a_{0,34} & a_{0,35} \cdots a_{0,38} \\ a_{0,41} & a_{0,42} & a_{0,43} & a_{0,44} & a_{0,45} \cdots a_{0,48} \\ 0 & 0 & 0 & 0 & a_{0,55} \cdots a_{0,58} \\ \vdots & \ddots & \ddots & \ddots & \ddots \quad \vdots \\ 0 & 0 & 0 & 0 & a_{0,85} \cdots a_{0,88} \end{bmatrix} = \ldots + \begin{bmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \\ \epsilon_{4,t} \\ \epsilon_{5,t} \\ \epsilon_{6,t} \\ \epsilon_{7,t} \\ \epsilon_{8,t} \end{bmatrix}' .$$

[16] We set the hyperparameters of the inverse Wishart distribution in a conventional way: $\alpha_0 = n+1$ and $S_0 = \mathbb{I}_n$ (Dieppe et al., 2016). Appendix B provides further details.

Without loss of generality, we identify the first and fifth shocks in the SVAR model respectively as the US and SOE monetary policy shocks:

$$y_t^* a_{0,11} + \pi_t^* a_{0,21} + cs_t^* a_{0,31} + r_t^* a_{0,41} = \epsilon_{1,t} \ , \tag{9}$$

$$y_t^* a_{0,15} + \pi_t^* a_{0,25} + cs_t^* a_{0,35} + r_t^* a_{0,45} + y_t a_{0,55} + \pi_t a_{0,65} + r_t a_{0,75} + e_t a_{0,85} = \epsilon_{5,t} \ . \tag{10}$$

The systematic component of US monetary policy: Rearranging terms in Equation (9), we obtain the Federal Reserve's monetary policy rule:

$$r_t^* = -a_{0,41}^{-1} a_{0,11} y_t^* - a_{0,41}^{-1} a_{0,21} \pi_t^* - a_{0,41}^{-1} a_{0,31} cs_t^* + a_{0,41}^{-1} \epsilon_{1,t} \ , \tag{11}$$

where $-a_{0,41}^{-1} a_{0,11} = \psi_{y^*}$, $-a_{0,41}^{-1} a_{0,21} = \psi_{\pi^*}$, $-a_{0,41}^{-1} a_{0,31} = \psi_{cs^*}$ and $a_{0,41}^{-1} = \sigma^*$.

To characterize the systematic component of US monetary policy, we impose the following two restrictions:

Restriction 1. The contemporaneous responses of the US policy rate to, respectively, US output and US inflation are positive: $\psi_{y^*} > 0$ and $\psi_{\pi^*} > 0$.

Restriction 2. The contemporaneous reaction of the US policy rate to the Baa corporate credit spread is negative: $\psi_{cs^*} < 0$.

Restriction 1 is motivated by the seminal contribution of Taylor (1993) and is consistent with Arias et al. (2019).[17] Restriction 2 is not imposed in Arias et al. (2019) and deserves some comments. This restriction entails that the Federal Reserve typically leans against the credit spread by cutting the fed funds rate in response to a tightening of credit market conditions. This view is strongly supported by the empirical evidence provided by Caldara and Herbst (2019).[18] It is also consistent with the restrictions

[17] Arias et al. (2019) include the price level (rather than the inflation rate) in their SVAR model. Instead, for the sake of comparability with the benchmark SVAR study of Bjørnland (2009) for advanced SOEs, we work with the inflation rate. Our main results are robust to replacing the inflation rate with the price level. Regarding the timing assumption implied by Restriction 1, where the policy rate reacts to the contemporaneous values of output and inflation, we follow the argument of Arias et al. (2019): monetary authorities crunch a large battery of real-time indicators to nowcast the current state of the economy.

[18] Gilchrist and Zakrajšek (2012) highlight the information content of the corporate credit spread and its predictive power to forecast the state of the business cycle. Curdia and Woodford (2010, 2016) present a normative DSGE-based analysis that rationalizes a systematic easing of monetary policy in response to a worsening of credit conditions.

imposed by Baumeister and Hamilton (2018), Groshenny and Javed (2023), Rüth and Van der Veken (2023) and Castelnuovo et al. (2025). Combining Restrictions 1 and 2, we obtain the following characterization of US monetary policy:

$$r_t^* = \underbrace{\psi_{y^*}}_{>0} y_t^* + \underbrace{\psi_{\pi^*}}_{>0} \pi_t^* + \underbrace{\psi_{cs^*}}_{<0} cs_t^* + \sigma^* \epsilon_{1,t} \ , \tag{12}$$

which highlights that SOE variables have no impact on the US policy rate.

The systematic component of monetary policy in SOEs: The SOE monetary policy rule, from Equation (10), is given by:

$$\begin{aligned} r_t = & -a_{0,75}^{-1} a_{0,15} y_t^* - a_{0,75}^{-1} a_{0,25} \pi_t^* - a_{0,75}^{-1} a_{0,35} cs_t^* - a_{0,75}^{-1} a_{0,45} r_t^* \\ & -a_{0,75}^{-1} a_{0,55} y_t - a_{0,75}^{-1} a_{0,65} \pi_t - a_{0,75}^{-1} a_{0,85} e_t + a_{0,75}^{-1} \epsilon_{5,t} \ , \end{aligned} \tag{13}$$

where $-a_{0,75}^{-1} a_{0,55} = \psi_y$, $-a_{0,75}^{-1} a_{0,65} = \psi_\pi$, $-a_{0,75}^{-1} a_{0,85} = \psi_e$ and $a_{0,75}^{-1} = \sigma$.

To identify the systematic component of SOE monetary policy, we impose the following two restrictions:

Restriction 3. The contemporaneous reactions of the SOE policy rate respectively to domestic output and inflation are positive: $\psi_y > 0$ and $\psi_\pi > 0$.

Restriction 4: The contemporaneous reaction of the SOE policy rate to the real bilateral SOE/US exchange rate is positive: $\psi_e > 0$.

Restriction 3 is analogous to Restriction 1. Restriction 4 is specific to the SOE monetary policy rule and is motivated by Taylor (2001). This restriction entails that the SOE central bank usually leans against the real SOE/US exchange rate, cutting its policy rate in response to an appreciation of the domestic currency, and increasing it in response to a depreciation.[19] This restriction embodies policymakers' wisdom that a real appreciation is an opportunity to ease domestic monetary conditions, while a

[19] Calvo and Reinhart (2002), Reinhart and Rogoff (2004), Obstfeld (2013) and Ilzetzki et al. (2019) report that many central banks react to the dollar exchange rate. This finding is consistent with the central role of the dollar in the international monetary and financial system (Gopinath et al., 2020; Gourinchas et al., 2019).

real depreciation of the currency calls for an increase in the policy rate (Obstfeld and Rogoff, 1995a; Taylor, 2001). Restriction 4 is supported by the SVAR-based evidence provided by (Bjørnland, 2009; Bjørnland and Halvorsen, 2014). It is also consistent with estimated Taylor-type rules in DSGE models (Lubik and Schorfheide, 2007; Kam et al., 2009; Justiniano and Preston, 2010).[20] Braig et al. (2024) demonstrate the importance of imposing this restriction. Taken together, Restrictions 3 and 4 leave the systematic reaction of the SOE central bank to foreign variables unrestricted, as in Cushman and Zha (1997), and imply that the SOE central bank follows a Taylor-type rule in line with Taylor (2001):

$$r_t = \underbrace{(-a_{0,75}^{-1}a_{0,15})}_{unrestricted} y_t^* + \underbrace{(-a_{0,75}^{-1}a_{0,25})}_{unrestricted} \pi_t^* + \underbrace{(-a_{0,75}^{-1}a_{0,35})}_{unrestricted} cs_t^* + \underbrace{(-a_{0,75}^{-1}a_{0,45})}_{unrestricted} r_t^*$$
$$+ \underbrace{(-a_{0,75}^{-1}a_{0,55})}_{\psi_y>0} y_t + \underbrace{(-a_{0,75}^{-1}a_{0,65})}_{\psi_\pi>0} \pi_t + \underbrace{(-a_{0,75}^{-1}a_{0,85})}_{\psi_e>0} e_t + \underbrace{(a_{0,75}^{-1})}_{\sigma} \epsilon_{5,t} \,. \tag{14}$$

4 Does UIP hold conditional on monetary shocks?

To evaluate the extent of UIP-deviations triggered by SOE and US monetary policy shocks, we follow Eichenbaum and Evans (1995) and Bjørnland (2009) and compute the conditional excess returns generated by a SOE and a US monetary tightening, denoted respectively Λ_t^{SOE} and Λ_t^{US}:

$$\Lambda_t^{SOE} = r_t^{SOE} - r_t^{US} - 4 \times (\mathbb{E}_t\{s_{t+1}\} - s_t)\,, \tag{15}$$

$$\Lambda_t^{US} = r_t^{US} - r_t^{SOE} + 4 \times (\mathbb{E}_t\{s_{t+1}\} - s_t)\,, \tag{16}$$

where s_t is the bilateral SOE/US log nominal exchange rate, defined so that a fall in s_t corresponds to an appreciation of the SOE currency against the USD. The quarterly change in the exchange rate is multiplied by 4 to be consistent with the annualized short-term nominal interest rates. Under the null hypothesis that UIP holds conditional on monetary disturbances, these excess returns should be equal to zero across

[20] Egorov and Mukhin (2023) show that, when prices are invoiced and sticky in dollars, it can be desirable for non-US central banks to attenuate the dollar exchange rate.

all forecast horizons: $\mathbb{E}_t\{\Lambda_{t+j}^{US}\} = 0$ and $\mathbb{E}_t\{\Lambda_{t+j}^{SOE}\} = 0$, for all $j \geqslant 0$.[21] Following Bjørnland (2009), we construct the impulse response functions of the excess returns directly from the impulse response functions of the RER, and the SOE and US inflation rates.[22]

Figures 1 and 2 convey our baseline results by reporting the impulse responses of selected variables to a SOE and a US monetary shock respectively. In both figures, each column corresponds to a particular SOE (Australia, Canada, New Zealand, Norway, Sweden, UK), the first and second rows display the impulse responses of the US and SOE policy rates, the third row shows the response of the interest differential, while the fourth and fifth rows present the responses of the RER and UIP-deviations. Solid lines in Figure 1, and dashed lines in Figure 2, depict the point-wise posterior median responses, respectively to a SOE and a US one-standard deviation contractionary monetary policy shock. The dark and the light shaded areas represent respectively the 68% and 90% equal-tailed posterior probability bands.[23]

Looking at Figure 1, we observe that, across all SOEs, the policy rate increases by about 20-30 basis points on impact following a domestic contractionary monetary policy shock. The short-term increase in the policy rate is significant in all SOEs. In most cases, the median impulse response of the policy rate is hump-shaped and remains positive over the whole forecast horizon. The block-exogenous structure of the model implies that the federal funds rate is unaffected by the SOE disturbance. Accordingly, the impulse responses of the SOE-US interest differentials are identical to the responses of the SOE policy rates. In all SOEs, the exchange rate displays a significant appreciation on impact (based on 68% posterior bands). For Canada, New Zealand and the UK, this instantaneous appreciation is immediately followed by a gradual depreciation, in line with Dornbusch's overshooting hypothesis. For Norway and Sweden, the peak appreciation is delayed by a couple of quarters, while for Australia, the peak appreciation occurs two years post-shock. Last and most important for our purpose, excess returns triggered by SOE disturbances are quantitatively modest and statistically insignificant across all horizons.

[21]See Faust and Rogers (2003) and Scholl and Uhlig (2008) for further discussions on conditional UIP tests.

[22]See Appendix E for a detailed description of the methodology to construct IRF of excess returns.

[23]IRFs of all variables to SOE and US shocks are provided in Appendices C.1 and C.2.

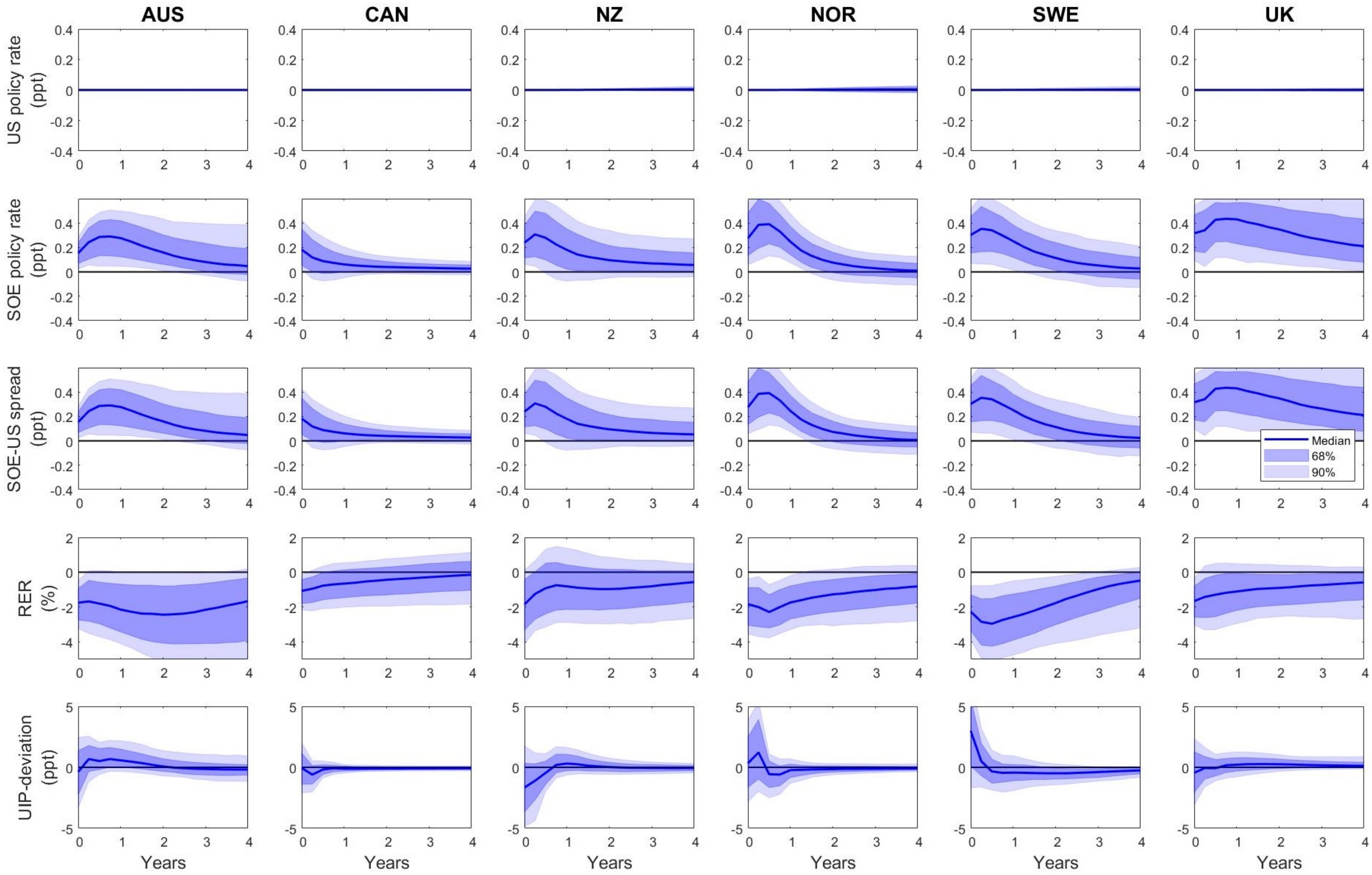

Figure 1: IRFs to a one-standard-deviation SOE contractionary monetary shock. Solid lines depict the point-wise posterior median responses. Shaded areas represent the 68% and 90% equal-tailed posterior probability bands.

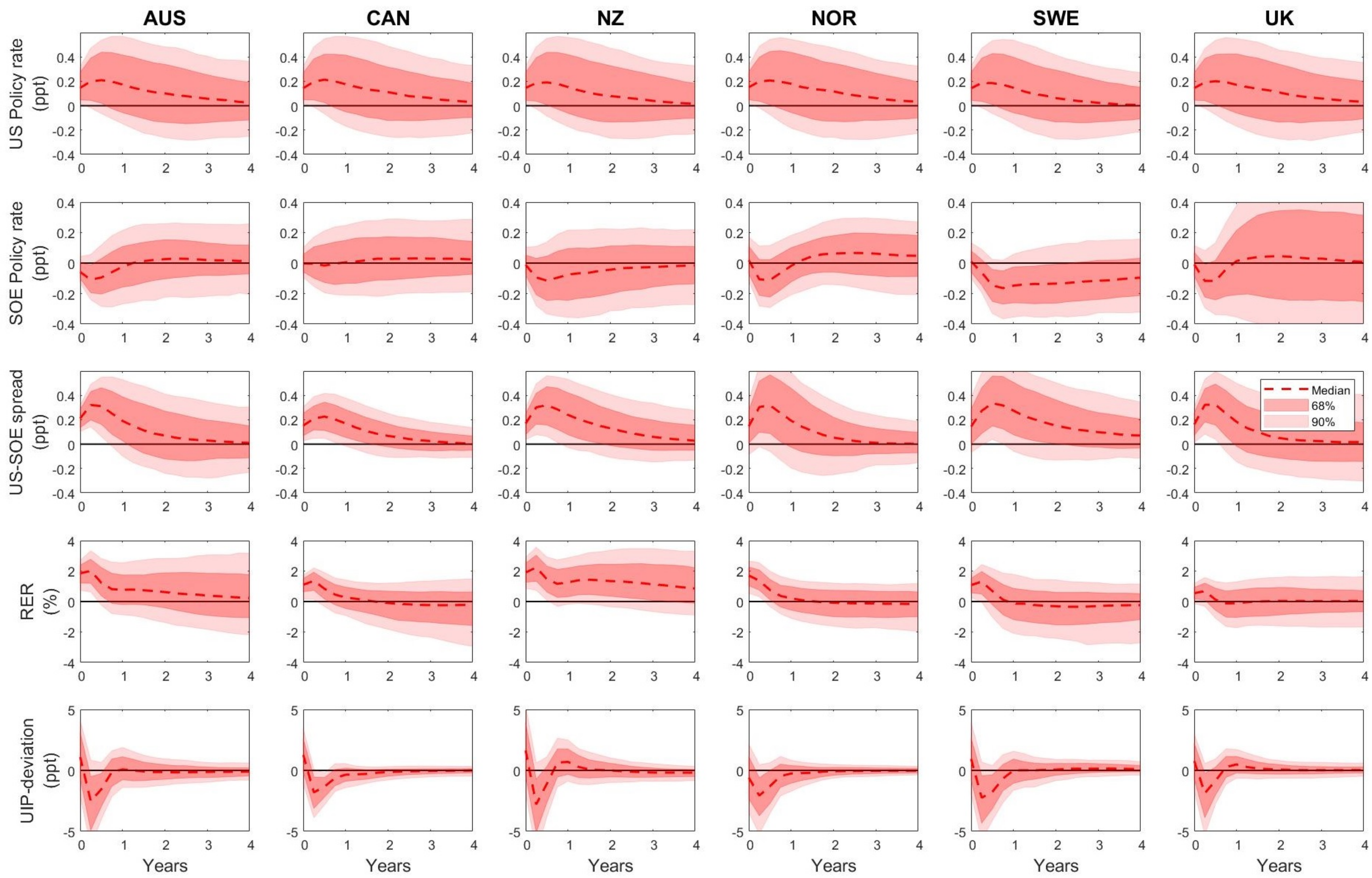

Figure 2: IRFs to a one-standard-deviation US contractionary monetary shock. Dashed lines depict the point-wise posterior median responses. Shaded areas represent the 68% and 90% equal-tailed posterior probability bands.

Turning to Figure 2 and the effects of a surprise fed funds rate hike, we note first that the responses of the US policy rate are identical across the six SVAR models, reflecting the block exogeneity restrictions. The fed funds rate increases by almost 20 basis points on impact and follows a hump-shaped dynamics thereafter, remaining in positive territory over the four-year horizon. SOE policy rates endogenously react in various ways to the US monetary shock. However, the general tendency that emerges across the six SOEs indicates that, except in Canada, SOE central banks seem to respond in the short-run to the Federal Reserve's tightening by cutting their policy rate – posterior median responses of SOE policy rates remain in negative territory for about a year after the US shock – presumably to attenuate the spillover effects of the US monetary contraction on their economies. Thus, the general reaction of SOE monetary authorities to a US shock accentuates the positive hump-shaped responses of the US-SOE policy spreads. For all SOEs, the exchange rate peak response is large and significant, and it occurs either immediately or one quarter after the shock, roughly in line with Dornbusch's overshooting hypothesis. Finally, UIP-deviations generated by US monetary shocks are short-lived and moderate, being briefly borderline significant based on the 68% posterior bands.[24]

In a nutshell, we find little evidence of large and persistent UIP deviations following SOE or US monetary shifts. Our baseline empirical results align with Bjørnland (2009), who documents exchange rate movements broadly consistent with UIP conditional on SOE monetary disturbances, and with Rüth (2020), who finds little evidence of UIP violations conditional on US monetary shocks. In contrast, Eichenbaum and Evans (1995), Faust and Rogers (2003) and Scholl and Uhlig (2008) record evidence of large deviations from UIP conditional on US shocks.

To understand why UIP is not rejected by the data conditional on monetary shocks, we examine visually the joint behavior of the real exchange rate and policy spread after a shock.[25] For the sake of exposition, we consider a US monetary policy shock

[24] The estimated contemporaneous coefficients for SOE and US monetary policy rules are provided in Appendix C.4.

[25] As documented by Eichenbaum and Evans (1995), the impulse responses of real and nominal exchange rates to a US monetary shock are observationally equivalent, presumably because of the presence of nominal rigidities. We have checked and we can confirm that this is also the case in our application, for all SOEs considered, conditional on US as well as SOE shocks. Hence, our explanation based on the response of the real exchange rate would carry through if, in line with UIP,

(Figure 2) and focus on posterior median estimates. Remember that an increase in s_t indicates an appreciation of the USD. Rearranging terms in Equation (16), we get:

$$4 \times (s_t - \mathbb{E}_t\{s_{t+1}\}) \approx r_t^{US} - r_t^{SOE} - \Lambda_t^{US} \, . \tag{17}$$

As pointed out by Scholl and Uhlig (2008), a positive interest-differential path ($r_{t+j}^{US} - r_{t+j}^{SOE} > 0$, for all $j \geqslant 0$) is a necessary condition for the USD to depreciate following its initial appreciation. In line with this theoretical requirement, Figure 2 demonstrates that, following a US monetary tightening, the USD appreciates on impact and then starts (immediately or one quarter after the shock) to gradually depreciate, while the US-SOE policy spread remains positive throughout the entire forecast horizon. This persistent positive spread rationalizes the observed almost-perfect Dornbusch overshooting pattern. Put differently, the expected USD depreciation nearly offsets the positive US-SOE interest differential, thereby preserving the parity condition. A similar analysis can be applied to interpret the effects of SOE monetary policy shocks shown in Figure 1.

