MASTERARBEIT | MASTER'S THESIS

Titel | Title

Federal Reserve and European Central Bank Monetary Policy Spillovers in Europe

verfasst von | submitted by

Matthias Paul Walter BSc

angestrebter akademischer Grad | in partial fulfilment of the requirements for the degree of

Master of Science (MSc)

Wien | Vienna, 2025

Studienkennzahl lt. Studienblatt | Degree programme code as it appears on the student record sheet:	UA 066 913
Studienrichtung lt. Studienblatt | Degree programme as it appears on the student record sheet:	Masterstudium Applied Economics
Betreut von | Supervisor:	Univ.-Prof. Alejandro Cunat PhD

Abstract

This thesis examines the spillover effects of Federal Reserve (Fed) and European Central Bank (ECB) monetary policy decisions from 2001 to 2019 across a set of European economies and the United States. Using a Bayesian Global Vector Autoregressive model with a Stochastic Search Variable Selection prior, I analyse how these spillovers propagate. Since monetary policy after the Great Recession was constrained by the zero lower bound, I employ the Wu-Xia shadow policy rate to better capture the stance of monetary policy in both the United States and the Euro area.

While the magnitude of monetary policy shocks varies, the direction of responses remains consistent across economies: short-term interest rates respond strongly to contractionary shocks, whereas the effects on output growth are more muted. Inflation is largely unaffected. Surprisingly, ECB spillovers appear to be stronger than those of the Federal Reserve. However, Fed spillovers are sensitive to the sample period - when the last four years are excluded, the spillover effects align more closely with previous literature, indicating that the Fed's influence is as strong as, if not stronger than, that of the ECB.

Zusammenfassung

In dieser Arbeit werden die Spillover-Effekte der geldpolitischen Entscheidungen der US-Notenbank (Fed) und der Europäischen Zentralbank (EZB) von 2001 bis 2019 in einer Reihe von europäischen Volkswirtschaften und den Vereinigten Staaten untersucht. Mithilfe eines Bayesianischen Globalen Vektorautoregressiven Modells mit einem SSVS Prior analysiere ich die Effekte. Da die Geldpolitik nach der Weltfinanzkrise durch die Nullzinsgrenze eingeschränkt war, verwende ich den Wu-Xia-Schattenzinssatz, um geldpolitische Entscheidungen sowohl in den Vereinigten Staaten als auch im Euroraum besser zu erfassen.

Während das Ausmaß der geldpolitischen Schocks variiert, bleibt die Richtung der Reaktionen in den verschiedenen Volkswirtschaften konsistent: Ein kontraktiver Schock erhöht die kurzfristigen Zinssätze und senkt das Produktionswachstum, aber Auswirkungen auf die Inflation sind nicht erkennbar. Überraschenderweise, scheinen die Spillover-Effekte der EZB stärker zu sein als jene der US-Notenbank. Die Spillover-Effekte der Fed hängen jedoch vom Zeitraum der Stichprobe ab - schließt man die letzten vier Jahre aus, ergeben sich Spillover-Effekte, die eher mit der früheren Literatur übereinstimmen und zeigen, dass der Einfluss der Fed genauso stark oder stärker ist als jener der EZB.

Contents

1 Introduction

Globalization, encompassing both trade and finance, has despite occasional slowdowns reached unprecedented levels over the past few decades. Economies have become increasingly integrated into a global system, and with this heightened interconnectedness there are also implications that policy decisions made abroad can exert effects domestically. In turn, this might constrain the policy autonomy of domestic decision-makers, including central bankers. Rey (2015) argued for the idea that the Mundell-Flemming trilemma has morphed into a dilemma. The view what monetary policy needs to forgo one of the three among monetary independence, free capital flows, or fixed exchange rates is being replaced by the choice between having independent monetary policy, while also managing the capital account, or having free capital flows while being subject to policy decisions abroad. Flexible exchange rates alone are not able to isolate an economy, and central bank coordination may be necessary. Such views are not necessarily shared, be it on a theoretical basis that policy coordination is not needed (Obstfeld and Rogoff, 2002), or on an empirical one as a direct rebuke to the notion that Mundell-Fleeming trilemma morphed into a dilemma (Georgiadis and Mehl, 2015). But such debates do underscore the interest between the connection of monetary policy and its effects abroad.

This increased interest has led to a substantial body of literature on what is commonly referred to as monetary policy spillovers. While most of the literature, including this thesis, take an empirical approach, there are also contributions that emphasize a theoretical background - primarily within static Mundell-Fleming type frameworks, such as Degasperi et al. (2020), Blanchard (2021), and Gourinchas (2018). However, henceforth, the focus of this discussion remains on empirical contributions.

In their summary of the Global Financial Cycle, Miranda-Agrippino and Rey (2022) outline two major channels: a financial channel, which affects variables such as asset prices, credit spreads, capital flows, and measures of risk aversion, and a second channel related to trade, output, and commodity prices. They note that monetary policy is the primary driver behind both of them. As the US dollar is the current dominant currency, the Federal Reserve (Fed) is the most extensively studied central bank. However, some research also examines spillovers originating from the European Central Bank (ECB). In contrast, even less attention has been given to other central banks of larger economies, both in terms of the volume of literature and the magnitude of their monetary policy spillovers. Many of these studies compare Fed spillovers to those of the respective central bank of interest, with the Fed often having a greater impact. For instance, research on the Bank of Japan (BOJ) includes Wang et al. (2015) and Inoue and Okimoto (2022), while studies on the Bank of England (BOE) include Gerko and Rey (2017), Weale and Wieladek (2016), and Hesse et al. (2018). Spillovers from the People's Bank of China (PBC) are examined in Miranda-Agrippino et al. (2020). Overall, the literature suggests that regional spillovers exist, but, as mentioned, the Fed's overall effects are stronger.