Taking stock, our baseline findings indicate that UIP holds reasonably well conditional on monetary shocks. In the next section, we perform three checks to assess the robustness of this result.

5 Robustness checks

We now examine the robustness of our baseline findings through three sensitivity checks: (i) a shorter estimation period that excludes Zero Lower Bound (ZLB) episodes, (ii) the inclusion of a country-specific 'Commodity Terms of Trade' variable in the foreign block, and (iii) the addition of an SOE corporate credit spread to the domestic block.[26] Beyond confirming the strength of our main result, these checks deepen our understanding by demonstrating how different observed patterns of exchange-rate overshooting are empirically linked to specific policy-spread paths, thereby ensuring that UIP is generally maintained.

we considered the nominal exchange rate instead of the real exchange rate.

[26] In all robustness checks, the lag order is $p = 1$. The estimated contemporaneous coefficients of the SOE and US monetary policy rules are provided in Appendix D.

5.1 A shorter sample period to exclude ZLB episodes

In our baseline estimation, the sample period runs from 1992:Q1 to 2019:Q4 and our dataset features shadow rate data for the US, Sweden and the UK. To ascertain that our main result is not driven by unconventional monetary policy measures or the use of shadow rates, we re-estimate the six SVAR models over a shorter 'pre-GFC period' that goes from 1992:Q1 to 2008:Q3, excluding ZLB episodes and unconventional monetary interventions. We can thus work with standard measures of short-term nominal interest rates for all countries, instead of shadow rates (cf. Appendix). Therefore, this exercise should in principle yield a cleaner identification of *conventional* monetary policy shocks. Figures 3 and 4 report the estimated impulse responses of selected variables to SOE and US shocks respectively.

Looking at the bottom row in Figure 3 reveals that, conditional on SOE monetary shocks, UIP holds reasonably well over the Great Moderation period for all SOE-US pairs, except the UK-US couple which briefly exhibits a (borderline significant) negative excess return on impact. The penultimate row indicates that the Dornbusch overshooting hypothesis seems to be validated, as the exchange-rate peak response occurs on impact and is significant for all SOEs (based on the 68% posterior bands). The intuition behind these findings is the same as in the baseline: For each SOE-US pair, the dynamic path of the policy spread (which remains positive throughout the forecast horizon) and the exchange rate instantaneous overshooting dynamics are jointly roughly compatible with UIP.

Turning to Figure 4, we see that, over the pre-GFC period, a one-standard-deviation US monetary shock triggers a relatively modest increase in the fed funds rate on impact. Moreover, the monetary tightening appears to be short-lived as the posterior median response of the fed funds rate falls below its pre-shock level around one year after the shock. Interestingly, Arias et al. (2019) report similar findings. The reaction of SOE central banks remains insignificant across all horizons, with the exception of Canada whose policy rate appears to follow the fed funds rate closely.[27] Consequently,

[27]To some extent, Australia, New Zealand and Sweden also display a modest propensity to follow US monetary policy during the Great Moderation period. This behavior may evoke the 'fear of floating' hypothesis (Calvo and Reinhart, 2002), according to which many central banks adjust domestic rates to mitigate currency fluctuations. Comparing our pre-GFC results against our baseline results,

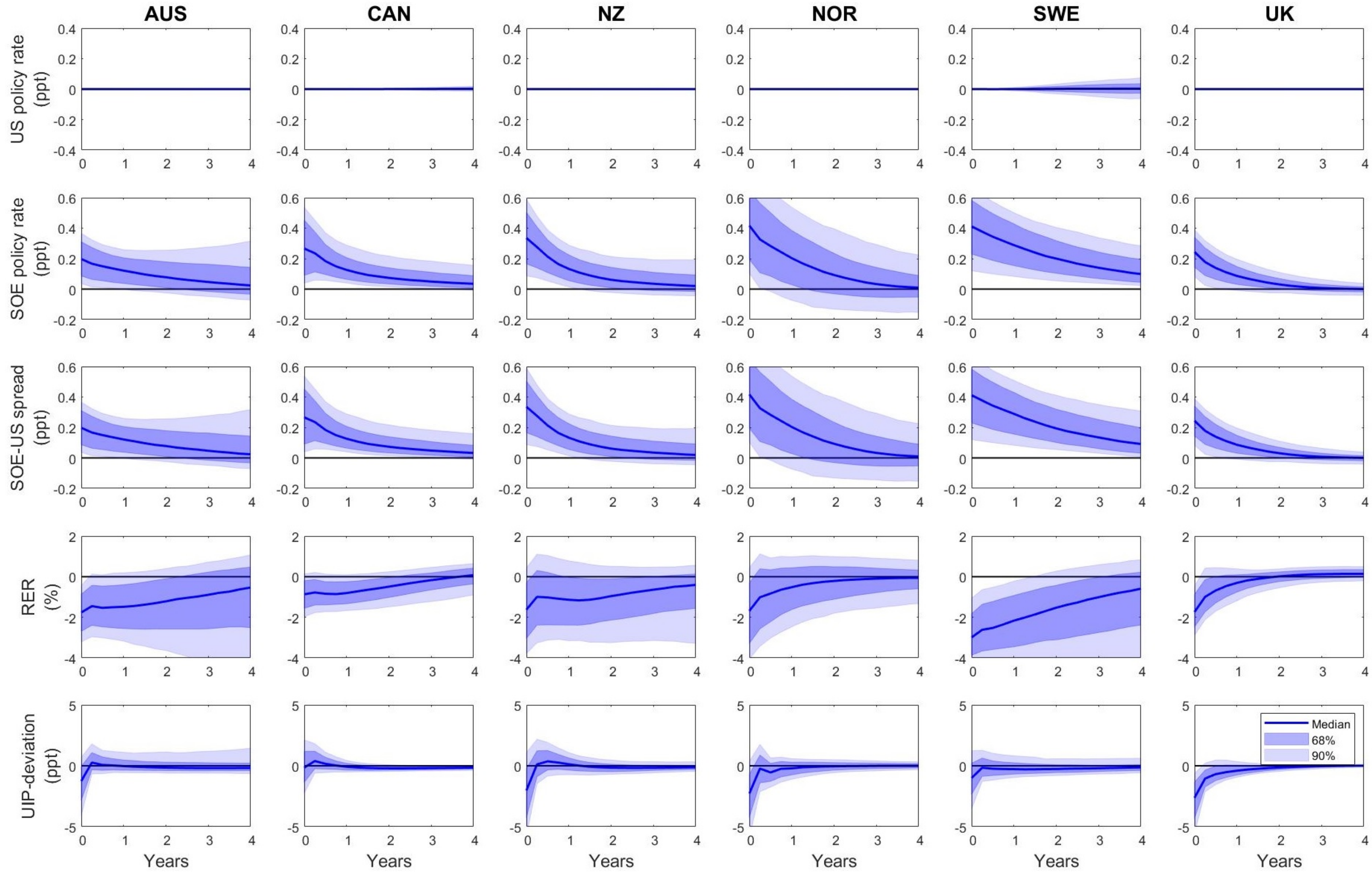

Figure 3: IRFs to a one-standard-deviation **SOE shock for the period 1992:Q1 to 2008:Q3**. Solid lines depict point-wise posterior median responses. Shaded areas represent 68% and 90% equal-tailed posterior probability bands.

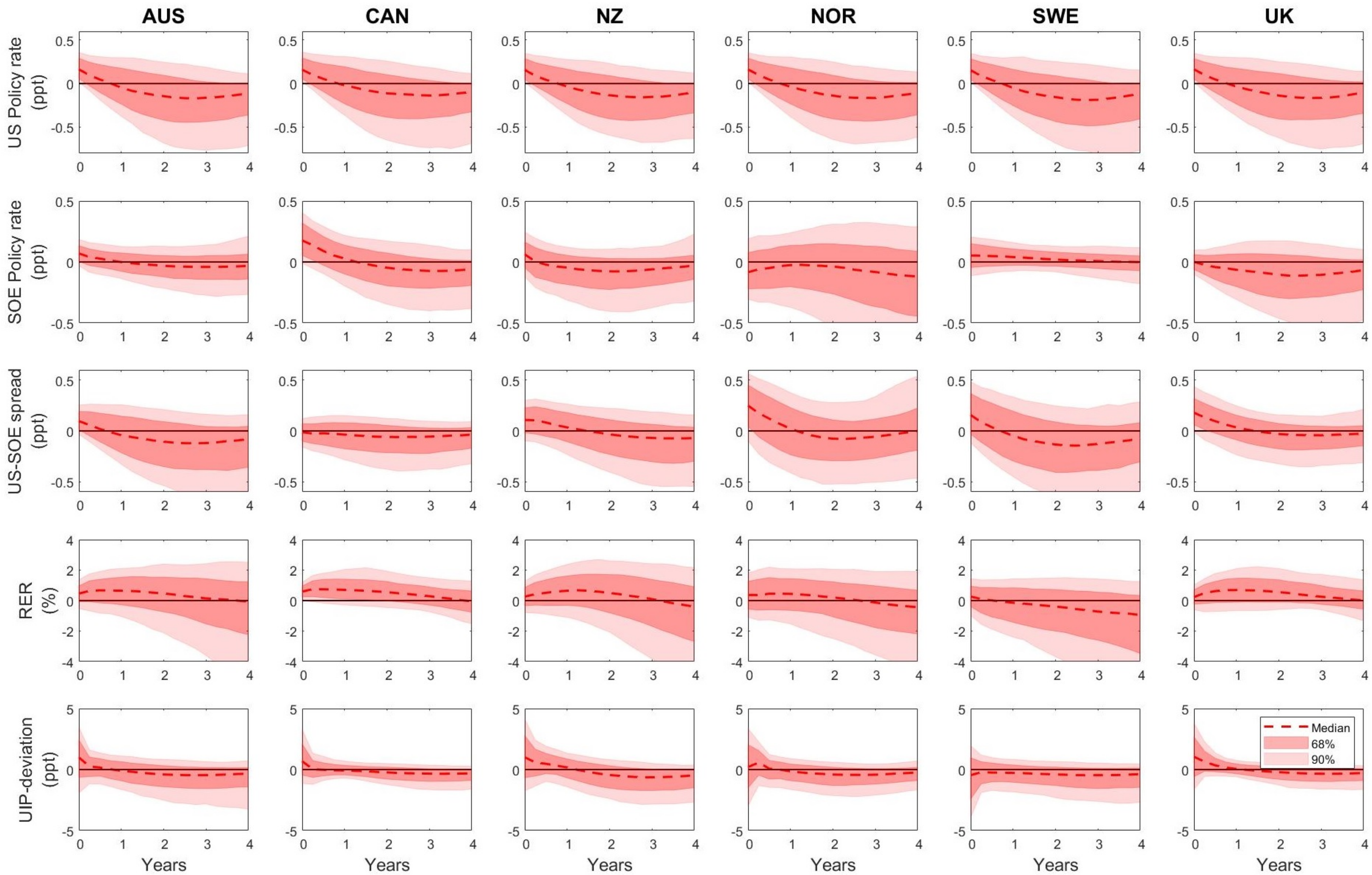

Figure 4: IRFs to a one-standard-deviation **US shock for the period 1992:Q1 to 2008:Q3**. Solid lines depict point-wise posterior median responses. Shaded areas represent 68% and 90% equal-tailed posterior probability bands.

the US-SOE interest differentials tend to mirror the fed funds rate trajectory, trending below pre-shock levels one to two years post-impact. The depicted policy-spread paths imply a negative, and quantitatively small, cumulative interest differential for most SOEs. Given these small negative cumulated spreads, exchange rates should exhibit soft delayed overshooting to satisfy UIP (Scholl and Uhlig, 2008).[28] This logic seems validated by our results: for most SOEs, excess returns remain modest and insignificant while the posterior median response of the RER displays a mild hump-shaped trajectory.[29] These findings corroborate the theoretical prediction of Scholl and Uhlig (2008) and illustrate that the absence of Dornbusch's overshooting does not imply that UIP is rejected.

5.2 Including a SOE-specific Terms of Trade index

Our second check estimates, for each SOE, a 9-variable SVAR model that adds a SOE-specific 'Commodity Terms of Trade' index in the foreign block. This check is motivated by the fact that Australia, Canada, New Zealand and Norway are typically classified as commodity exporters, i.e., economies for which the RER and the terms of trade are historically strongly linked (Chen and Rogoff, 2003). For these particular SOEs, it is reasonable to conceive that the monetary authority pays attention, and potentially reacts, to fluctuations in the terms of trade. Omitting to control for terms of trade movements may thus lead to biased parameter estimates of the SOE interest-rate rule, and thereby, to misidentified SOE monetary policy shocks. We thus extend Equation (14) to include the commodity Terms of Trade (cp^*) in the SOE Taylor-type rule without imposing further restrictions:

we extrapolate that SOE central banks may have responded to US monetary surprises differently in the Great Moderation era than in the post-GFC period. Further extrapolating, it could be that conventional and unconventional US monetary policy shocks trigger different kinds of spill-over effects (Bauer and Neely, 2014; Neely, 2015; Bhattarai et al., 2021). These interesting questions lie beyond the scope of our paper. The crucial point for our purpose is the following: US and SOE monetary policies are endogenous, and our approach identifies their systematic component to discipline the response of the *policy-spread path* which, according to UIP, is the forcing variable driving exchange-rate dynamics.

[28] Closely related, Müller et al. (2024) show that a positive cumulated interest differential coupled with delayed overshooting implies deviations from UIP.

[29] Rüth and Van der Veken (2023) find little evidence of forward discount premia, while delayed overshooting persists.

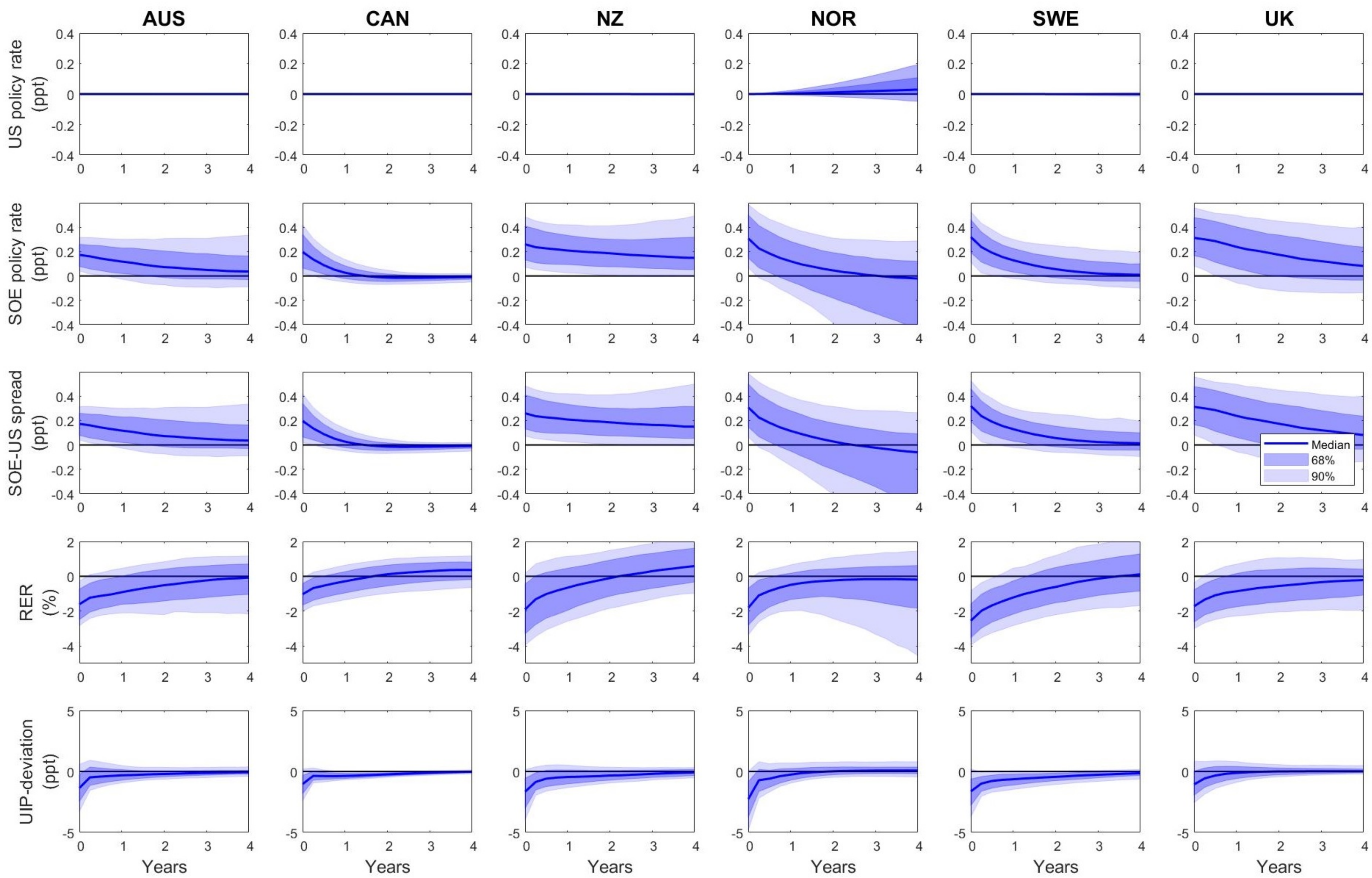

Figure 5: IRFs to a one-standard-deviation **SOE shock** controlling for **SOE Terms of Trade**. Sample period: 1992:Q1 to 2019:Q4. Solid lines depict point-wise posterior median responses. Shaded areas represent 68% and 90% equal-tailed posterior probability bands.

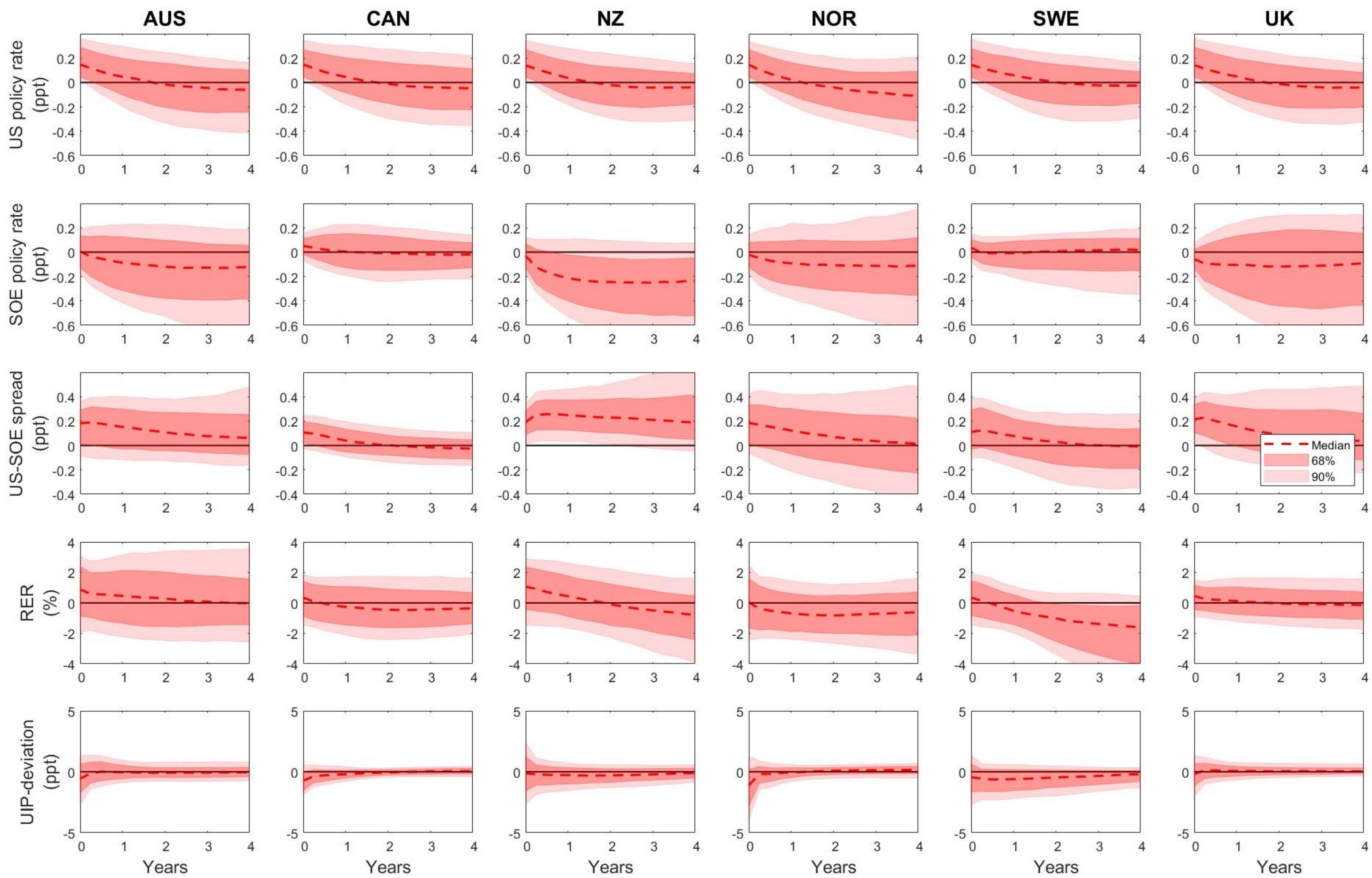

Figure 6: IRFs to a one-standard-deviation **US shock** controlling for **SOE Terms of Trade**. Sample period: 1992:Q1 to 2019:Q4. Solid lines depict point-wise posterior median responses. Shaded areas represent 68% and 90% equal-tailed posterior probability bands.

$$
\begin{aligned}
r_t = & \underbrace{\left(-a_{0,75}^{-1} a_{0,65}\right)}_{\psi_y>0} y_t + \underbrace{\left(-a_{0,75}^{-1} a_{0,85}\right)}_{\psi_\pi>0} \pi_t + \underbrace{\left(-a_{0,75}^{-1} a_{0,95}\right)}_{\psi_e>0} e_t \\
& + \underbrace{\left(-a_{0,75}^{-1} a_{0,15}\right)}_{unrestricted} y_t^* + \underbrace{\left(-a_{0,75}^{-1} a_{0,25}\right)}_{unrestricted} \pi_t^* + \underbrace{\left(-a_{0,75}^{-1} a_{0,35}\right)}_{unrestricted} cs_t^* \\
& + \underbrace{\left(-a_{0,75}^{-1} a_{0,45}\right)}_{unrestricted} r_t^* + \underbrace{\left(-a_{0,75}^{-1} a_{0,55}\right)}_{unrestricted} cp_t^* + \underbrace{\left(a_{0,75}^{-1}\right)}_{\sigma} \epsilon_{5,t} \, .
\end{aligned} \tag{18}
$$

The sample period runs from 1992:Q1 to 2019:Q4, as in the baseline case, and we use shadow rates for the US, UK and Sweden. Figure 5 displays the effects of SOE monetary shocks. It shows that the Dornbusch overshooting hypothesis is validated across all six SOEs, while UIP deviations remain generally short-lived and negligible, except for the Sweden-US pair which exhibits borderline significant excess returns in the first year. Considering the consequences of US monetary shocks, Figure 6 reports little evidence of excess returns. Interestingly, RER responses indicate a complete absence of any kind of overshooting, instantaneous or delayed. Wrapping up, our main result that UIP usually holds conditional on monetary disturbances, irrespective of the specific exchange-rate dynamics observed, appears robust to the inclusion of a SOE-specific Terms of Trade index.[30]

5.3 Including a SOE corporate credit spread

Our last check estimates, for each SOE, a 9-variable SVAR model that incorporates a country-specific corporate credit spread into the SOE block. This exercise is motivated by empirical evidence that US monetary policy responds to shifts in financial conditions. In particular, Caldara and Herbst (2019) show that accounting for the Federal Reserve's systematic reaction to credit conditions is crucial to properly identify US monetary policy shocks and their real effects. Beckers (2020) offers evidence that Australian monetary policy responds to domestic credit conditions, and shows that omitting this aspect leads to underestimating the real effects of monetary policy. It is likely that a similar argument also applies to some extent to the other SOEs

[30] Our results are robust to replacing the SOE-specific commodity TOT index with the Spot Crude Oil Price: West Texas Intermediate (https://fred.stlouisfed.org/series/WTISPLC), as in Terrell et al. (2026).

considered here. We thus include a SOE-specific credit spread as a fifth variable in the SOE block. Due to the limited availability of SOE corporate yield data, the estimation period runs from 2000:Q1 to 2019:Q4.[31] The policy rates for the US, Sweden and the UK are measured by shadow rates, as in the baseline, to account for unconventional monetary policy measures during ZLB episodes. In line with our baseline identification scheme, we impose an additional sign restriction (Restriction 5) on the SOE central bank's interest-rate rule:

Restrictions 5. The contemporaneous response of the SOE policy rate to the SOE credit spread is negative: $\psi_{cs} < 0$.

Restriction 5 is the analog, for the SOE monetary authority, of Restriction 2 for the Federal Reserve. Restriction 5 means that the SOE central bank, guided by a concern for financial stability, typically cuts its policy rate in response to an increase in the domestic credit spread. The SOE monetary policy rule now reads:

$$
\begin{aligned}
r_t = {} & \underbrace{(-a_{0,85}^{-1} a_{0,15})}_{unrestricted} y_t^* + \underbrace{(-a_{0,85}^{-1} a_{0,25})}_{unrestricted} \pi_t^* + \underbrace{(-a_{0,85}^{-1} a_{0,35})}_{unrestricted} cs_t^* \\
& + \underbrace{(-a_{0,85}^{-1} a_{0,45})}_{unrestricted} r_t^* + \underbrace{(-a_{0,85}^{-1} a_{0,55})}_{\psi_y > 0} y_t + \underbrace{(-a_{0,85}^{-1} a_{0,65})}_{\psi_\pi > 0} \pi_t \\
& + \underbrace{(-a_{0,85}^{-1} a_{0,75})}_{\psi_{cs} < 0} cs_t + \underbrace{(-a_{0,85}^{-1} a_{0,95})}_{\psi_e > 0} e_t + \underbrace{(a_{0,85}^{-1})}_{\sigma} \epsilon_{5,t}.
\end{aligned} \tag{19}
$$

Results conditional on SOE and US shocks are reported in Figures 7 and 8 respectively. Figure 7 shows little evidence of large deviations from UIP following SOE monetary disturbances, while exchange rate responses are broadly consistent with Dornbusch overshooting. Turning to Figure 8, its main message is that UIP broadly holds conditional on US shocks. Interestingly, we observe pronounced accommodative responses from SOE central banks to the US monetary tightening, thereby generating large and

[31] Appendix A provides a detailed description of the data used to construct the SOE credit spreads. We thank Olav Syrstad for providing the Norwegian credit spread data.

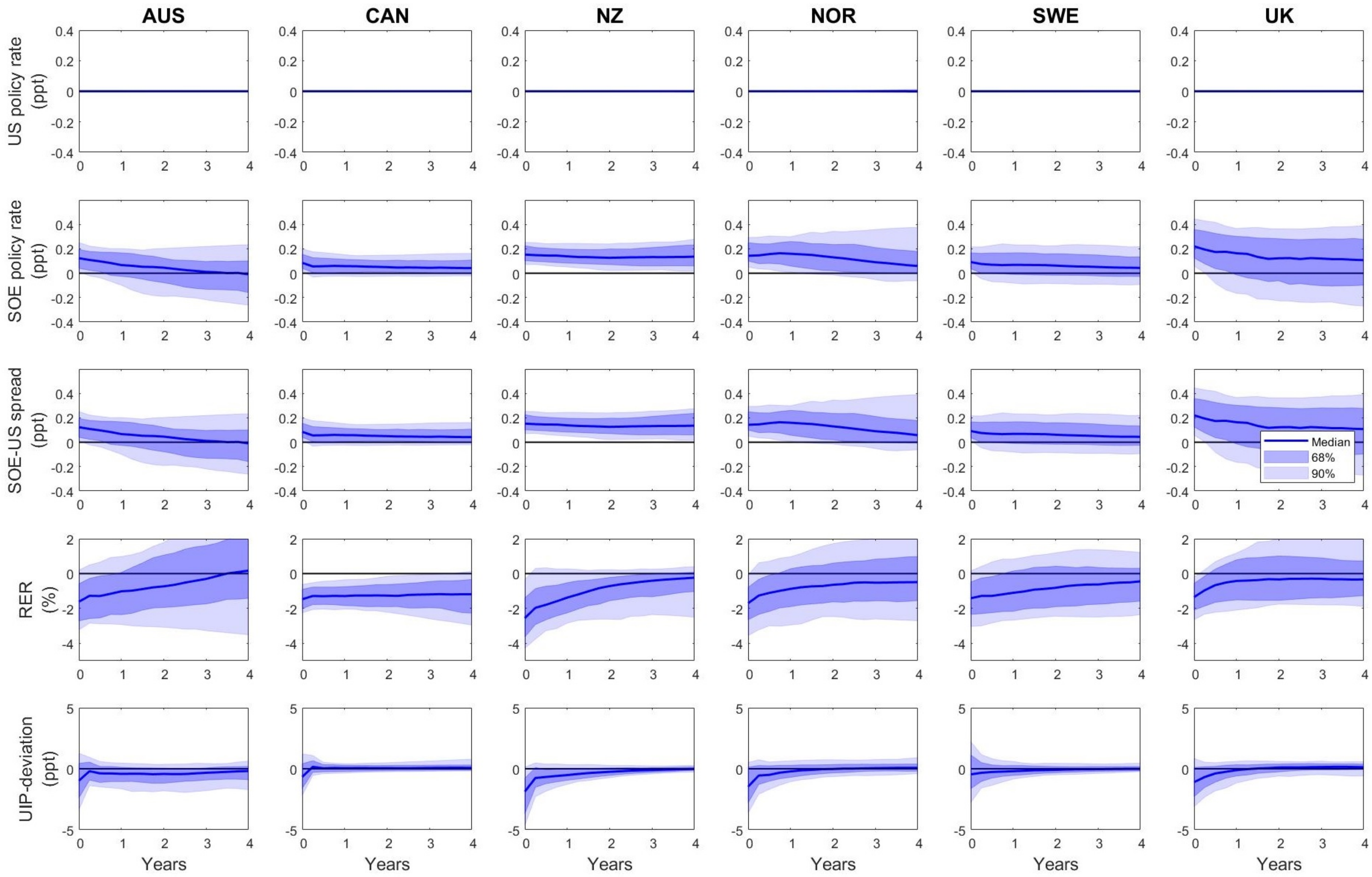

Figure 7: IRFs to a one-standard-deviation **SOE shock** controlling for **SOE credit spread**. Sample period: 2000:Q1 to 2019:Q4. Solid lines depict point-wise posterior median responses. Shaded areas represent 68% and 90% equal-tailed posterior probability bands.

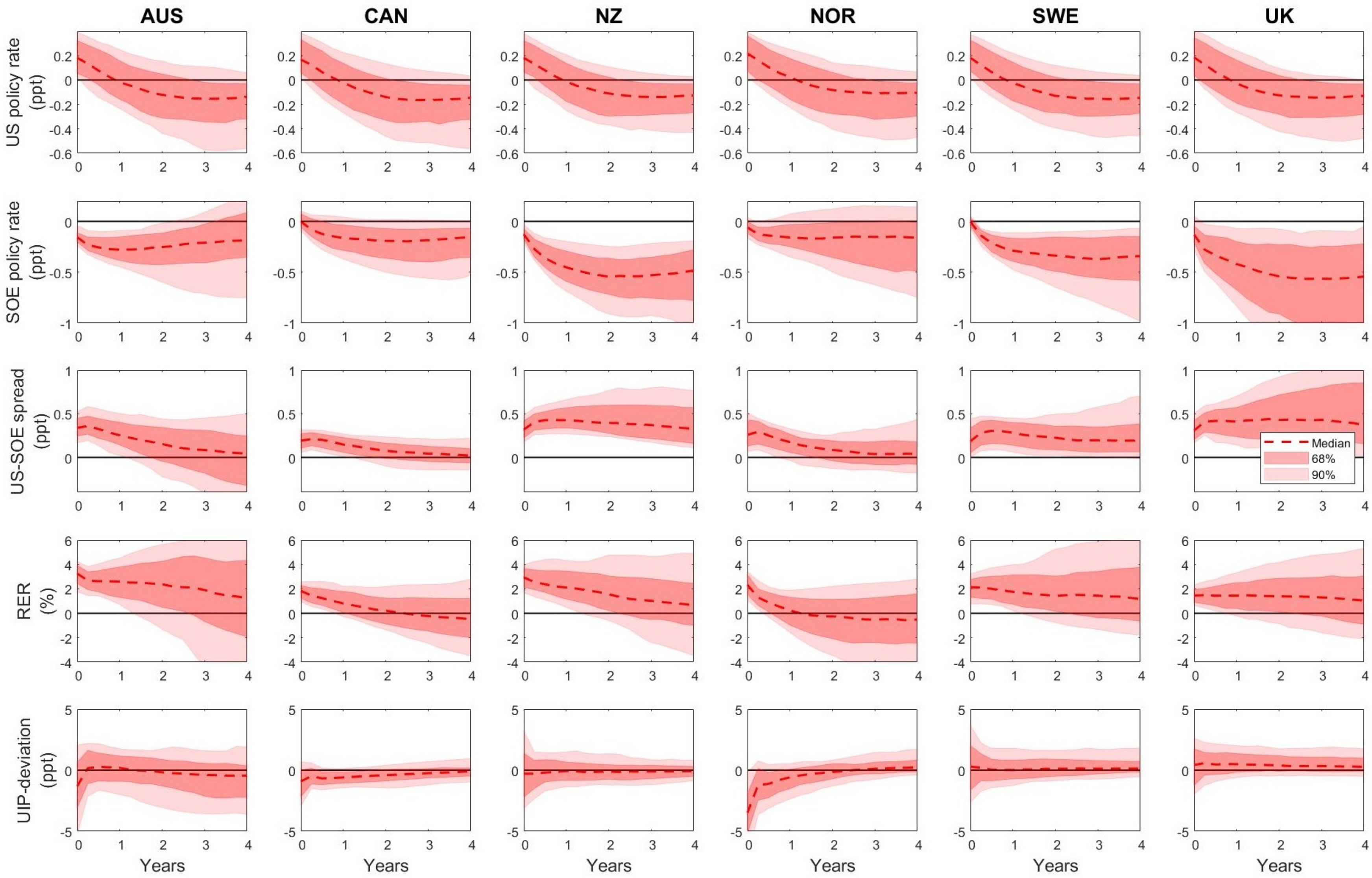

Figure 8: IRFs to a one-standard-deviation **US shock** controlling for **SOE credit spread**. Sample period: 2000:Q1 to 2019:Q4. Solid lines depict point-wise posterior median responses. Shaded areas represent 68% and 90% equal-tailed posterior probability bands.

persistent positive US-SOE interest differentials.[32] In accordance with UIP, exchange rates exhibit pronounced instantaneous overshooting. These results underscore the robustness of our baseline finding: Conditional on monetary shocks, UIP generally holds, irrespective of the specific exchange rate dynamics.

6 Conclusion

This paper provides a re-evaluation of the empirical evidence on uncovered interest parity conditional on monetary disturbances (Faust and Rogers, 2003; Scholl and Uhlig, 2008; Bjørnland, 2009). We focus on six advanced small open economies and show that UIP holds reasonably well conditional on domestic and US monetary policy shocks, notwithstanding diverse exchange-rate adjustment patterns.

We obtain this result by employing an innovative Bayesian structural VAR framework that integrates block exogeneity (Cushman and Zha, 1997) with sign-restrictions on policy parameters (Arias et al., 2019). Our econometric strategy identifies jointly the domestic (SOE) and foreign (US) monetary policy rules, providing a robust identification of the SOE and US expected policy rate paths, and taking into account the reaction of the SOE central bank to shifts in US monetary policy. Hence, our approach places coherent discipline on the dynamic response of the home to foreign interest differential to SOE and US monetary shocks. This simultaneous identification of the systematic component of the home and foreign monetary policies serves as the key feature of our conditional UIP test, since the parity condition predicts that currency movements are tied to the expected path of the interest differential.

Our study reveals little evidence of large and persistent UIP-deviations conditional on SOE and US monetary disturbances. Whether the currency exhibits immediate or delayed overshooting, the parity condition generally remains valid. By disciplining the dynamic response of the domestic to foreign policy rate spread, our framework reconciles observed variations in exchange-rate dynamics with the fundamental requirement of UIP. Our finding that UIP holds conditional on monetary shocks is consistent with

[32] Overall, our results from the baseline estimation and the various robustness checks suggest that the way SOE central banks react to US monetary policy may have evolved over time. Uncovering the underlying factors driving this change lies beyond the scope of this paper and represents an interesting avenue for future research. See footnote 27.

Rüth (2020), Rüth and Van der Veken (2023) and Müller et al. (2024) for US shocks, and Bjørnland (2009) for SOE shocks.

The conditional nature of our methodology contrasts with traditional unconditional evaluations – which aggregate a complex mix of historical shocks – documenting the empirical failure of the UIP condition (Fama, 1984; Froot and Thaler, 1990).[33] Our approach isolates SOE and US monetary policy surprises. By concentrating on these innovations, which are presumably quickly spotted and well-understood by financial market participants, we find that the underlying money market arbitrage remains reasonably effective and resilient. Our results imply that macroeconomists building open-economy DSGE models to analyze the transmission of monetary policy shocks might want to think twice before altering the standard UIP condition.

[33] See also Engel (1996) and Burnside et al. (2011).

References

Adolfson, M., Andersson, M. K., Lindé, J., Villani, M., and Vredin, A. (2007a). Modern forecasting models in action: Improving macroeconomic analyses at central banks. *International Journal of Central Banking*, 3(4):111–144.

Adolfson, M., Laséen, S., Lindé, J., and Villani, M. (2007b). Bayesian estimation of an open economy DSGE model with incomplete pass-through. *Journal of International Economics*, 72(2):481–511.

Adolfson, M., Laséen, S., Lindé, J., and Villani, M. (2008). Evaluating an estimated new Keynesian small open economy model. *Journal of Economic Dynamics and Control*, 32(8):2690–2721.

Arias, J. E., Caldara, D., and Rubio-Ramirez, J. F. (2019). The systematic component of monetary policy in SVARs: An agnostic identification procedure. *Journal of Monetary Economics*, 101:1–13.

Arias, J. E., Rubio-Ramírez, J. F., and Waggoner, D. F. (2018). Inference based on structural vector autoregressions identified with sign and zero restrictions: Theory and applications. *Econometrica*, 86(2):685–720.

Bauer, M. D. and Neely, C. J. (2014). International channels of the Fed's unconventional monetary policy. *Journal of International Money and Finance*, 44:24–46.

Baumeister, C. and Hamilton, J. D. (2018). Inference in structural vector autoregressions when the identifying assumptions are not fully believed: Re-evaluating the role of monetary policy in economic fluctuations. *Journal of Monetary Economics*, 100:48–65.

Beckers, B. (2020). Credit spreads, monetary policy and the price puzzle. *RBA Research Discussion Paper*, 2020(01).

Bhattarai, S., Chatterjee, A., and Park, W. Y. (2021). Effects of US quantitative easing on emerging market economies. *Journal of Economic Dynamics and Control*, 122.

Bjørnland, H. C. (2009). Monetary policy and exchange rate overshooting: Dornbusch was right after all. *Journal of International Economics*, 79(1):64–77.

Bjørnland, H. C. and Halvorsen, J. I. (2014). How does monetary policy respond to exchange rate movements? New international evidence. *Oxford Bulletin of Economics and Statistics*, 76(2):208–232.

Braig, M., Rüth, S. K., and Van der Veken, W. (2024). Exchange Rate Overshooting: Unraveling the Puzzles. *mimeo, University of Erfurt*.

Burnside, C., Eichenbaum, M., Kleshchelski, I., and Rebelo, S. (2011). Do Peso Problems Explain the Returns to the Carry Trade? *The Review of Financial Studies*, 24(3):853–891.

Caldara, D. and Herbst, E. (2019). Monetary policy, real activity, and credit spreads: Evidence from Bayesian proxy SVARs. *American Economic Journal: Macroeconomics*, 11(1):157–192.

Calvo, G. A. and Reinhart, C. M. (2002). Fear of floating. *The Quarterly Journal of economics*, 117(2):379–408.

Castelnuovo, E., Pellegrino, G., and Ranzato, G. (2022). Delayed Overshooting Puzzle: Does Systematic Monetary Policy Matter? *Department of Economics and Management "Marco Fanno", University of Padova*.

Castelnuovo, E., Pellegrino, G., and Særkjær, L. (2025). Monetary Policy Shocks and Narrative Restrictions: Rules Matter. *CESifo Working Paper*, 12246.

Chen, Y.-c. and Rogoff, K. (2003). Commodity currencies. *Journal of international Economics*, 60(1):133–160.

Christiano, L., Trabandt, M., and Walentin, K. (2011). Introducing Financial Frictions and Unemployment Into a Small Open Economy Model. *Journal of Economic Dynamics and Control*, 35(12):1999–2041.

Clarida, R. and Gali, J. (1994). Sources of real exchange rate fluctuations: how important are nominal shocks? *Carnegie-Rochester Conference Series on Public Policy*, 41:1–56.

Corsetti, G. (2008). New Open Economy Macroeconomics. *The New Palgrave Dictionary of Economics*.

Curdia, V. and Woodford, M. (2010). Credit spreads and monetary policy. *Journal of Money, Credit and Banking*, 42:3–35.

Curdia, V. and Woodford, M. (2016). Credit frictions and optimal monetary policy. *Journal of Monetary Economics*, 84:30–65.

Cushman, D. O. and Zha, T. (1997). Identifying monetary policy in a small open economy under flexible exchange rates. *Journal of Monetary economics*, 39(3):433–448.

De Rezende, R. B. and Ristiniemi, A. (2023). A shadow rate without a lower bound constraint. *Journal of Banking & Finance*, 146:106686.

Dieppe, A., Legrand, R., and Roye, B. V. (2016). The BEAR toolbox (ECB Working PaperNo. 1934). *European Central Bank*.

Dornbusch, R. (1976). Expectations and exchange rate dynamics. *Journal of Political Economy*, 84(6):1161–1176.

Egorov, K. and Mukhin, D. (2023). Optimal Policy under Dollar Pricing. *SAFE Working Paper*, 377.

Eichenbaum, M. and 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.

Engel, C. (1996). The forward disount anomaly and the risk premium: A survey of recent evidence. *Journal of Empirical Finance*, 3(2):123–192.

Engel, C. (2014). Exchange rates and interest parity. *Handbook of International Economics*, 4:453–522.

Fama, E. F. (1984). Forward and spot exchange rates. *Journal of Monetary Economics*, 14(3):319–338.

Faust, J. and Rogers, J. H. (2003). Monetary policy's role in exchange rate behavior. *Journal of Monetary Economics*, 50(7):1403–1424.

Fisher, L. A. and Huh, H.-s. (2023). Systematic monetary policy in a SVAR for Australia. *Economic Modelling*, 128:106519.

Froot, K. A. and Thaler, R. H. (1990). Anomalies: Foreign Exchange. *Journal of Economic Perspectives*, 4(3):179–192.

Fry, R. and Pagan, A. (2011). Sign restrictions in structural vector autoregressions: a critical review. *Journal of Economic Literature*, 49(4):938–960.

Galí, J. (2020). Uncovered interest parity, forward guidance and the exchange rate. *Journal of Money, Credit and Banking*, 52(S2):465–496.

Gilchrist, S. and Zakrajšek, E. (2012). Credit Spreads and Business Cycle Fluctuations. *American Economic Review*, 102(4):1692–1720.

Gopinath, G., Boz, E., Casas, C., Diez, F., Gourinchas, P.-O., and Plagborg-Møller, M. (2020). Dominant Currency Paradigm. *American Economic Review*, 110(3):677–719.

Gourinchas, P.-O. (2021). The Dollar Hegemon? Evidence and Implications for Policymakers. *The Asian Monetary Policy Forum*, in Steven J. Davis, Edward S Robinson and Bernard Yeung (ed.), Ch.7:264–300.

Gourinchas, P.-O., Rey, H., and Sauzet, M. (2019). The International Monetary and Financial System. *Annual Review of Economics*, 11:859–893.

Grabek, G. and Klos, B. (2013). Unemployment in the Estimated New Keynesian SoePL-2012 DSGE Model. *NBP Working Papers*, 144.

Groshenny, N. and Javed, N. (2023). Dornbusch's overshooting and the systematic component of monetary policy in SOE-SVARs. *TEPP Working Paper*, 2023(8).

Hoffmann, M., Kliem, M., Krause, M., Moyen, S., and Šauer, R. (2021). Rebalancing the euro area: Is wage adjustment in Germany the answer? *Journal of International Money and Finance*, 119:102497.

Ilzetzki, E., Reinhart, C. M., and Rogoff, K. S. (2019). Exchange arrangements entering the twenty-first century: Which anchor will hold? *The Quarterly Journal of Economics*, 134(2):599–646.

Jääskelä, J. P. and Jennings, D. (2011). Monetary policy and the exchange rate: Evaluation of VAR models. *Journal of International Money and Finance*, 30(7):1358–1374.

Justiniano, A. and Preston, B. (2010). Can structural small open-economy models account for the influence of foreign disturbances? *Journal of International Economics*, 81(1):61–74.

Kam, T., Lees, K., and Liu, P. (2009). Uncovering the hit list for small inflation targeters: A Bayesian structural analysis. *Journal of Money, Credit and Banking*, 41(4):583–618.

Kim, S. (2005). Monetary policy, foreign exchange policy, and delayed overshooting. *Journal of Money, Credit and Banking*, 37(4):775–782.

Kim, S. and Lim, K. (2018). Effects of monetary policy shocks on exchange rate in small open Economies. *Journal of Macroeconomics*, 56:324–339.

Kim, S. and Roubini, N. (2000). Exchange rate anomalies in the industrial countries: A solution with a structural VAR approach. *Journal of Monetary economics*, 45(3):561–586.

Kim, S.-H., Moon, S., and Velasco, C. (2017). Delayed overshooting: is it an '80s puzzle? *Journal of Political Economy*, 125(5):1570–1598.

Koop, G., Korobilis, D., et al. (2010). Bayesian multivariate time series methods for empirical macroeconomics. *Foundations and Trends® in Econometrics*, 3(4):267–358.

Landry, A. (2009). Expectations and exchange rate dynamics: A state-dependent pricing approach. *Journal of International Economics*, 78(1):60–71.

Lane, P. R. (2001). The new open economy macroeconomics: A survey. *Journal of International Economics*, 54(2):235–266.

Leeper, E. M., Sims, C., and Zha, T. (1996). What does monetary policy do? *Brookings Papers on Economic Activity*, 1996(2):1–78.

Lubik, T. A. and Schorfheide, F. (2006). A Bayesian look at New Open Economy Macroeconomics. *NBER Macroeconomics Annual 2005*, 20:312–382.

Lubik, T. A. and Schorfheide, F. (2007). Do central banks respond to exchange rate movements? A structural investigation. *Journal of Monetary Economics*, 54(4):1069–1087.

McCallum, B. T. (1994). A reconsideration of the uncovered interest parity relationship. *Journal of Monetary Economics*, 33(1):105–132.

Miranda-Agrippino, S. and Rey, H. (2020). U.S. Monetary Policy and the Global Financial Cycle. *Review of Economic Studies*, 87(6):2754–2776.

Müller, G. J., Wolf, M., and Hettig, T. (2024). Delayed overshooting: The case for information rigidities. *American Economic Journal: Macroeconomics*, 16(3):310–342.

Neely, C. J. (2015). Unconventional monetary policy had large international effects. *Journal of Banking & Finance*, 52:101–111.

Obstfeld, M. (2013). Crises and the international system. *International Economic Journal*, 27(2):143–155.

Obstfeld, M. and Rogoff, K. (1995a). The mirage of fixed exchange rates. *Journal of Economic Perspectives*, 9(4):73–96.

Obstfeld, M. and Rogoff, K. (1995b). Exchange rate dynamics redux. *Journal of Political Economy*, 103(3):624–660.

Read, M. (2023). Estimating the effects of monetary policy in Australia using sign-restricted Structural Vector Autoregressions. *Economic Record*, forthcoming.

Reinhart, C. M. and Rogoff, K. S. (2004). The modern history of exchange rate arrangements: a reinterpretation. *The Quarterly Journal of Economics*, 119(1):1–48.

Rogers, J. H. (1999). Monetary shocks and real exchange rates. *Journal of International Economics*, 49(2):269–288.

Rubio-Ramirez, J. F., Waggoner, D. F., and Zha, T. (2010). Structural vector autoregressions: Theory of identification and algorithms for inference. *The Review of Economic Studies*, 77(2):665–696.

Rüth, S. K. (2020). Shifts in monetary policy and exchange rate dynamics: Is Dornbusch's overshooting hypothesis intact, after all? *Journal of International Economics*, 126:103344.

Rüth, S. K. and Van der Veken, W. (2023). Monetary policy and exchange rate anomalies in set-identified SVARs: Revisited. *Journal of Applied Econometrics*.

Scholl, A. and 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.

Taylor, J. B. (1993). Discretion versus policy rules in practice. In *Carnegie-Rochester Conference Series on Public Policy*, volume 39, pages 195–214. Elsevier.

Taylor, J. B. (2001). The role of the exchange rate in monetary-policy rules. *American Economic Review*, 91(2):263–267.

Terrell, M., Haque, Q., Cross, J. L., and Doko Tchatoka, F. (2026). Monetary Policy Shocks and Exchange Rate Dynamics in Small Open Economies. *Journal of Applied Econometrics*.

Wolf, C. K. (2020). Svar (mis) identification and the real effects of monetary policy shocks. *American Economic Journal: Macroeconomics*, 12(4):1–32.

Wu, J. C. and Xia, F. D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, 48(2-3):253–291.

Yang, Y., Zhang, R., and Zhang, S. (2024). Deciphering Dollar Exchange Rates and Interest Parity. *Available at SSRN 4712390*.

Online Appendix

A Data Sources

The dataset spans from 1992:Q1 to 2019:Q4. Where required, series are seasonally adjusted using Eviews Census X-13.

A.1 United States

- **Real Gross Domestic Product** (Billions of Chained 2012 Dollars, Seasonally Adjusted Annual Rate)
  - Source: FRED Economic Data (GDPC1)
- **Consumer Price Index: All Items for the United States** (Index 2015=100, Not Seasonally Adjusted)
  - Source: FRED Economic Data (USACPIALLMINMEI)
- **Federal Funds Effective Rate** (Percent, Not Seasonally Adjusted)
  - Source: FRED Economic Data (FEDFUNDS)
- **Shadow rate** (Percent)
  - Source: Wu and Xia (2016)
- **Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity** (Percent, Not Seasonally Adjusted)
  - Source: FRED Economic Data (BAA10YM)

A.2 Australia

- **Real Gross Domestic Product for Australia** (Domestic Currency, Seasonally Adjusted)
  - Source: FRED Economic Data (NGDPRSAXDCAUQ)
- **Consumer Price Index: All Items: Total: Total for Australia** (Index 2015=100, Not Seasonally Adjusted)
  - Source: FRED Economic Data (AUSCPIALLQINMEI)
- **3-Month or 90-day Rates and Yields: Interbank Rates for Australia** (Percent, Not Seasonally Adjusted)
  - Source: FRED Economic Data (IR3TIB01AUQ156N)

- **Exchange rate** [**]
  - Source: Reserve Bank of Australia (Refinitiv Datastream, AUUSDSP)
- **Commodity Terms of Trade**
  - Description: Commodity Export Price Index, Individual Commodites Weighted by Ratio of Exports to GDP.
  - Source: International Monetary Fund (Country code: 193)
    * https://www.imf.org/en/Research/commodity-prices
- **Credit spread**
  - Description: Credit market spread between Australian large business variable lending rate and 3-month Bank Accepted Bill (BAB) rate.
  - Source: Reserve Bank of Australia
    * https://www.rba.gov.au/publications/rdp/2020/2020-01/supplementary-information.html

A.3 Canada

- **Real Gross Domestic Product for Canada** (Domestic Currency, Seasonally Adjusted)
  - Source: FRED Economic Data (NGDPRSAXDCCAQ)
- **Consumer Price Index: All Items: Total: Total for Canada** (Index 2015=100, Not Seasonally Adjusted)
  - Source: FRED Economic Data (CANCPIALLQINMEI)
- **3-Month or 90-day Rates and Yields: Interbank Rates for Canada** (Percent, Not Seasonally Adjusted)
  - Source: FRED Economic Data (IR3TIB01CAQ156N)
- **Exchange rate**
  - Source: Bank of Canada (Refinitiv Datastream, CNXRUSD)
- **Commodity Terms of Trade**
  - Description: Commodity Export Price Index, Individual Commodites Weighted by Ratio of Exports to GDP.
  - Source: International Monetary Fund (Country code: 156)

[**] For each SOE, we calculate real exchange rate from the nominal exchange rate and the US and domestic price levels, such that, $ln(e_t) = ln(s_t) + ln(p_t^*) - ln(p_t)$; where $ln(e_t)$ and $ln(s_t)$ are the logs of real and nominal exchange rates, respectively and $ln(p_t^*)$ and $ln(p_t)$ are the logs of US and domestic consumer price indices, respectively.

        * https://www.imf.org/en/Research/commodity-prices

- **Credit spread**
    - Description: Credit spread is calculated as the yield in the S&P Canada Investment Grade Corporate Bond Index (Code: SPFICAV) less the Canada, Government Bond Yield: 3 Year Benchmark (End Month)(Code: CNB14068; CANSIM-Statistic Canada).

A.4 New Zealand

- **Production-based gross domestic product (GDP)** (Real, NZD, Seasonally Adjusted)
    - Source: Statistics New Zealand (GDP06.Q.QT0.rs)
- **Consumer Price Index: All Items for New Zealand** (Index 2015=100, Not Seasonally Adjusted)
    - Source: FRED Economic Data (NZLCPIALLQINMEI)
- **3-Month or 90-day Rates and Yields: Interbank Rates for New Zealand** (Percent, Not Seasonally Adjusted)
    - Source: FRED Economic Data (IR3TIB01NZQ156N)
- **Exchange rate**
    - Source: Reserve Bank of New Zealand (EXR.MS11.D06)
- **Commodity Terms of Trade**
    - Description: Commodity Export Price Index, Individual Commodites Weighted by Ratio of Exports to GDP.
    - Source: International Monetary Fund (Country code: 196)
        * https://www.imf.org/en/Research/commodity-prices
- **Credit spread**
    - Description: Credit spread is calculated as the yield in the S&P New Zealand Investment Grade Corporate Bond Index (Code: SPNZICZ) less the New Zealand Government Bond Yield, 2 Years (Code:NZGBY2Y; Reserve Bank of New Zealand).

A.5 Norway

- **Real Gross Domestic Product for Norway** (Millions of Chained 2010 National Currency, Seasonally Adjusted)
    - Source: FRED Economic Data (CLVMNACSCAB1GQNO)

- **Consumer Price Index: All Items for Norway** (Index 2015=100, Not Seasonally Adjusted)
  - Source: FRED Economic Data (NORCPIALLQINMEI)
- **3-Month or 90-day Rates and Yields: Interbank Rates for Norway** (Percent, Not Seasonally Adjusted)
  - Source: FRED Economic Data (IR3TIB01NOQ156N)
- **Exchange rate**
  - Source: Norges Bank (Refinitiv Datastream, NWXRUSD)
- **Commodity Terms of Trade**
  - Description: Commodity Export Price Index, Individual Commodites Weighted by Ratio of Exports to GDP.
  - Source: International Monetary Fund (Country code: 142)
    - https://www.imf.org/en/Research/commodity-prices
- **Credit spread**
  - Description: Risk-premium new 5-years bond. Index made up of Norwegian industrial issuers. Percentage points over 3 month NIBOR. (RPREM.IND.M060)

A.6 Sweden

- **Real Gross Domestic Product for Sweden** (Millions of Chained 2010 National Currency, Seasonally Adjusted)
  - Source: FRED Economic Data (CLVMNACSCAB1GQSE)
- **Consumer Price Index: All Items for Sweden** (Index 2015=100, Not Seasonally Adjusted)
  - Source: FRED Economic Data (SWECPIALLQINMEI)
- **3-Month or 90-day Rates and Yields: Interbank Rates for Sweden** (Percent, Not Seasonally Adjusted)
  - Source: FRED Economic Data (IR3TIB01SEQ156N)
- **Shadow rate** (Percent)
  - Source: De Rezende and Ristiniemi (2023)
- **Exchange rate**
  - Source: Sveriges Riksbank Bank (Refinitiv Datastream, SDXRUSD)

- **Commodity Terms of Trade**
  - Description: Commodity Export Price Index, Individual Commodites Weighted by Ratio of Exports to GDP.
  - Source: International Monetary Fund (Country code: 144)
    * https://www.imf.org/en/Research/commodity-prices
- **Credit spread**
  - Description: Credit spread is calculated as the yield in the S&P Sweden Investment Grade Corporate Bond Index (Code: SPSEICR) less the Swedish Government Bond, maturity 2 years (Code: SEGVB2Y; Sveriges Riksbank, Refinitiv Datastream).

A.7 United Kingdom

- **Real Gross Domestic Product for United Kingdom** (Millions of Chained 2010 National Currency, Seasonally Adjusted)
  - Source: FRED Economic Data (CLVMNACSCAB1GQUK)
- **Consumer Price Index of All Items in the United Kingdom** (Index 2015=100, Not Seasonally Adjusted)
  - Source: FRED Economic Data (GBRCPIALLQINMEI)
- **3-Month or 90-day Rates and Yields: Interbank Rates for the United Kingdom** (Percent, Not Seasonally Adjusted)
  - Source: FRED Economic Data (IR3TIB01GBQ156N)
- **Shadow rate** (Percent)
  - Source: https://sites.google.com/view/jingcynthiawu/shadow-rates
- **Exchange rate**
  - Source: Bank of England (Refinitiv Datastream, UKXRUSD)
- **Commodity Terms of Trade**
  - Description: Commodity Export Price Index, Individual Commodites Weighted by Ratio of Exports to GDP.
  - Source: International Monetary Fund (Country code: 112)
    * https://www.imf.org/en/Research/commodity-prices
- **Credit spread**
  - Description: Credit spread is calculated as the yield in the S&P U.K. Investment Grade Corporate Bond Index (Code: SPUKICG) less the Long-Term Government Bond Yields: 10-year: Main (Including Benchmark) for the United Kingdom (Code: IRLTLT01GBQ156N; FRED Economic Data).

B The Structural Vector Autoregression (SVAR) model

Our methodology draws heavily on Arias et al. (2018) and Arias et al. (2019). First, consider the SVAR model:

$$\mathbf{y_t'A_0} = \sum_{l=1}^{p} \mathbf{y}_{t-l}'\mathbf{A}_l + \mathbf{c}' + \epsilon_{\mathbf{t}}' \ , \qquad \text{for } 1 \leq \mathbf{t} \leq \mathbf{T} \tag{1}$$

where $\mathbf{y_t'} = \begin{bmatrix} \mathbf{y_{1t}'} & \mathbf{y_{2t}'} \end{bmatrix}$. $\mathbf{y_{1t}}$ is a $(n_1 \times 1)$ vector of US variables and $\mathbf{y_{2t}}$ is a $(n_2 \times 1)$ vector of SOE variables, with $n = n_1 + n_2$ denoting the total number of variables. Similarly, the vector of structural shocks $\epsilon_{\mathbf{t}}$ is divided into two blocks, $\epsilon_{\mathbf{t}}' = \begin{bmatrix} \epsilon_{1t}' & \epsilon_{2t}' \end{bmatrix}$. $\mathbf{A_i}$, for $0 \leq i \leq p$, are $(n \times n)$ matrices of structural parameters, with $\mathbf{A_0}$ invertible. $\mathbf{c}$ is a $(n \times 1)$ vector of constants, p is the lag length, and $\mathbf{T}$ is the sample size. Conditional on past information and initial conditions $\mathbf{y}_0, ..., \mathbf{y}_{1-p}$, the vector $\epsilon_{\mathbf{t}}$ is Gaussian with mean zero and covariance matrix $\mathbb{I}_n$. Following Rubio-Ramirez et al. (2010), we can write the SVAR in compact form:

$$\mathbf{y_t'A_0} = \mathbf{x_t'A_+} + \epsilon_t' \ , \tag{2}$$

where $\mathbf{x_t'} = [\mathbf{y_{t-1}'} \dots \mathbf{y_{t-p}'} \ \ 1]$. $\mathbf{A_0}$ and $\mathbf{A_+} = [\mathbf{A_1'} \dots \mathbf{A_p'} \ \ \mathbf{c}']$ are matrices of structural parameters.

Post-multiplying Equation (2) by $\mathbf{A_0^{-1}}$, we obtain the reduced form VAR model:

$$\mathbf{y_t'} = \mathbf{x_t'B} + u_t' \ , \tag{3}$$

where $\mathbf{B} = \mathbf{A_+A_0^{-1}}, u_t' = \epsilon_t'\mathbf{A_0^{-1}}$ and $\mathbb{E}[u_t u_t'] = \mathbf{\Sigma} = (\mathbf{A_0A_0'})^{-1}$. $\mathbf{B}$ is the matrix of reduced-form coefficients and $\mathbf{\Sigma}$ is the residual variance-covariance matrix.

B.1 Impulse response functions

The impulse response functions (IRFs) are defined as follows:

Definition 1. *Let* $(\mathbf{A_0},\ \mathbf{A}_+)$ *be any value of structural parameters: The IRF of the* i*-th variable to the* j*-th structural shock at finite horizon* h *corresponds to the element in row* i *and column* j *of the matrix*

$$\mathbf{L}_h(\mathbf{A_0},\mathbf{A}_+) = (\mathbf{A_0}^{-1}\mathbf{J}'\mathbf{F}^h\mathbf{J})', \text{ where } \mathbf{F} = \begin{bmatrix} \mathbf{A}_1\mathbf{A_0}^{-1} & \mathbb{I}_n & \dots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{A}_{p-1}\mathbf{A_0}^{-1} & \mathbf{0} & \dots & \mathbb{I}_n \\ \mathbf{A}_p\mathbf{A_0}^{-1} & \mathbf{0} & \dots & \mathbf{0} \end{bmatrix} \text{ and } \mathbf{J} = \begin{bmatrix} \mathbb{I}_n \\ \mathbf{0} \\ \vdots \\ \mathbf{0} \end{bmatrix}$$

Importantly note that $\mathbf{L}_h(\mathbf{A}_0\mathbf{Q},\mathbf{A}_+\mathbf{Q}) = \mathbf{L}_h(\mathbf{A}_0,\mathbf{A}_+)\mathbf{Q}$ for $0 \leq h \leq \infty$ and $\mathbf{Q} \in O(n)$, where $O(n)$ denotes the set of all orthogonal matrices with dimensions n x n.

B.2 Set Identification by Sign and Zero Restrictions on $\mathbf{A}_0$

We follow closely the work of Arias et al. (2019) to achieve set identification by imposing sign and exclusion restrictions directly on the structural parameters in $\mathbf{A}_0$ matrix. Further, we impose two normalizing restrictions on the IRFs of US and SOE policy rates.

B.2.1 Sign restrictions

First, we impose sign restrictions on some elements of $\mathbf{A}_0$ and on IRFs of US and SOE policy rates at horizon 0. Following Arias et al. (2019), we stack $\mathbf{A}_0$ matrix and the IRFs at horizon 0 into a single matrix of dimension $k \times n$, which is denoted by $\mathbf{F}(\mathbf{A_0},\mathbf{A}_+)$:

$$\mathbf{F}(\mathbf{A_0},\mathbf{A}_+) = \begin{bmatrix} \mathbf{A}_0 \\ \mathbf{L_0}(\mathbf{A_0},\mathbf{A}_+) \end{bmatrix}_{k\times n} \quad \text{where } k = 2n \text{ in our case.}$$

Sign restrictions on $\mathbf{F}(\mathbf{A_0},\mathbf{A}_+)$ are represented by matrices $\mathbf{S}_j$ for $1 \leq j \leq n$, where the number of columns in $\mathbf{S}_j$ is equal to the number of rows in $\mathbf{F}(\mathbf{A_0},\mathbf{A}_+)$. $\mathbf{S}_j$ is a selection matrix with only one non-zero entry in each row. If the rank of $\mathbf{S}_j$ is s_j, then

s_j is the number of sign restrictions imposed to identify the j-th structural shock. The total number of sign restrictions are $s = \sum_{j=1}^{n} s_j$.[1]

Definition 2. *Let* $(\mathbf{A_0},\ \mathbf{A_+})$ *be any value of structural parameters. These parameters satisfy the sign restrictions if and only if*

$$\mathbf{S}_j\mathbf{F}(\mathbf{A_0}, \mathbf{A_+})\mathbf{e}_j > \mathbf{0}, \text{ for } 1 \leq j \leq n$$

where $\mathbf{e}_j$ denotes the j-th column of an identity matrix $\mathbb{I}_n$ of dimensions $n \times n$.

Algorithm 1: The following algorithm independently draws from the normal-generalized-normal $\mathcal{NGN}(\alpha,\ \beta,\ S,\ \Omega)$ distribution over the structural parameterization conditional on the sign restrictions.

1. Draw reduced-form parameters $(\mathbf{B}, \mathbf{\Sigma})$ independently from the $\mathcal{NIW}(\alpha,\ \beta,\ S,\ \Omega)$ distribution.
2. Draw $\mathbf{Q}$ independently from the uniform distribution over $O(n)$ using Theorem 1 (below), where $\mathbf{Q}$ is an $n \times n$ orthogonal matrix.
3. Keep $(\mathbf{A_0}, \mathbf{A_+}) = f_{Chol}^{-1}(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q})$ if the sign restrictions are satisfied.[2] This step is equivalent to keeping the draw if $\mathbf{S}_j\mathbf{F}(\mathbf{U}^{-1}\mathbf{Q}, \mathbf{B}\mathbf{U}^{-1}\mathbf{Q})\mathbf{e}_j > \mathbf{0}$, for $1 \leq j \leq n$, where $\mathbf{U}$ is upper triangular with positive diagonal and $\mathbf{\Sigma} = \mathbf{U}'\mathbf{U}$ is the Cholesky decomposition of $\mathbf{\Sigma}$.
4. Return to Step 1 until the required number of draws has been obtained.

To efficiently implement the first step of Algorithm 1 where each draw is serially uncorrelated, we follow Arias et al. (2018) and exploit the fact that the space of all structural parameters is equivalent to the product of the space of all reduced-form parameters and $O(n)$. This mapping is given by $(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) \rightarrow (\mathbf{A_0}, \mathbf{A_+}) = (\mathbf{U}^{-1}\mathbf{Q}, \mathbf{B}\mathbf{U}^{-1}\mathbf{Q})$, where $\mathbf{\Sigma} = \mathbf{U}'\mathbf{U}$ is the Cholesky decomposition of $\mathbf{\Sigma}$ such that $\mathbf{U}$ is upper triangu-

[1] See Arias et al. (2013) for specific examples on imposing sign restrictions using $\mathbf{S}_j$ matrices.

[2] f_{Chol} defines the mapping from $(\mathbf{A_0}, \mathbf{A_+})$ to $(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q})$ as:

$f_{Chol}(\mathbf{A_0}, \mathbf{A_+}) = (\underbrace{\mathbf{A_+}\mathbf{A_0}^{-1}}_{\mathbf{B}}, \underbrace{(\mathbf{A_0}\mathbf{A}_0')^{-1}}_{\mathbf{\Sigma}}, \underbrace{Chol((\mathbf{A_0}\mathbf{A}_0')^{-1})\mathbf{A_0}}_{\mathbf{Q}})$; where *Chol* is the Cholesky decomposition. See Arias et al. (2018) for details.

lar with positive diagonal and $\mathbf{Q}$ is an element of $O(n)$. The likelihood is flat over the space of orthogonal matrices because $(\mathbf{U}^{-1}, \mathbf{BU}^{-1})$ is observationally equivalent to $(\mathbf{U}^{-1}\mathbf{Q}, \mathbf{BU}^{-1}\mathbf{Q})$. Also, the likelihood at the reduced-form parameters $(\mathbf{B}, \mathbf{\Sigma})$ will be equal to the likelihood at the structural parameters $(\mathbf{U}^{-1}, \mathbf{BU}^{-1})$. A prior on the reduced-form parameters, together with the uniform distribution, induces a prior on the structural parameters via the above mapping. Thus, if we independently draw $(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q})$ from a uniform-independent-normal-inverse-Wishart distribution over the orthogonal reduced-form parameterization with parameters α, β, S, Ω, then we can transform these draws to $(\mathbf{A_0},\ \mathbf{A}_+)$ using a mapping function, f_{Chol}^{-1}. We, then, can independently draw from a normal-generalized-normal distribution over the structural parameterization, denoted by $\mathcal{NGN}(\alpha,\ \beta,\ S,\ \Omega)$, where its density over the structural parameterization induced by the uniform-normal-inverse-Wishart density over the orthogonal reduced-form parameterization is denoted by:[3]

$$\begin{aligned}\mathcal{NGN}_{(\alpha,\beta,S,\Omega)}(\mathbf{A_0}, \mathbf{A}_+) = \mathcal{UNIW}_{(\alpha,\beta,S,\Omega)}(f_{Chol}(\mathbf{A_0}, \mathbf{A}_+))\vartheta_{f_{Chol}}(\mathbf{A_0}, \mathbf{A}_+) \\ \propto \underbrace{|\det(\mathbf{A_0})|^{\nu-n} e^{-\frac{1}{2}\mathrm{vec}(\mathbf{A_0})'(\mathbb{I}_n \bigotimes \beta)\mathrm{vec}(\mathbf{A_0})}}_{\mathrm{generalized-normal}} \\ \times \underbrace{e^{-\frac{1}{2}\mathrm{vec}(\mathbf{A}_+ - S\mathbf{A_0})'(\mathbb{I}_n \bigotimes \Omega)^{-1}\mathrm{vec}(\mathbf{A}_+ - S\mathbf{A_0})}}_{\mathrm{conditionally-normal}}\end{aligned} \tag{4}$$

where $\vartheta_{f_{Chol}}(\mathbf{A_0}, \mathbf{A}_+) = 2^{\frac{n(n+1)}{2}}|\det(\mathbf{A_0})|^{-(2n+m+1)}$ is the volume element of f_{Chol} at $(\mathbf{A}_0, \mathbf{A}_+)$.

It is easy to independently draw from the uniform-normal-inverse-Wishart distribution. Matlab has routines for making independent draws from both the inverse-Wishart distribution and the normal distribution. There are efficient algorithms for making independent draws from the uniform distribution over $O(n)$. Canova and De Nicolo (2002), Uhlig (2005), and Rubio-Ramirez et al. (2010) all proposed algorithms to do this. The algorithm of Rubio-Ramirez et al. (2010) is the most efficient, particularly for larger SVAR systems (e.g., $n > 4$).[4] Rubio-Ramirez et al. (2010) results are based on the following well-known theorem (corresponds to

[3]See Arias et al. (2018) and Arias et al. (2013) for details.
[4]See Rubio-Ramirez et al. (2010) for details.

theorem 4 in Arias et al. (2018)).

Theorem 1: *Let $\mathbf{X}$ be an $n \times n$ random matrix with each element having an independent standard normal distribution. Let $\mathbf{X} = \mathbf{QR}$ be the QR decomposition of $\mathbf{X}$ with the diagonal of $\mathbf{R}$ normalized to be positive. The random matrix $\mathbf{Q}$ is orthogonal and is a draw from the uniform distribution over $O(n)$.*[5]

B.2.2 Zero restrictions

Second, we impose zero restrictions on some elements of $\mathbf{A_0}$. For the sake of consistency, we use the function $\mathbf{F}(\mathbf{A_0}, \mathbf{A}_+) = \mathbf{A_0}$ to impose zero restrictions on $\mathbf{A_0}$ matrix. In our case we do not impose any zero restrictions on the IRFs but this can easily be extended by stacking $\mathbf{L_0}(\mathbf{A_0}, \mathbf{A}_+)$ in $\mathbf{F}(\mathbf{A_0}, \mathbf{A}_+)$, similar to the case of imposing sign restrictions. Zero restrictions can be represented by matrices $\mathbf{Z}_j$ for $1 \leq j \leq n$, where the number of columns in $\mathbf{Z}_j$ is equal to the number of rows in $\mathbf{F}(\mathbf{A_0}, \mathbf{A}_+)$. If the rank of $\mathbf{Z}_j$ is z_j, then z_j is the number of zero restrictions associated with the j-th structural shock. The total number of zero restrictions is $z = \sum_{j=1}^{n} z_j$.[6]

Definition 2. *Let $(\mathbf{A_0},\ \mathbf{A}_+)$ be any value of structural parameters. These parameters satisfy the zero restrictions if and only if*

$$\mathbf{Z}_j\mathbf{F}(\mathbf{A_0}, \mathbf{A}_+)\mathbf{e}_j = \mathbf{0}, \text{ for } 1 \leq j \leq n\ .$$

Similar to sign restrictions, $\mathbf{e}_j$ denotes the j-th column of $\mathbb{I}_n$, where $\mathbb{I}_n$ is the identity matrix of dimension $n \times n$.

From the definition of $f_{_{Chol}}$ and the fact that $\mathbf{F}(\mathbf{A}_0\mathbf{Q}, \mathbf{A}_+\mathbf{Q}) = \mathbf{F}(\mathbf{A}_0, \mathbf{A}_+)\mathbf{Q}$, the zero restrictions in the orthogonal reduced-form parameterization are:

$$\mathbf{Z}_j\mathbf{F}(f^{-1}_{_{Chol}}(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}))\mathbf{e}_j = \mathbf{Z}_j\mathbf{F}(f^{-1}_{_{Chol}}(\mathbf{B}, \mathbf{\Sigma}, \mathbb{I}_n))\mathbf{Q}\mathbf{e}_j = 0 \qquad \text{for } 1 \leq j \leq n$$

This means that the zero restrictions in the orthogonal reduced-form parameteriza-

[5] For proof see Stewart (1980).

[6] See Arias et al. (2013) for specific examples on imposing zero-restrictions using $\mathbf{Z}_j$ matrices.

tion are really just linear restrictions on each column of the orthogonal matrix $\mathbf{Q}$, conditional on the reduced-form parameters $(\mathbf{B}, \mathbf{\Sigma})$. It is this observation that is key to being able to make independent draws from the set of all structural parameters satisfying the zero restrictions (Arias et al., 2018).

Algorithm 2: The following algorithm makes independent draws from a distribution over the structural parameterization conditional on the zero restrictions. We use it to impose zero restrictions on $\mathbf{A_0}$ in order to implement block exogeneity.

1. Draw $(\mathbf{B}, \mathbf{\Sigma})$ independently from the $\mathcal{NIW}(\alpha,\ \beta,\ S,\ \Omega)$ distribution.
2. For $1 \leq j \leq n$, draw $\mathbf{x}_j \in \mathbb{R}^{n+1-j-z_j}$ independently from a standard normal distribution and set $\mathbf{w}_j = \mathbf{x}_j/||\mathbf{x}_j||$.
3. Define $\mathbf{Q} = [\mathbf{q}_1 \dots \mathbf{q}_n]$ recursively by $\mathbf{q}_j = \mathbf{K}_j \mathbf{w}_j$ for any matrix $\mathbf{K}_j$ whose columns form an orthonormal basis for the null space of the $(j-1+z_j) \times n$ matrix.[7]

$$\mathbf{M}_j = [\mathbf{q}_1 \dots \mathbf{q}_{j-1} \quad (\mathbf{Z}_j \mathbf{F}(f_{Chol}^{-1}(\mathbf{B}, \mathbf{\Sigma}, \mathbb{I}_n)))']'.$$

By construction, $\mathbf{q}_j$ is perpendicular to the rows of $\mathbf{M}_j$ and $||\mathbf{x}_j|| = ||\mathbf{w}_j|| = 1$. Thus, the matrix $\mathbf{Q}$ obtained through Steps 2 and 3 is orthogonal and

$$\mathbf{Z}_j \mathbf{F}(f_{Chol}^{-1}(\mathbf{B}, \mathbf{\Sigma}, \mathbb{I}_n))\mathbf{Q}\mathbf{e}_j = 0 \qquad \text{for } 1 \leq j \leq n$$

4. Set $(\mathbf{A_0}, \mathbf{A}_+) = f_{Chol}^{-1}(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q})$.
5. Return to Step 1 until the required number of draws has been obtained.

B.2.3 Implementing block exogeneity

From Equation 1:[8]

$$\mathbf{y_t'} = \begin{bmatrix} \mathbf{y_{1t}'} & \mathbf{y_{2t}'} \end{bmatrix}, \qquad \mathbf{A}_l = \begin{bmatrix} A_{11,l} & A_{12,l} \\ \\ A_{21,l} & A_{22,l} \end{bmatrix}, \qquad \epsilon_\mathbf{t}' = \begin{bmatrix} \epsilon_{1t}' & \epsilon_{2t}' \end{bmatrix}$$

[7] The computation of each $\mathbf{K}_j$ requires a single QR-decompostion of an $n \times n$ invertible matrix. In Matlab $\mathbf{K}_j = \text{null}(\mathbf{M}_j)$.

[8] For simplicity, we omit constant terms in the exposition.

where $\mathbf{y'_{1t}}$ is $1 \times n_1$, $\mathbf{y'_{2t}}$ is $1 \times n_2$, $n_1 + n_2 = n$, $A_{11,l}$ is $n_1 \times n_1$, $A_{12,l}$ is $n_1 \times n_2$, $A_{21,l}$ is $n_2 \times n_1$, $A_{22,l}$ is $n_2 \times n_2$, ϵ'_{1t} is $1 \times n_1$ and ϵ'_{2t} is $1 \times n_2$.

Cushman and Zha (1997) implement block exogeneity by restricting $A_{21,l} = 0$ for $l = 0, 1, ..., p$. These restrictions mean that the domestic block ($\mathbf{y'_{2t}}$) does not influence the foreign block ($\mathbf{y'_{1t}}$), neither contemporaneously, nor in a dynamic way through lags. However, when using the methodology of Arias et al. (2018), one can only impose $(n-k)$ zero restrictions per equation, where k corresponds to the k^{th} equation in the system.[9] As a result, we can only impose zero restrictions on the contemporaneous structural matrix $\mathbf{A}_0$: $A_{21,l} = 0$, for $l = 0$, and are unable to impose $A_{21,l} = 0$ for $l = 1, ..., p$. To circumvent this technical obstacle, we implement block exogeneity on the lagged matrices by using extremely tight priors with distribution centered at zero for all the reduced-form coefficients of domestic variables appearing in the foreign block. Specifically, we use a special case of Independent Normal Inverse Wishart ($\mathcal{NIW}$) priors where we adopt conventional Minnesota priors for the reduced-form VAR coefficients, β.[10]

B.2.4 Independent $\mathcal{NIW}$ priors and posteriors

Arias et al. (2019) use Natural Conjugate $\mathcal{NIW}$ priors for the reduced form parameters, $\mathbf{B}$ and $\mathbf{\Sigma}$:

$$\beta \sim \mathcal{N}(\beta_0, \mathbf{\Sigma} \otimes \Phi_0), \tag{5}$$

$$\mathbf{\Sigma} \sim \mathcal{IW}(S_0, \alpha_0), \tag{6}$$

where matrix Φ_0 contains the hyperparameters that control the tightness of distribution of reduced form parameters, the residual variance-covariance matrix $\mathbf{\Sigma}$ has an inverse Wishart distribution with scale matrix S_0 and degrees of freedom α_0.

However, these priors are not suited for the purpose of implementing block exogeneity. Natural Conjugate $\mathcal{NIW}$ priors employ Kronecker structure for the variance-covariance matrix of the reduced-form parameters. Hence, the variances are

[9] See also Arias et al. (2021) page # 92 and Kilian and Lütkepohl (2017) page # 481.

[10] $\beta = vec(\mathbf{B})$.

proportional to one another. As a result, imposing block exogeneity on one equation would impose it on all equations (Dieppe et al., 2016; Koop et al., 2010). Moreover, the structure implied by the Kronecker product requires that every equation has the same set of explanatory variables (Koop et al., 2010), meaning that if we remove a variable in one equation, that variable would be removed from all equations.

The techniques developed by Arias et al. (2018) can be used for any prior distributions. Hence, instead of using Natural Conjugate $\mathcal{NIW}$ priors which are problematic for our purpose of implementing block exogeneity, we use Independent $\mathcal{NIW}$ priors over the reduced-form parameters. The prior distributions of the reduced-form parameters from Equation (3) take the form:

$$\beta \sim \mathcal{N}(\beta_0, \Omega_0), \tag{7}$$

$$\mathbf{\Sigma} \sim \mathcal{IW}(S_0, \alpha_0), \tag{8}$$

where the residual variance-covariance matrix $\mathbf{\Sigma}$ has an inverse Wishart distribution with scale matrix S_0 and degrees of freedom α_0.[11]

We follow standard Minnesota priors for the prior distribution of the reduced form coefficients β in Equation (7), where the distribution is centered at 1 for the coefficients of own 1st lags, and for the rest, the distributions are centered at 0, including the constants (Kilian and Lütkepohl, 2017; Dieppe et al., 2016). Ω_0 is the prior variance-covariance matrix of β. Unlike the case of the Natural Conjugate $\mathcal{NIW}$ priors, here Ω_0 is independent of the residual variance-covariance matrix $\mathbf{\Sigma}$. Moreover, Ω_0 is a diagonal matrix containing the hyperparameters that control the variance of the distributions. Ω_0 takes the following form, where for simplicity we only consider the first lag of the first equation and the constant:

[11] We set the hyperparameters of inverse Wishart distribution in a conventional way: $\alpha_0 = n + 1$ and $S_0 = \mathbb{I}_n$ (Dieppe et al., 2016).

$$\Omega_0 = \begin{bmatrix} \sigma_1^2(\lambda_1\lambda_4)^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots \\ 0 & (\lambda_1/L^{\lambda_3})^2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \dots \\ 0 & 0 & (\sigma_1/\sigma_2)^2(\lambda_1\lambda_2/L^{\lambda_3})^2 & 0 & 0 & 0 & 0 & 0 & 0 & \dots \\ 0 & 0 & 0 & (\sigma_1/\sigma_3)^2(\lambda_1\lambda_2/L^{\lambda_3})^2 & 0 & 0 & 0 & 0 & 0 & \dots \\ 0 & 0 & 0 & 0 & (\sigma_1/\sigma_4)^2(\lambda_1\lambda_2/L^{\lambda_3})^2 & 0 & 0 & 0 & 0 & \dots \\ 0 & 0 & 0 & 0 & 0 & (\sigma_1/\sigma_5)^2(\lambda_1\lambda_2\lambda_5/L^{\lambda_3})^2 & 0 & 0 & 0 & \dots \\ 0 & 0 & 0 & 0 & 0 & 0 & (\sigma_1/\sigma_6)^2(\lambda_1\lambda_2\lambda_5/L^{\lambda_3})^2 & 0 & 0 & \dots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & (\sigma_1/\sigma_7)^2(\lambda_1\lambda_2\lambda_5/L^{\lambda_3})^2 & 0 & \dots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & (\sigma_1/\sigma_8)^2(\lambda_1\lambda_2\lambda_5/L^{\lambda_3})^2 & \dots \\ \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \end{bmatrix}$$

The diagonal elements of Ω_0 can be written in the following form:

$$\sigma_{c_i}^2 = \sigma_i^2(\lambda_1\lambda_4)^2 \qquad \text{if constant} \tag{9}$$

$$\sigma_{ii}^2 = (\lambda_1/L^{\lambda_3})^2 \qquad \text{if } i = j \tag{10}$$

$$\sigma_{ij}^2 = (\sigma_i/\sigma_j)^2(\lambda_1\lambda_2/L^{\lambda_3})^2 \qquad \text{if } i \neq j \tag{11}$$

$$\sigma_{for_{ij}}^2 = (\sigma_i/\sigma_j)^2(\lambda_1\lambda_2\lambda_5/L^{\lambda_3})^2 \qquad \text{if } i \neq j \text{ and } n_1 < j \leq n \tag{12}$$

where σ_i^2 and σ_j^2 denote the OLS residual variance of the auto-regressive models estimated for variables i and j. n_1 denotes the number of foreign variables.

Equations (31), (32) and (33) are the standard Minnesota priors. We follow Dieppe et al. (2016) and introduce hyperparamter (λ_5) in Equation (34). λ_5 is applied only on the foreign block and controls the tightness of the distributions of domestic variables in the foreign block. We set $\lambda_5 = 1e-8$. This small value imposes highly informative priors on the parameters of the domestic variables in the foreign block, where the distribution is centered at zero. We select standard prior variances for the rest of the parameters ($\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 1$). Thus, we implement block exogeneity through a special case of Independent $\mathcal{NIW}$ priors, where the reduced-form coefficients follow Minnesota priors with an additional hyperparameter. Finally, if the prior distribution over the reduced-form parameters is $\mathcal{NIW}(\alpha_0, \beta_0, S_0, \Omega_0)$, then the posterior distribution over the reduced-form parameters is $\mathcal{NIW}(\tilde{\alpha}, \tilde{\beta}, \tilde{S}, \tilde{\Omega})$, where

$$\begin{aligned}
\tilde{\alpha} &= \mathbf{T} + \alpha_0, \\
\tilde{\Omega} &= [\Omega_0^{-1} + Z'VZ]^{-1}, \\
\tilde{\beta} &= \tilde{\Omega}[\Omega_0^{-1}\beta_0 + Z'V\mathbf{Y}] \\
\tilde{S} &= S_0 + (\mathbf{Y} - \mathbf{X}\hat{\mathbf{B}})'(\mathbf{Y} - \mathbf{X}\hat{\mathbf{B}}),
\end{aligned}$$

where $\mathbf{Y} = [\mathbf{y_1} \cdots \mathbf{y_T}]'$, $\mathbf{X} = [\mathbf{x_1} \cdots \mathbf{x_T}]'$, $V = \mathbf{\Sigma}^{-1} \otimes \mathbb{I}_\mathbf{T}$, $Z = \mathbb{I}_n \otimes \mathbf{X}$ and $\hat{\mathbf{B}} = \tilde{\beta} + chol(\tilde{\Omega})' * RAND((n*p+1)*n, 1)$.

B.2.5 The Importance Sampler

Algorithm 2 draws independently from a distribution over the structural parameterization conditional on the zero restrictions that is not equal to the $\mathcal{NGN}(\alpha,\ \beta,\ S,\ \Omega)$ distribution conditional on the zero restrictions. Since the objective is to independently draw from the $\mathcal{NGN}(\alpha,\ \beta,\ S,\ \Omega)$ distribution over the structural parameterization conditional on the zero restrictions, we employ the following importance sampler algorithm.[12]

Algorithm 3: The following algorithm independently draws from the $\mathcal{NGN}(\alpha,\ \beta,\ S,\ \Omega)$ distribution over the structural parameterization conditional on the sign and zero restrictions.

1. Use Algorithm 2 to independently draw $(\mathbf{A}_0, \mathbf{A}_+)$.
2. If $(\mathbf{A}_0, \mathbf{A}_+)$ satisfies the sign restrictions, then set its importance weight to

$$\frac{\mathcal{NGN}_{(\alpha,\beta,S,\Omega)}(\mathbf{A}_0, \mathbf{A}_+)}{\mathcal{NIW}_{(\alpha,\beta,S,\Omega)}(\mathbf{B}, \mathbf{\Sigma})\ \vartheta_{(g \circ f_{Chol})|\mathcal{Z}}(\mathbf{A}_0, \mathbf{A}_+)} \propto \frac{|\det \mathbf{A}_0|^{-(2n+m+1)}}{\vartheta_{(g \circ f_{Chol})|\mathcal{Z}}(\mathbf{A}_0, \mathbf{A}_+)},$$

where $(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) = f_{Chol}(\mathbf{A}_0, \mathbf{A}_+)$ and $\mathcal{Z}$ denotes the set of all structural parameters that satisfy the zero restrictions. Otherwise, set its importance weight to zero.
3. Return to Step 1 until the required number of draws has been obtained.
4. Re-sample with replacement using the importance weights.

[12]see Arias et al. (2018) for details.

C Additional results from the baseline models

C.1 IRFs to a one standard deviation SOE monetary policy shocks for each SOE

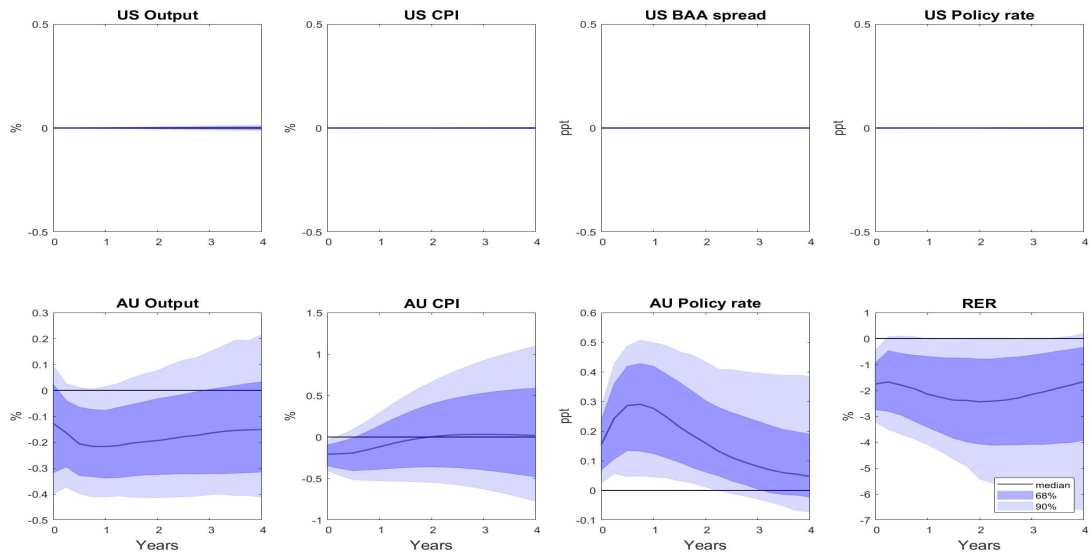

Figure 1: Australia - IRFs to a one standard deviation SOE contractionary monetary policy shock

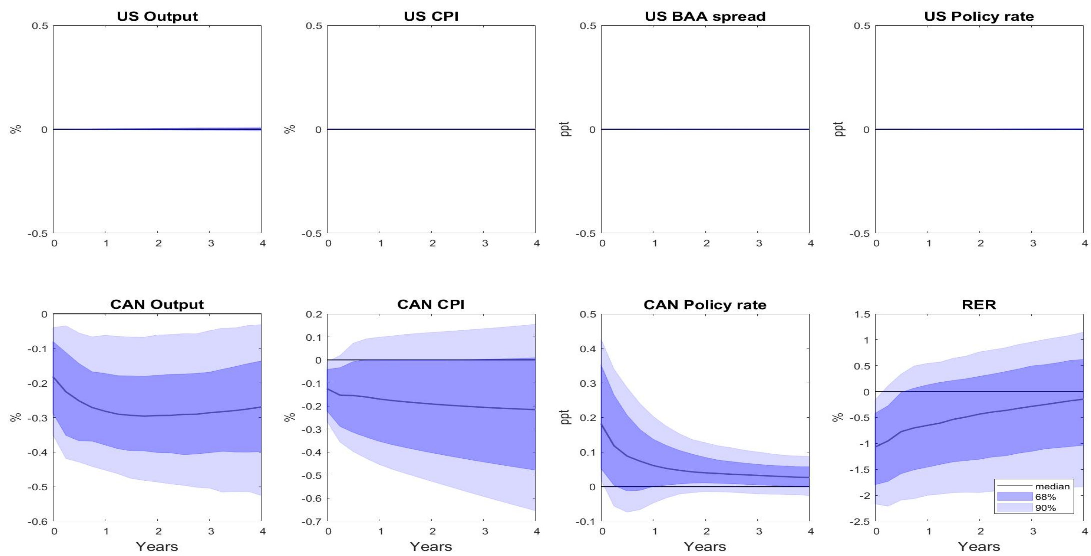

Figure 2: Canada - IRFs to a one standard deviation SOE contractionary monetary policy shock

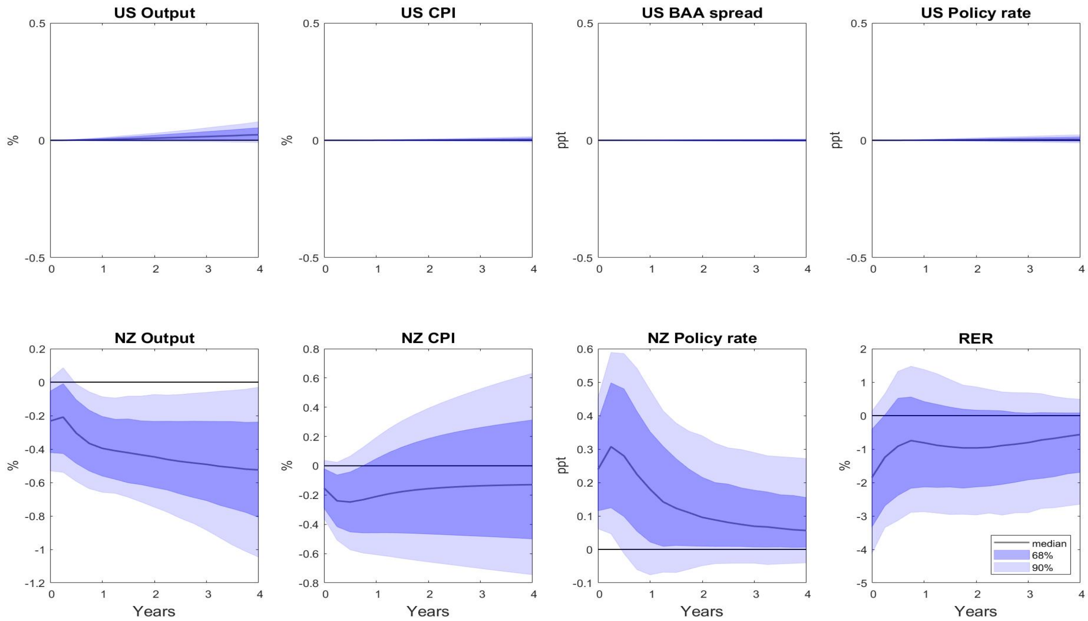

Figure 3: New Zealand - IRFs to a one standard deviation SOE contractionary monetary policy shock

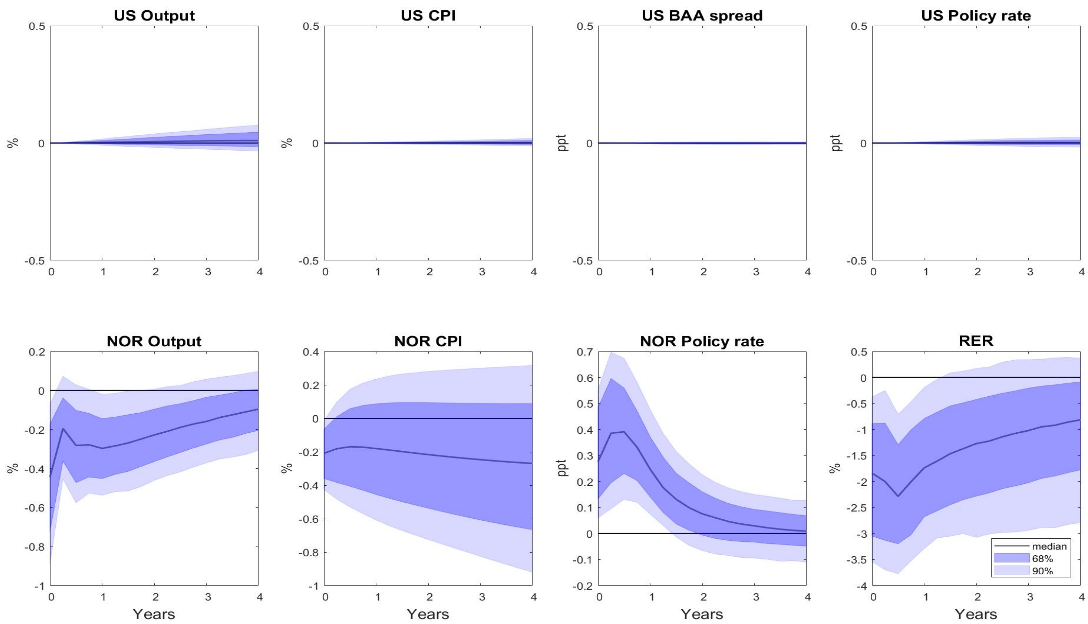

Figure 4: Norway - IRFs to a one standard deviation SOE contractionary monetary policy shock

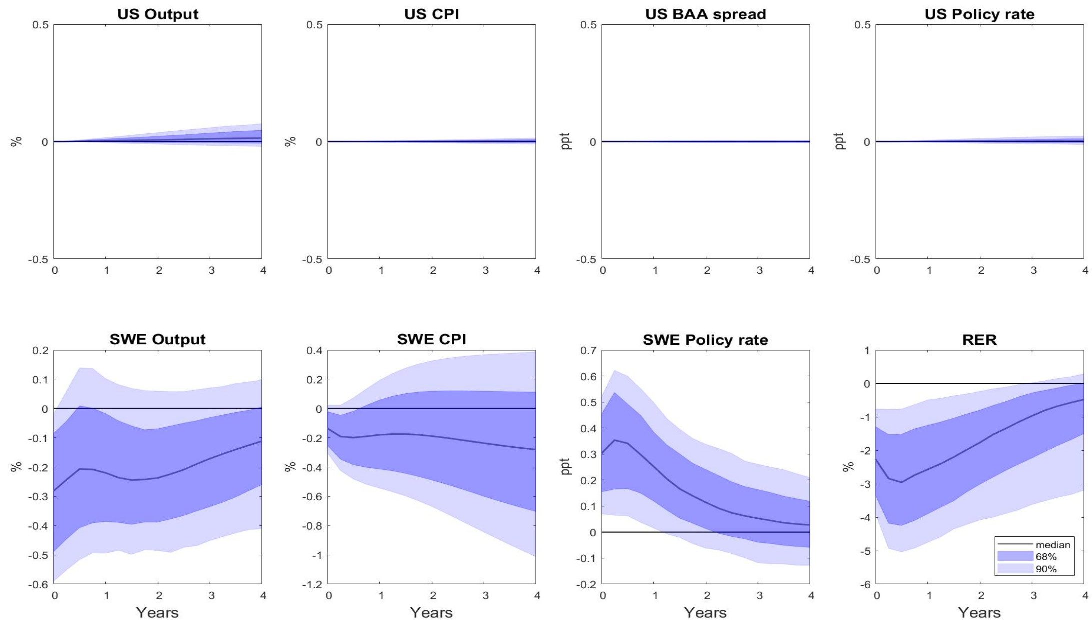

Figure 5: Sweden - IRFs to a one standard deviation SOE contractionary monetary policy shock

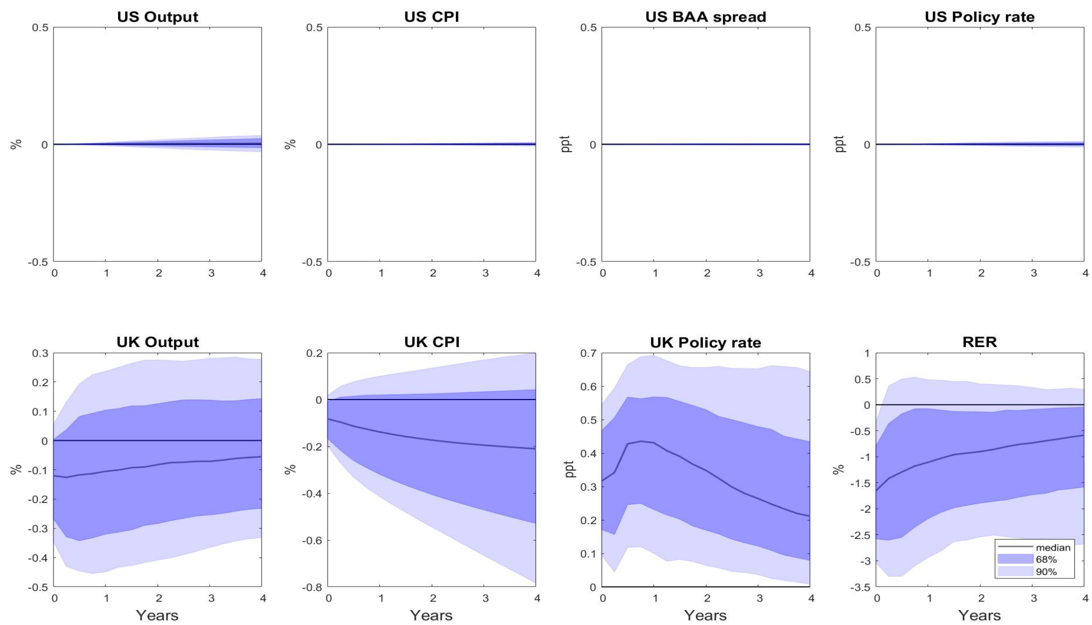

Figure 6: UK - IRFs to a one standard deviation SOE contractionary monetary policy shock

C.2 IRFs to a one standard deviation US monetary policy shocks for each SOE

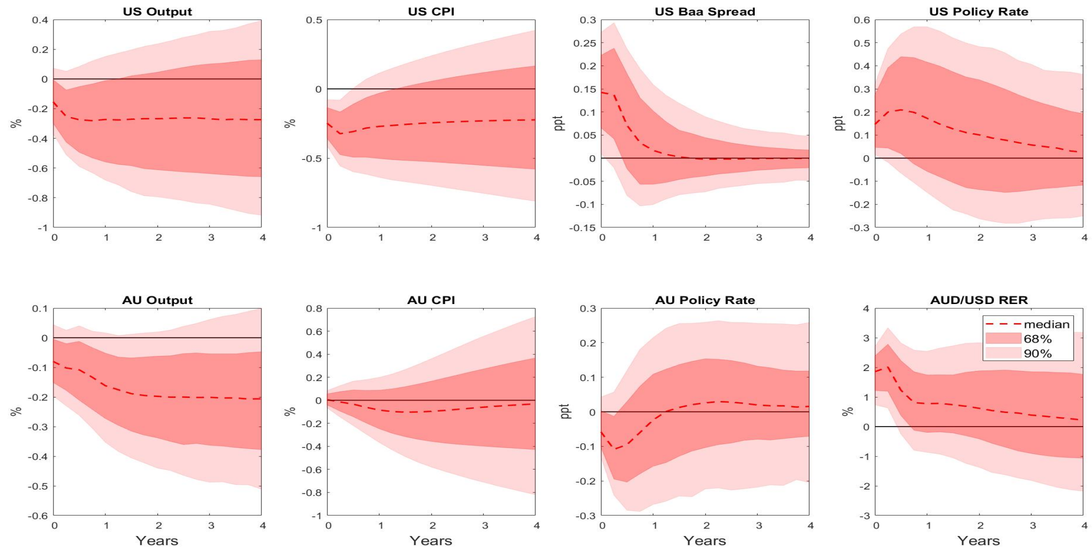

Figure 7: Australia - IRFs to a one standard deviation US contractionary monetary policy shock

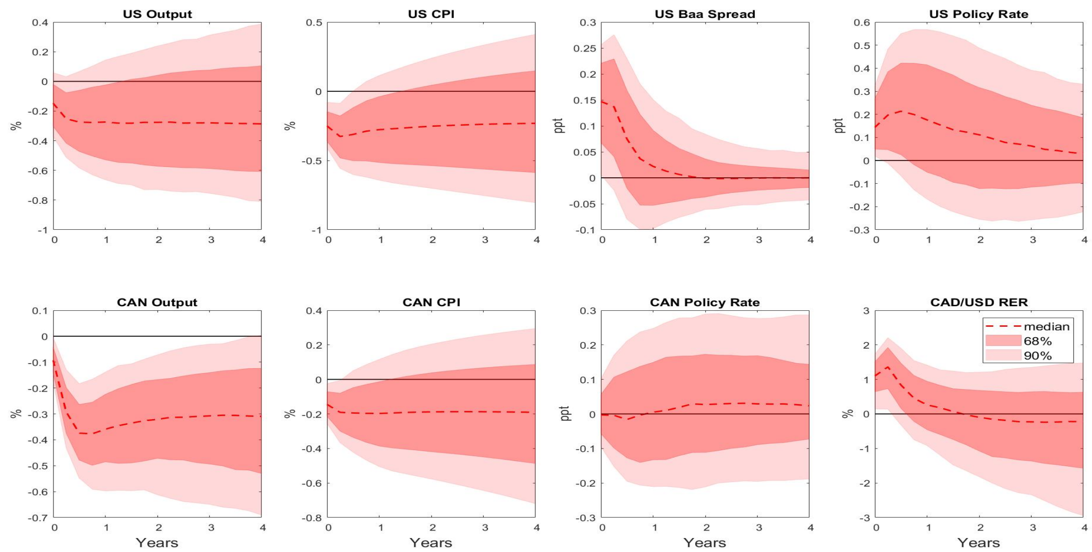

Figure 8: Canada - IRFs to a one standard deviation US contractionary monetary policy shock

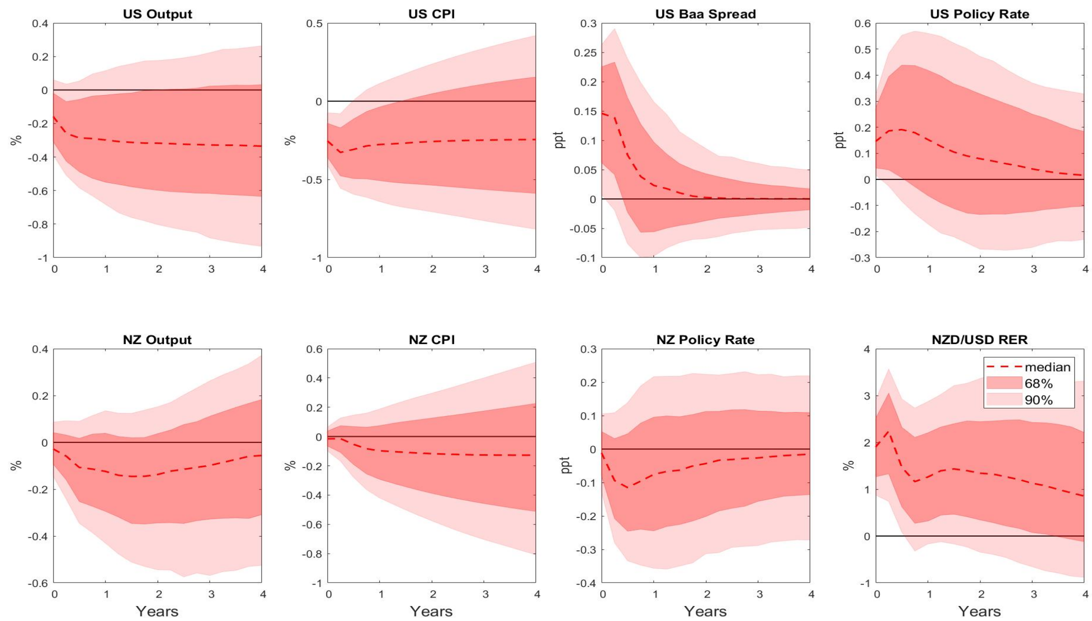

Figure 9: New Zealand - IRFs to a one standard deviation US contractionary monetary policy shock

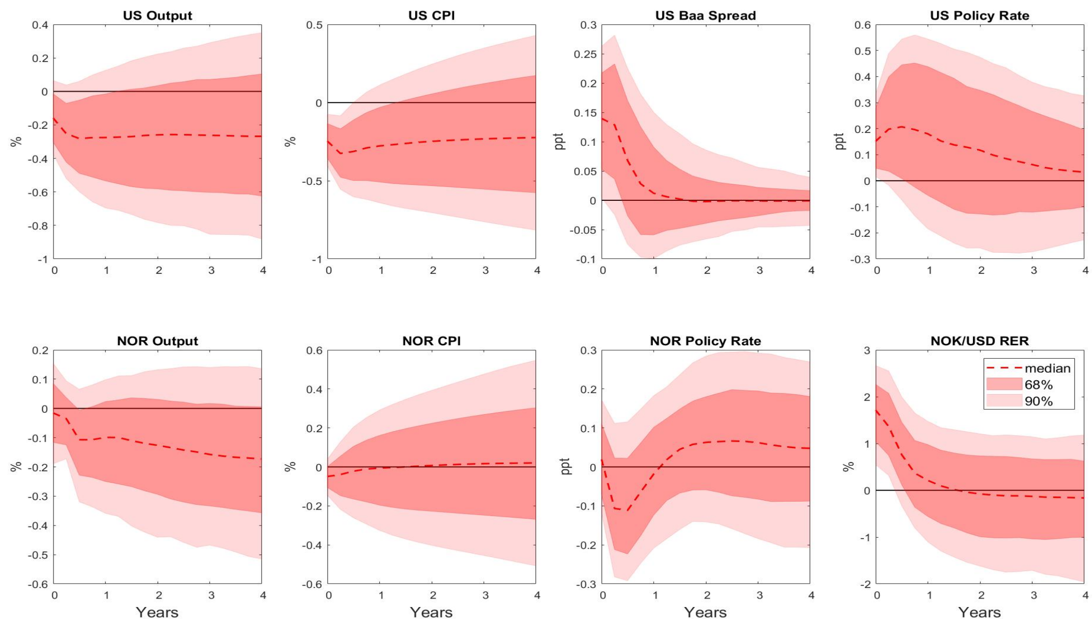

Figure 10: Norway - IRFs to a one standard deviation US contractionary monetary policy shock

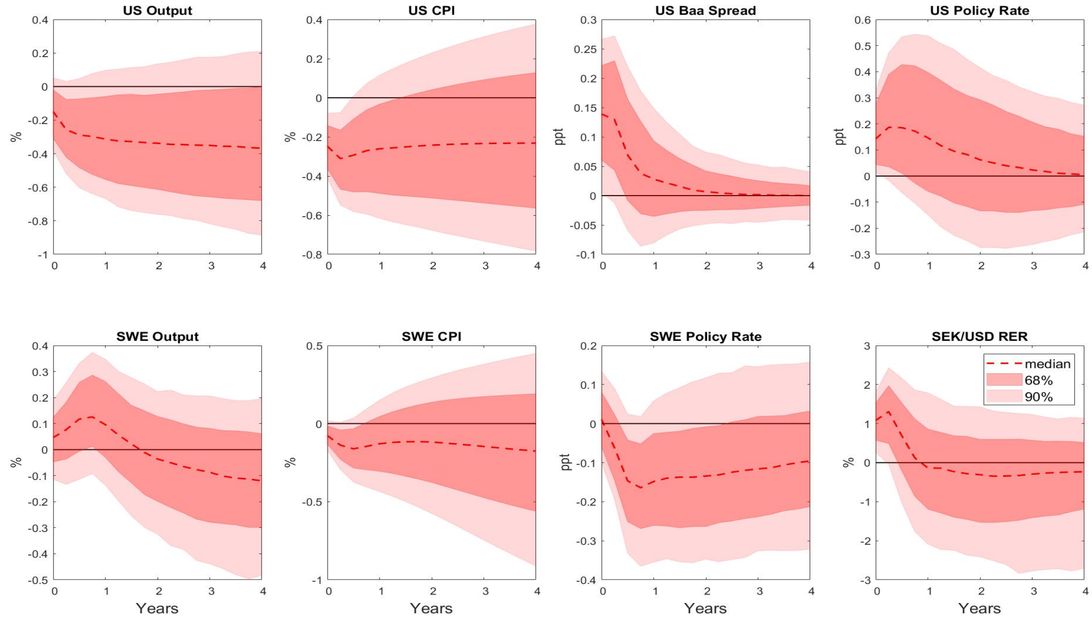

Figure 11: Sweden - IRFs to a one standard deviation US contractionary monetary policy shock

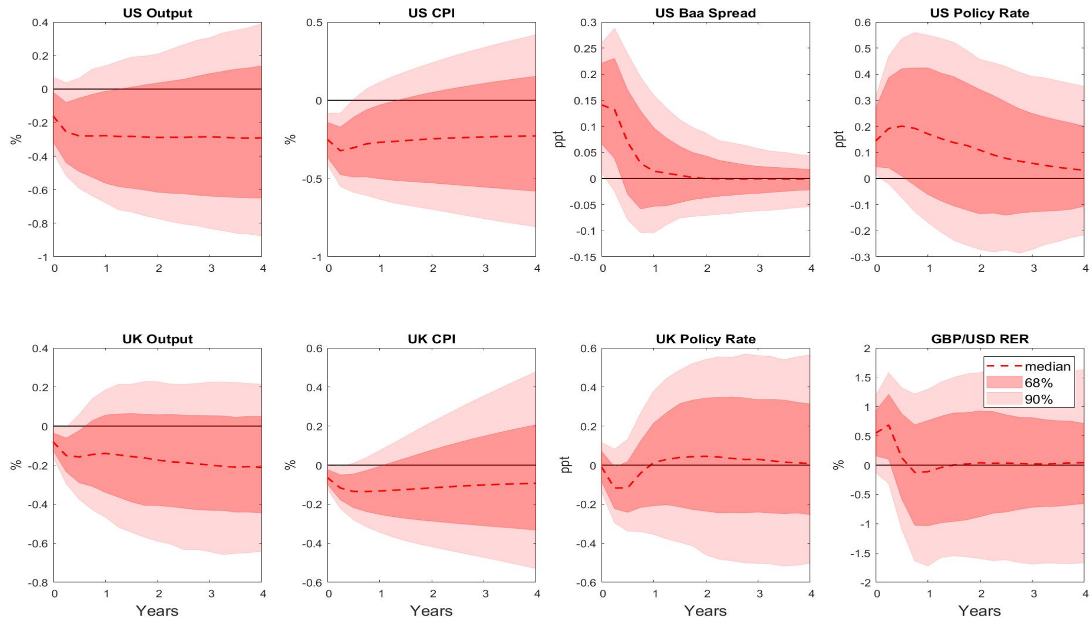

Figure 12: UK - IRFs to a one standard deviation US contractionary monetary policy shock

C.3 Forecast error variance decomposition

Figure 13 shows the forecast-error variance decomposition of the six SOE/US real exchange rates. With the exception of Canada and New Zealand, domestic monetary policy shocks account for a greater share of the RER volatility than US shocks. Depending on the country, domestic monetary policy shocks roughly explain 10 to 25 percents of the volatility of the exchange rate in the short run, while the share attributed to US shocks varies from 3 to 18 percents. Depending on the country, the joint contribution of US and SOE monetary disturbances to the short-run volatility of the SOE/US RER ranges from 25 to 35 percents.

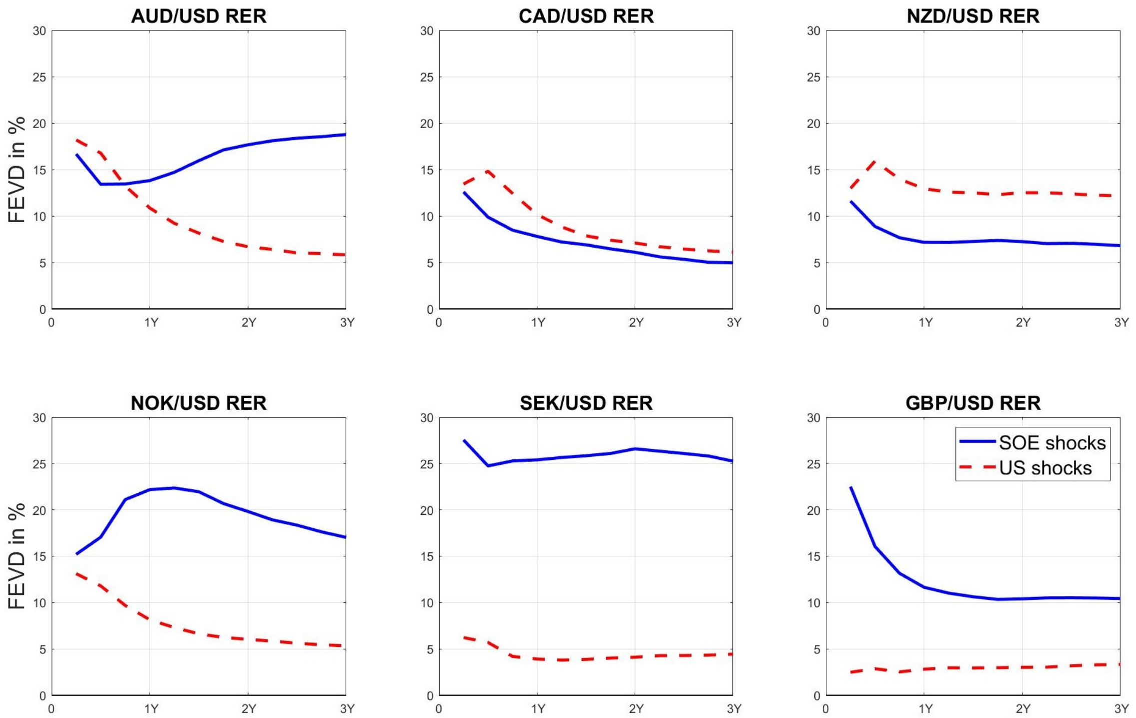

Figure 13: Forecast error variance decomposition of the SOE/US RER. *Note:* In each panel, the solid line represents the posterior median estimate of the contribution of SOE monetary shocks to the forecast-error variance of the RER, while the dashed line shows the contribution of US monetary shocks.

C.4 Contemporaneous coefficients in SOE and US monetary policy equations

Panel A: SOE monetary policy rules			
SOEs	ψ_y	ψ_π	ψ_e
AUS	0.72	0.65	0.09
	[0.24;2.20]	[0.17;2.75]	[0.02;0.35]
CAN	0.99	1.32	0.16
	[0.24;3.10]	[0.37;3.63]	[0.05;0.49]
NZ	0.87	1.44	0.11
	[0.24;3.99]	[0.36;5.49]	[0.03;0.46]
NOR	0.62	1.31	0.16
	[0.16;2.73]	[0.34;5.80]	[0.04;0.69]
SWE	0.94	1.92	0.14
	[0.21;4.01]	[0.58;8.11]	[0.04;0.64]
UK	1.85	3.64	0.18
	[0.54;7.48]	[0.79;14.28]	[0.05;0.72]
Panel B: US monetary policy rules			
US/SOEs	ψ_{y^*}	ψ_{π^*}	ψ_{cs^*}
Average (All SOEs)	0.42	0.39	-0.56
	[0.12;0.93]	[0.11;1.01]	[-1.36;-0.16]

Table 1: Contemporaneous coefficients in SOE and US monetary policy equations estimated over full sample period from 1992:Q1 to 2019:Q4. *Note:* Panel A reports the parameter estimates for each individual SOE central bank rule. Panel B reports the average parameter estimates for the US monetary policy rules across all six SOEs. The main entries correspond to the posterior median estimates, and the entries inside the brackets denote the respective 68% probability intervals.

The estimates in Panel A reveal that all six SOE central banks systematically adjust interest rates consistent with conventional Taylor-type rules. The posterior medians for the output coefficients (ψ_y) range from 0.62 in Norway to 1.85 in the UK, while the inflation coefficients (ψ_π) exceed unity across all SOEs except Australia (0.65). This implies a policy rate hike in response to an increase in output or inflation. The contemporaneous exchange rate coefficients (ψ_e) are positive and statistically significant, ranging from 0.09 in Australia to 0.18 in the UK, confirming a systematic policy tightening in response to currency depreciation. Moreover, the positively bounded probability intervals provide evidence that there is a large mass of realizations of the policy coefficient related to exchange rate fluctuations, suggesting that SOE central banks paid non-negligible attention to disturbances in their domestic currencies.

Panel B shows that the Federal Reserve reacts predictably to developments in the US economy, with an average output coefficient (ψ_{y^*}) of 0.42 and an inflation coefficient (ψ_{π^*}) of 0.39. Crucially, our framework captures the systematic response to the financial environment in the US; the average credit spread coefficient (ψ_{cs^*}) is -0.56, with the 68% probability interval [-1.36; -0.16] bounded below zero. This indicates a statistically significant and aggressive Fed funds rate cut to buffer the macroeconomy against tightening credit conditions.

D Additional results

D.1 Robustness check 1 (Excluding ZLB episodes)

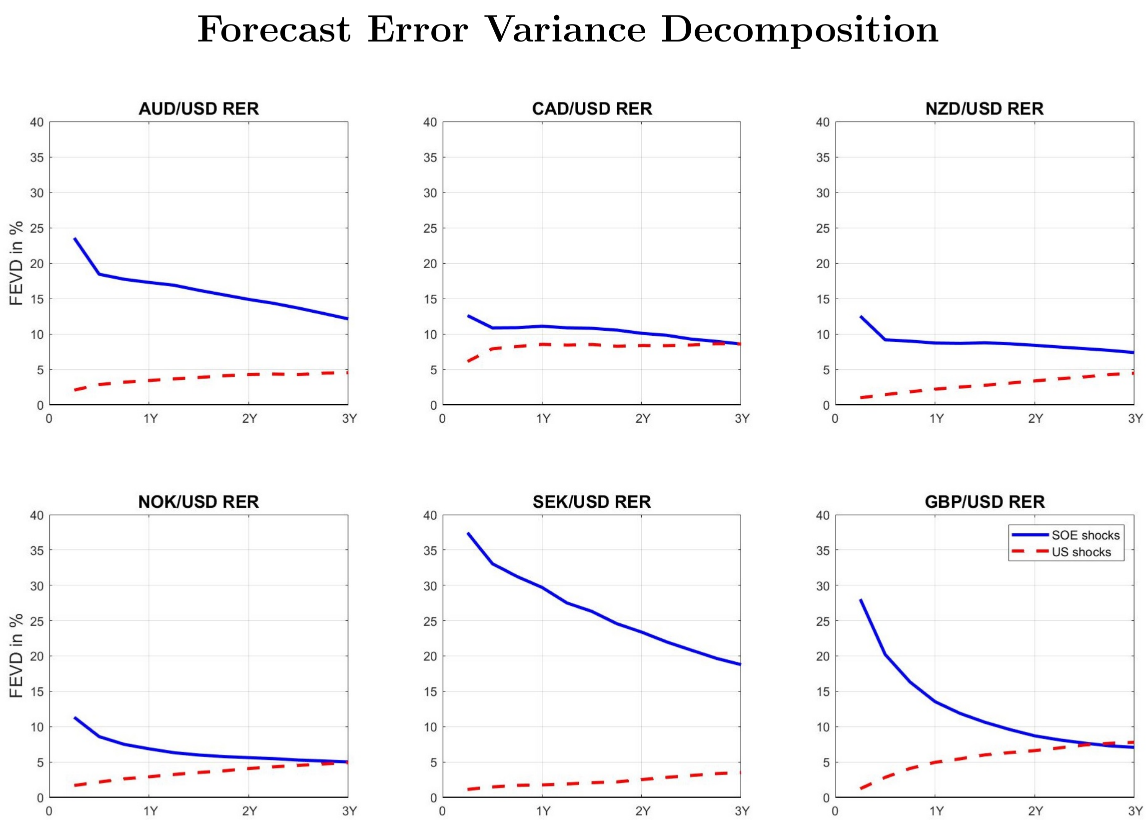

Figure 14: Contribution of one-standard deviation US and domestic monetary policy shocks to time-series fluctuations for Robustness check 1 (Excluding ZLB episodes). *Note:* The solid lines are the contribution of domestic monetary policy shock and dashed lines are the contribution of US monetary policy shock.

Contemporaneous coefficients in SOE and US monetary policy equations

Panel A: SOE monetary policy rules			
SOEs	ψ_y	ψ_π	ψ_e
AUS	0.72	0.73	0.11
	[0.19;2.77]	[0.16;2.56]	[0.02;0.45]
CAN	1.16	1.42	0.24
	[0.30;4.00]	[0.46;4.36]	[0.06;0.70]
NZ	0.99	1.67	0.14
	[0.29;3.80]	[0.45;6.31]	[0.04;0.56]
NOR	0.79	1.80	0.20
	[0.21;3.06]	[0.46;6.93]	[0.05;0.79]
SWE	1.19	2.03	0.15
	[0.31;4.65]	[0.55;7.90]	[0.03;0.72]
UK	1.21	2.62	0.14
	[0.30;5.12]	[0.87;9.29]	[0.03;0.65]

Panel B: US monetary policy rules			
US/SOEs	ψ_{y^*}	ψ_{π^*}	ψ_{cs^*}
Average (All SOEs)	0.51	0.73	-0.99
	[0.15;1.22]	[0.20;1.90]	[-2.10;-0.30]

Table 2: Contemporaneous coefficients in SOE and US monetary policy equations estimated over shorter sample period from 1992:Q1 to 2008:Q3. *Note:* Panel A reports the parameter estimates for each individual SOE central bank rule. Panel B reports the average parameter estimates for the US monetary policy rules across all six SOEs. The main entries correspond to the posterior median estimates, and the entries inside the brackets denote the respective 68% probability intervals.

In Panel A, the contemporaneous parameters for the SOE central banks mirror those in the baseline model but exhibit a generally more aggressive stabilization stance. The posterior medians for the output coefficients (ψ_y) increase across all SOEs, ranging from 0.72 in Australia to 1.21 in the UK, while the inflation coefficients (ψ_π) range from 0.73 to 2.62, exceeding unity in all SOEs, except Australia. This implies a policy rate hike in response to an increase in output or inflation. The coefficients related to exchange rate fluctuations (ψ_e) remain significantly positive, ranging from 0.11 in Australia to 0.24 in Canada, confirming a systematic policy tightening in response to currency depreciation. The positively bounded probability intervals suggest that SOE central banks paid non-negligible attention to fluctuations in their domestic currencies.

In Panel B, the SOE averages for the US monetary policy rule reflect a stronger systematic response to conventional macroeconomic fundamentals than seen in the full sample. The average US output coefficient (ψ_{y^*}) increases to 0.51, and the inflation coefficient (ψ_{π^*}) sharpens to 0.73. The average systematic response to the credit spread (ψ_{cs^*}) deepens to -0.99, with the 68% probability interval [-2.10; -0.30] bounded below zero. This shows that the Federal Reserve cut the fed funds rate more aggressively in response to credit spread spikes during the Great Moderation era.

D.2 Robustness check 2 (Including an SOE-specific 'Commodity Terms of Trade')

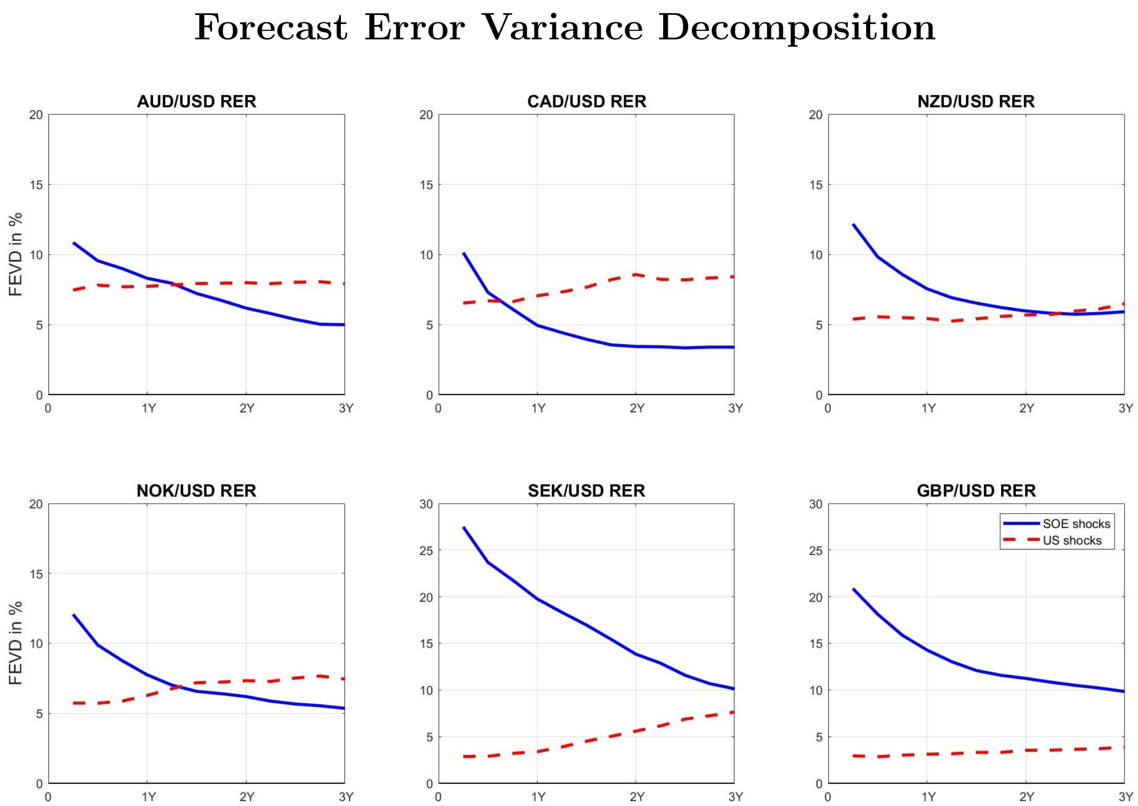

Figure 15: Contribution of one-standard deviation US and domestic monetary policy shocks to time-series fluctuations for Robustness check 2 (SOE Commodity Terms of Trade). *Note:* The solid lines are the contribution of domestic monetary policy shock and dashed lines are the contribution of US monetary policy shock.

Contemporaneous coefficients in SOE and US monetary policy equations

Panel A: SOE monetary policy rules			
SOEs	ψ_y	ψ_π	ψ_e
AUS	0.77	0.75	0.11
	[0.25;2.50]	[0.20;2.50]	[0.03;0.43]
CAN	0.83	1.14	0.16
	[0.23;2.28]	[0.31;2.95]	[0.04;0.44]
NZ	0.96	1.51	0.14
	[0.25;3.90]	[0.38;5.69]	[0.04;0.62]
NOR	0.61	1.38	0.17
	[0.16;2.11]	[0.38;4.91]	[0.04;0.69]
SWE	0.98	1.83	0.12
	[0.26;3.77]	[0.47;6.52]	[0.02;0.58]
UK	2.08	3.32	0.19
	[0.61;6.76]	[0.89;12.47]	[0.04;0.78]

Panel B: US monetary policy rules				
US/SOEs	ψ_{y^*}	ψ_{π^*}	ψ_{cs^*}	ψ_{cp^*}
Average (All SOEs)	0.58	0.81	-0.89	-1.25
	[0.18;1.45]	[0.22;2.24]	[-2.19;-0.26]	[-3.36;-0.12]

Table 3: Contemporaneous coefficients in SOE and US monetary policy equations estimated over full sample from 1992:Q1 to 2019:Q4 for 9-variable SVAR models that include commodity terms of trade. *Note:* Panel A reports the parameter estimates for each individual SOE central bank rule. Panel B reports the average parameter estimates for the US monetary policy rules across all six SOEs. The main entries correspond to the posterior median estimates, and the entries inside the brackets denote the respective 68% probability intervals.

Panel A shows that SOE policy parameters mirror those of our baseline when allowing for unrestricted contemporaneous feedback from the commodity terms of trade (cp_t^*). The posterior medians for output coefficients (ψ_y) range from 0.61 in Norway to 2.08 in the UK, while inflation coefficients (ψ_π) exceed unity in all SOEs except Australia (0.75). This implies a policy rate hike in response to an increase in output or inflation. The exchange rate coefficients (ψ_e) remain significantly positive, ranging from 0.11 in Australia to 0.19 in the UK, confirming a systematic policy tightening in response to currency depreciation. The positively bounded probability intervals suggest that SOE central banks paid non-negligible attention to fluctuations in their domestic currencies.

In Panel B, the SOE averages for the US monetary policy rule reveal a responsive Federal Reserve. The average US output coefficient (ψ_{y^*}) stands at 0.58, while the inflation coefficient (ψ_{π^*}) sharpens to 0.81. The systematic accommodation of financial frictions remains intact, with the average credit spread coefficient (ψ_{cs^*}) estimated at -0.89. Crucially, the commodity terms of trade parameter (ψ_{cp^*}) yields an average posterior median of -1.25, with its 68% probability interval [-3.36; -0.12] bounded below zero. This provides evidence that the Federal Reserve systematically responds to commodity price pressures by adjusting the fed funds rate.

D.3 Robustness check 3 (Including an SOE corporate credit spread)

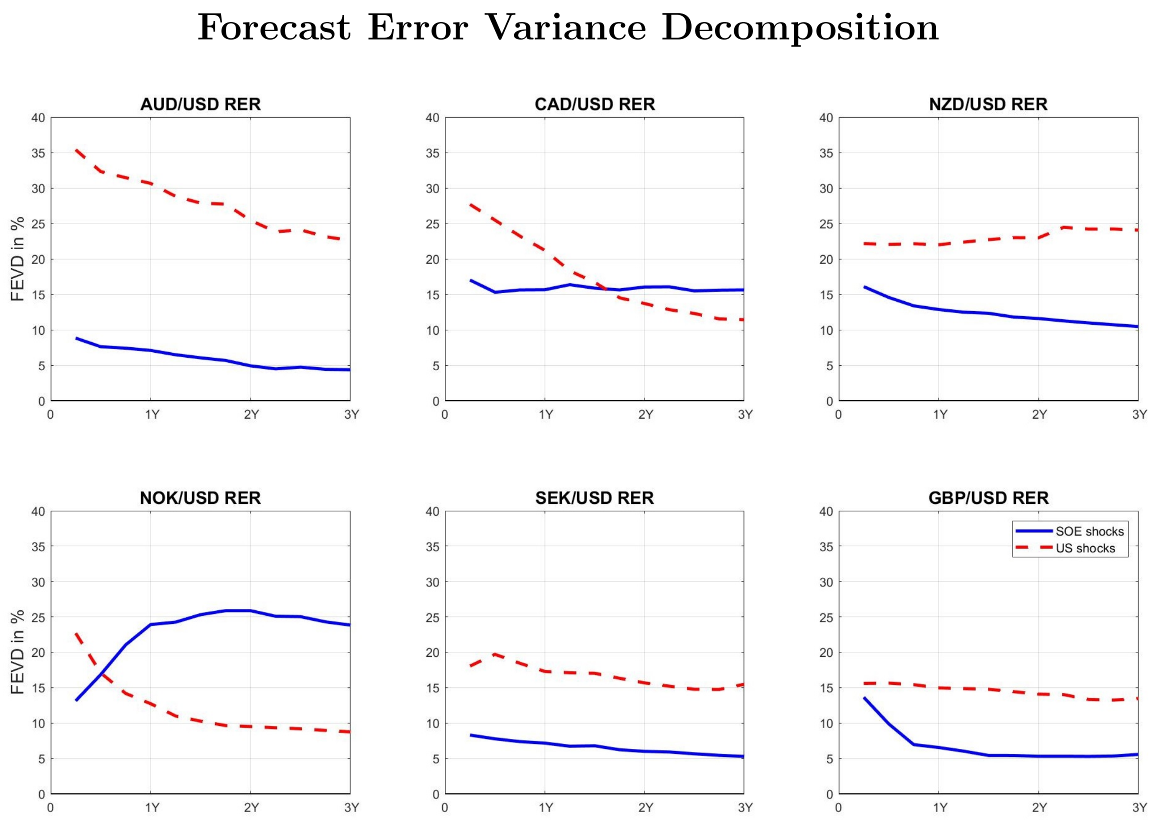

Figure 16: Contribution of one-standard deviation US and domestic monetary policy shocks to time-series fluctuations for Robustness check 3 (SOE corporate credit spread). *Note:* The solid lines are the contribution of domestic monetary policy shock and dashed lines are the contribution of US monetary policy shock.

Contemporaneous coefficients in SOE and US monetary policy equations

Panel A: SOE monetary policy rules				
SOEs	ψ_y	ψ_π	ψ_{cs}	ψ_e
AUS	0.64	0.70	-3.00	0.10
	[0.16;2.84]	[0.19;2.51]	[-8.48;-0.91]	[0.02;0.50]
CAN	0.63	0.60	-0.90	0.08
	[0.19;1.56]	[0.19;1.86]	[-2.65;-0.33]	[0.02;0.31]
NZ	0.94	0.81	-1.35	0.06
	[0.23;3.89]	[0.23;5.83]	[-7.50;-0.32]	[0.01;0.40]
NOR	0.41	0.64	-2.47	0.11
	[0.13;1.22]	[0.16;2.52]	[-10.21;-0.58]	[0.03;0.45]
SWE	0.27	0.94	-0.74	0.06
	[0.07;1.06]	[0.26;2.09]	[-2.32;-0.23]	[0.02;0.19]
UK	1.19	2.25	-1.74	0.19
	[0.33;3.90]	[0.65;8.46]	[-6.07;-0.57]	[0.04;0.44]

Panel B: US monetary policy rules			
US/SOEs	ψ_{y^*}	ψ_{π^*}	ψ_{cs^*}
Average (All SOEs)	0.47	0.46	-0.59
	[0.14;1.26]	[0.11;1.34]	[-1.59;-0.18]

Table 4: Contemporaneous coefficients in SOE and US monetary policy equations estimated over sample period from 2000:Q1 to 2019:Q4 for 9-variable SVAR models that include an SOE corporate credit spread. *Note:* Panel A reports the parameter estimates for each individual SOE central bank rule. Panel B reports the average parameter estimates for the US monetary policy rules across all six SOEs. The main entries correspond to the posterior median estimates, and the entries inside the brackets denote the respective 68% probability intervals.

In Panel A, the posterior medians of the output coefficients (ψ_y) range from 0.27 in Sweden to 1.19 in the UK, and the inflation coefficients (ψ_π) remain below unity in all SOEs except the UK (2.25). The domestic credit spread coefficients (ψ_{cs}) are significantly negative, ranging from -0.74 in Sweden to -3.00 in Australia. This suggests that SOE central banks systematically lean against domestic credit spreads, implementing expansionary monetary policy to shield financial markets from tightening corporate borrowing costs. The exchange rate coefficients (ψ_e) remain significantly positive, ranging from 0.06 in New Zealand and Sweden to 0.19 in the UK, confirming a systematic policy tightening in response to currency depreciation. The positively bounded probability intervals suggest that SOE central banks paid non-negligible attention to fluctuations in their domestic currencies while simultaneously managing domestic financial stabilization goals.

In Panel B, the SOE averages for the coefficients in the US monetary policy rule show that the Federal Reserve continues to react predictably to the US macroeconomic fundamentals, yielding an average output coefficient (ψ_{y^*}) of 0.47 and an inflation coefficient (ψ_{π^*}) of 0.46. The systematic reaction to credit frictions remains intact, with the average credit spread coefficient (ψ_{cs^*}) estimated at -0.59, and its 68% probability interval [-1.59; -0.18] lying in negative territory.

E UIP derivation

E.1 Data transformation and units

- By convention, interest rates are always annualized. Moreover, we are expressing policy rates in percent. For example, let's assume that the cash rate in NZ in 1994:Q2 was equal to 2.50%. Then, in our dataset used to estimate the SVAR model, we would read $r^{NZ}_{1994:Q2} = 2.50$. IRFs of policy rates are thus expressed in percentage points.
- We use **annualized quarterly inflation rates expressed in percent**. For example, let's assume that the annualized quarter-to-quarter inflation rate in NZ in 1994:Q2 was equal to 5.40% :

$$\left(\frac{P^{NZ}_{94:Q2} - P^{NZ}_{94:Q1}}{P^{NZ}_{94:Q1}} \right) \times 400 = 5.4,$$

  then, in our dataset, we would read $\pi^{APP,NZ}_{1994:Q2} = 5.4$.

E.2 Introducing UIP

Let i_t denote the **net** nominal interest rate on a **one-year** riskless domestic bond. Let i^*_t denote the **net** nominal interest rate on a **one-year** riskless foreign bond. Note that i_t and i^*_t are not expressed in percent. Let S_t denote the nominal exchange rate at time t, while S_{t+1} denotes the nominal exchange rate one year from t.
Hence, $E_t\left(\frac{S_{t+1}}{S_t}\right)$ is the expectation at time t of the depreciation rate over the coming year. $\frac{S_{t+1}}{S_t}$ is the realized depreciation over the year that elapsed between t and $t+1$. In this example, a period is a year. Instead, in our application, a period is a quarter. In this example, UIP is given by:

- UIP:

$$1 + i_t = (1 + i^*_t)\, E_t \left(\frac{S_{t+1}}{S_t} \right)$$

- Taking logs on both sides, UIP implies:

$$i_t \approx i^*_t + \log\left(\frac{E_t S_{t+1}}{S_t} \right)$$
$$i_t \approx i^*_t + \log\left(E_t S_{t+1}\right) - \log\left(S_t\right)$$

- The ex-post (realized) deviation from UIP (the so-called excess return), denoted Λ_t, is given by:

$$\Lambda_t \equiv i^*_t - i_t + s_{t+1} - s_t$$

  where $s_t \equiv \log S_t$. Note that the excess return Λ_t is <u>not expressed in percent</u>.

E.3 Defining excess returns

We wish to compute the excess return (i.e. deviation from UIP), denoted Λ_t.
In the paper, we use the following formula:

$$\Lambda_t = r_t^* - r_t + 4 \times (s_{t+1} - s_t)$$

where r_t and r_t^* are the domestic and foreign short-term nominal interest rates annualized and expressed in percent, and s_t denotes $100 \times$ the log of the nominal exchange rate:

$$s_t \equiv \log(S_t) \times 100$$

Since we use quarterly data, $(s_{t+1} - s_t)$ represents the quarterly depreciation rate expressed in percentage points. Since r_t and r_t^* are expressed in annualized terms, we need to annualize the quarterly depreciation rate by multiplying $(s_{t+1} - s_t)$ by 4:

- Annualized depreciation rate expressed in percent:

$$4 \times (s_{t+1} - s_t)$$

- Annualized excess returns in percent: Λ_t^{APP}

$$\Lambda_t^{APP} = r_t^* - r_t + 4 \times (s_{t+1} - s_t) \tag{13}$$

E.4 Computing Excess returns without using nominal exchange rate data

Computing excess returns involves the depreciation rate of the *nominal* exchange rate. However, our vector of variables features the *real* exchange rate. Here are the steps to compute the excess returns Λ_t^{APP} without using the nominal exchange rate.

- The log of the nominal exchange rate is:

$$\log(S_t) \times 100 \equiv s_t \equiv rer_t - p_t^* + p_t$$

  where rer_t is the log of the real exchange rate expressed in percentage points, p_t and p_t^* are the log of the domestic and foreign price levels respectively, also expressed in percentage points.

- The quarterly (not annualized) nominal depreciation rate in percentage points is:

$$\begin{aligned}
s_{t+1} - s_t &= \left(rer_{t+1} - p_{t+1}^* + p_{t+1}\right) - \left(rer_t - p_t^* + p_t\right) \\
&= rer_{t+1} - p_{t+1}^* + p_{t+1} - rer_t + p_t^* - p_t \\
&= rer_{t+1} - rer_t - p_{t+1}^* + p_t^* + p_{t+1} - p_t \\
&= rer_{t+1} - rer_t - \left(p_{t+1}^* - p_t^*\right) + \left(p_{t+1} - p_t\right)
\end{aligned}$$

- The quarterly net inflation rate (**not annualized, in percent**), denoted $\widetilde{\pi}_t$:

$$\begin{aligned}
\widetilde{\pi}_t &\equiv \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right) \times 100 \\
\widetilde{\pi}_t &\approx \log\left(1 + \frac{P_t - P_{t-1}}{P_{t-1}}\right) \times 100 \approx \log\left(1 + \frac{P_t}{P_{t-1}} - 1\right) \times 100 \\
\widetilde{\pi}_t &\approx \log\left(\frac{P_t}{P_{t-1}}\right) \times 100 = \log\left(P_t\right) \times 100 - \log\left(P_{t-1}\right) \times 100 \\
\widetilde{\pi}_t &\approx p_t - p_{t-1}
\end{aligned}$$

- The quarterly (not annualized) nominal depreciation rate (in percent) becomes:

$$s_{t+1} - s_t = rer_{t+1} - rer_t - \widetilde{\pi}^*_{t+1} + \widetilde{\pi}_{t+1}$$

- Annualized Excess Returns in percent: Λ_t^{APP}

$$\begin{aligned}
\Lambda_t^{APP} &= r_t^* - r_t + 4 \times \left(s_{t+1} - s_t\right) \\
&= r_t^* - r_t + 4 \times \left(rer_{t+1} - rer_t - \widetilde{\pi}^*_{t+1} + \widetilde{\pi}_{t+1}\right)
\end{aligned}$$

- To estimate the model and to report our results, we use the **annualized** quarterly net inflation rate **in percent,** denoted π_t^{APP}:

$$\pi_t^{APP} \equiv 4 \times \widetilde{\pi}_t$$

- Annualized Excess Returns in percent: Λ_t^{APP}

$$\begin{aligned}
\Lambda_t^{APP} &= r_t^* - r_t + 4 \times \left(rer_{t+1} - rer_t - \widetilde{\pi}^*_{t+1} + \widetilde{\pi}_{t+1}\right) \\
&= r_t^* - r_t + 4 \times \left(rer_{t+1} - rer_t\right) - 4 \times \widetilde{\pi}^*_{t+1} + 4 \times \widetilde{\pi}_{t+1} \\
&= r_t^{APP,US} - r_t^{APP,SOE} + 4 \times \left(rer_{t+1} - rer_t\right) - \pi_{t+1}^{APP,US} + \pi_{t+1}^{APP,SOE}
\end{aligned}$$

- Annualized Excess Returns in percent: Λ_t^{APP}

$$\Lambda_t^{APP} = r_t^{APP,US} - r_t^{APP,SOE} + 4 \times \left(rer_{t+1} - rer_t\right) - \pi_{t+1}^{APP,US} + \pi_{t+1}^{APP,SOE} \quad (14)$$

  where:

  - $r_t^{APP,US} \equiv r_t^*$ is the Fed funds rate, annualized and in percentage points, i.e. exactly as it enters in our SVAR.
  - $r_t^{APP,SOE} \equiv r_t$ is the SOE policy rate, annualized and in percentage points, i.e. exactly as it enters in our SVAR.
  - $rer_t = \log\left(RER_t\right) \times 100$, exactly as it enters in our SVAR.
  - $\pi_{t+1}^{APP,US} = \log\left(\frac{P_t^{US}}{P_{t-1}^{US}}\right) \times 400$ is the annualized quarterly CPI inflation rate for the US, expressed in percentage points, exactly as in our SVAR.
  - $\pi_{t+1}^{APP,SOE} = \log\left(\frac{P_t^{SOE}}{P_{t-1}^{SOE}}\right) \times 400$ is the annualized quarterly CPI inflation rate for the SOE, expressed in percentage points, exactly as in our SVAR.

E.5 Computing the IRF of the nominal exchange rate using the IRFs of the real exchange rate, foreign inflation rate and domestic inflation rate

We want to compute the impulse response of the *nominal* exchange rate. However, our vector of variables features the *real* exchange rate, as well as the domestic and foreign inflation rates. Here are the steps to compute the impulse response of the nominal exchange rate using the impulse responses of the real exchange rate, domestic and foreign inflation rates.

- The log of the nominal exchange rate is:

$$\log(S_t) \times 100 \equiv s_t \equiv rer_t - p_t^* + p_t$$

where rer_t is the log of the real exchange rate expressed in percentage points, p_t and p_t^* are the log of the domestic and foreign price levels respectively, also expressed in percentage points.

- The quarterly (not annualized) nominal depreciation rate in percentage points is:

$$\begin{aligned} s_{t+1} - s_t &= \left(rer_{t+1} - p_{t+1}^* + p_{t+1}\right) - \left(rer_t - p_t^* + p_t\right) \\ &= rer_{t+1} - p_{t+1}^* + p_{t+1} - rer_t + p_t^* - p_t \\ &= rer_{t+1} - rer_t - p_{t+1}^* + p_t^* + p_{t+1} - p_t \\ &= rer_{t+1} - rer_t - \left(p_{t+1}^* - p_t^*\right) + \left(p_{t+1} - p_t\right) \end{aligned}$$

- The quarterly net inflation rate (**not annualized, in percent**), denoted $\widetilde{\pi}_t$:

$$\begin{aligned} &\widetilde{\pi}_t \equiv \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right) \times 100 \\ &\widetilde{\pi}_t \approx \log\left(1 + \frac{P_t - P_{t-1}}{P_{t-1}}\right) \times 100 \approx \log\left(1 + \frac{P_t}{P_{t-1}} - 1\right) \times 100 \\ &\widetilde{\pi}_t \approx \log\left(\frac{P_t}{P_{t-1}}\right) \times 100 = \log(P_t) \times 100 - \log(P_{t-1}) \times 100 \\ &\widetilde{\pi}_t \approx p_t - p_{t-1} \end{aligned}$$

- The quarterly (not annualized) nominal depreciation rate (in percent) becomes:

$$s_{t+1} - s_t = rer_{t+1} - rer_t - \widetilde{\pi}_{t+1}^* + \widetilde{\pi}_{t+1}$$

- The quarterly annualized nominal depreciation rate (in percent) becomes:

$$\begin{aligned} 4 \times (s_{t+1} - s_t) &= 4 \times \left(rer_{t+1} - rer_t - \widetilde{\pi}_{t+1}^* + \widetilde{\pi}_{t+1}\right) \\ &= 4 \times (rer_{t+1} - rer_t) - 4 \times \left(\widetilde{\pi}_{t+1}^* + \widetilde{\pi}_{t+1}\right) \\ &= 4 \times (rer_{t+1} - rer_t) - 4\widetilde{\pi}_{t+1}^* + 4\widetilde{\pi}_{t+1} \\ &= 4 \times (rer_{t+1} - rer_t) - \pi_{t+1}^{APP,US} + \pi_{t+1}^{APP,SOE} \end{aligned}$$

where $\pi_t^{APP} \equiv 4 \times \widetilde{\pi}_t$ denotes the **annualized** quarterly net inflation rate **in percent.**

- The quarterly (not annualized) nominal depreciation rate (in percent) is:

$$
\begin{aligned}
s_{t+1} - s_t &= rer_{t+1} - rer_t - \frac{1}{4}\left(\pi_{t+1}^{APP,US} + \pi_{t+1}^{APP,SOE}\right) \\
s_{t+1} - s_t &= rer_{t+1} - rer_t - \frac{1}{4}\pi_{t+1}^{APP,US} + \frac{1}{4}\pi_{t+1}^{APP,SOE} \\
\Delta s_{t+1} &= \Delta rer_{t+1} - \frac{1}{4}\pi_{t+1}^{APP,US} + \frac{1}{4}\pi_{t+1}^{APP,SOE}
\end{aligned}
$$

- Lagging one period:

$$
\Delta s_t = \Delta rer_t - \frac{1}{4}\pi_t^{APP,US} + \frac{1}{4}\pi_t^{APP,SOE}
$$

- To obtain the impulse response of s_t to a shock ε_t, we simply need to cumulate the IRF of Δs_t.

$$
\begin{aligned}
\frac{\partial s_t}{\partial \varepsilon_t} &= \frac{\partial \Delta s_t}{\partial \varepsilon_t} \\
\frac{\partial s_{t+1}}{\partial \varepsilon_t} &= \frac{\partial \Delta s_t}{\partial \varepsilon_t} + \frac{\partial \Delta s_{t+1}}{\partial \varepsilon_t} \\
\frac{\partial s_{t+2}}{\partial \varepsilon_t} &= \frac{\partial \Delta s_t}{\partial \varepsilon_t} + \frac{\partial \Delta s_{t+1}}{\partial \varepsilon_t} + \frac{\partial \Delta s_{t+2}}{\partial \varepsilon_t} \\
&\vdots \\
\frac{\partial s_{t+j}}{\partial \varepsilon_t} &= \frac{\partial \Delta s_t}{\partial \varepsilon_t} + \frac{\partial \Delta s_{t+1}}{\partial \varepsilon_t} + \frac{\partial \Delta s_{t+2}}{\partial \varepsilon_t} + \cdots + \frac{\partial \Delta s_{t+j}}{\partial \varepsilon_t}
\end{aligned}
$$

References

Arias, J. E., Caldara, D., and Rubio-Ramirez, J. F. (2019). The systematic component of monetary policy in SVARs: An agnostic identification procedure. *Journal of Monetary Economics*, 101:1–13.

Arias, J. E., Rubio-Ramirez, J. F., and Waggoner, D. (2013). Inference Based on SVARs Identied with Sign and Zero Restrictions: Theory and Applications. Technical report, FEDEA.

Arias, J. E., Rubio-Ramírez, J. F., and Waggoner, D. F. (2018). Inference based on structural vector autoregressions identified with sign and zero restrictions: Theory and applications. *Econometrica*, 86(2):685–720.

Arias, J. E., Rubio-Ramírez, J. F., and Waggoner, D. F. (2021). Inference in Bayesian Proxy-SVARs. *Journal of Econometrics*, 225(1):88–106.

Canova, F. and De Nicolo, G. (2002). Monetary disturbances matter for business fluctuations in the G-7. *Journal of Monetary Economics*, 49(6):1131–1159.

Cushman, D. O. and Zha, T. (1997). Identifying monetary policy in a small open economy under flexible exchange rates. *Journal of Monetary economics*, 39(3):433–448.

De Rezende, R. B. and Ristiniemi, A. (2023). A shadow rate without a lower bound constraint. *Journal of Banking & Finance*, 146:106686.

Dieppe, A., Legrand, R., and Roye, B. V. (2016). The BEAR toolbox (ECB Working PaperNo. 1934). *European Central Bank*.

Kilian, L. and Lütkepohl, H. (2017). *Structural vector autoregressive analysis*. Cambridge University Press.

Koop, G., Korobilis, D., et al. (2010). Bayesian multivariate time series methods for empirical macroeconomics. *Foundations and Trends® in Econometrics*, 3(4):267–358.

Rubio-Ramirez, J. F., Waggoner, D. F., and Zha, T. (2010). Structural vector autoregressions: Theory of identification and algorithms for inference. *The Review of Economic Studies*, 77(2):665–696.

Stewart, G. W. (1980). The efficient generation of random orthogonal matrices with an application to condition estimators. *SIAM Journal on Numerical Analysis*, 17(3):403–409.

Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics*, 52(2):381–419.

Wu, J. C. and Xia, F. D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking*, 48(2-3):253–291.