When studying monetary policy spillovers, one important aspect is to identify the policy itself, but as central bank policy rates approached the zero lower bound (ZLB), identification and quantification of monetary policy became more challenging. Prominent approaches to capturing monetary policy surprises, particularly in the context of monetary policy spillovers, include high-frequency identification within a narrow window around central bank policy announcements (e.g., Miranda-Agrippino and Nenova (2022); Jarociński (2022); Kearns et al. (2023); Ca'Zorzi et al. (2020); Miranda-Agrippino and Ricco (2021); Kalemli-Ozcan (2019); Degasperi et al. (2020)). Alternatively, some methods focus on identifying policy effects through changes in central bank balance sheet sizes (e.g., Dedola et al. (2021); Burriel and Galesi (2018); Bhattarai et al. (2021); Haldane et al. (2016)) or by examining asset purchase programs, which are closely related (e.g., Weale and Wieladek (2016), Hesse et al. (2018)).

To address these challenges, one can also employ shadow policy rates. These rates track the central bank policy rate during "normal" times and extend below the ZLB during periods of expansionary unconventional policy. Shadow policy rates have been applied in the analysis of monetary policy spillovers, particularly within Global Vector Autoregressive (GVAR) models, as seen in studies by Hajek and Horvath (2018), Chen et al. (2017), and Benecká et al. (2020). In this thesis, I also employ shadow policy rates, as they effectively capture central bank policy across both conventional and unconventional regimes, which are both represented in my sample.

The main contribution of this thesis is a comparison of Fed and ECB spillovers in European non-euro economies. This work builds upon existing models while also accounting for the unconventional monetary policies prevalent after the Great Recession. I identify Fed and ECB monetary policy using shadow policy rates and estimate monetary policy spillovers within a Bayesian Global Vector Autoregressive model. The Bayesian approach is particularly suitable given that there are relatively few observations in my data and the dense parametrization in a GVAR model. Following established literature, the evaluation of spillovers focuses on the impulse responses of key economic variables in a selection of European non-euro area economies, as well as in the United States and the Euro area as a whole. Additional evaluation methods include the inspection of posterior inclusion probabilities and forecast error variance decompositions.

My main findings indicate the existence of monetary policy spillovers. Following a contractionary monetary policy shock, other central banks' policy rates, proxied by their short-term interest rates, also increase. Output growth is also affected and declines, although this effect is less pronounced. The size of the responses and the transmission channels vary across countries. A strong influence of ECB or Fed policy on a country's central bank policy does not necessarily lead to a large impact on the entire economy, and vice versa. Generally, Scandinavian countries' monetary policies are more strongly affected than those of Central and Eastern European countries. Surprisingly, I do not find an effect on prices. Furthermore, Fed policy appears to play an economically insignificant role. Contrary to existing literature, ECB policy seems to affect the US economy more than Fed policy affects the Euro area. However, the observation of weak Fed policy spillovers is not robust. When the last four years of the sample, during which the Fed tightened its policy, are excluded, Fed policy generates responses similar to those of an ECB shock. Additionally, in this scenario, Fed policy exerts a greater influence on ECB policy than vice versa.

The remainder of this thesis is structured as follows. Section 2 provides a review of the literature on monetary policy spillovers with a particular focus on studies comparing the impacts of Fed and ECB policies, as well as research closely aligned with this thesis. Section 3 details the econometric methods, data, and model specifications employed in the analysis. Section 4 presents the empirical results. Section 5 offers a robustness test and discusses limitations. Section 5 concludes.

2 Related literature

2.1 Fed and ECB comparisons

The existing literature includes studies that explore whether there is a hierarchy of central bank spillovers, examining whether one central bank dominates others and whether some economies remain unaffected by foreign monetary policy decisions. For instance, Jarociński (2022) compare spillovers from the Fed and the ECB, analysing the effects of information shocks and pure monetary policy shocks using event studies and vector autoregressions. The distinction between information shocks and pure monetary policy shocks is based on a high-frequency identification approach around central bank policy announcements, as developed in Jarociński and Karadi (2020). Their findings indicate that monetary policy shocks from the Fed spill over to Europe, while ECB policy does not similarly affect the United States with the Fed capable of counteracting decisions made in Europe. However, information shocks, which reflect central banks' communication about economic fundamentals, spill over in both directions. Notably, this analysis focuses exclusively on spillover effects between the Euro area and the United States.

Another study by Ca'Zorzi et al. (2020) employs the same identification strategy but extends the analysis to global effects. Using a Bayesian VAR model with a standard Minnesota prior, the authors confirm that the Fed is largely unaffected by ECB policies, while the reverse is not true. Their results show that Fed policy has more pronounced effects on real GDP, unemployment, and equity prices globally. However, somewhat unexpectedly, Fed policy does not have significant effects on global commodity prices. Moreover, while spillovers to variables such as output and equity prices are evident, their analysis reveals that consumer prices are mostly influenced by domestic monetary policy. Shocks from abroad tend to dissipate relatively quickly, leaving consumer price dynamics largely determined by local factors.

Further evidence on monetary policy spillovers, identified through high-frequency identification, is brought forth by Miranda-Agrippino and Nenova (2022). Utilizing daily local projections and bilateral vector autoregressive models, they note that monetary tightening by either the Fed or the ECB leads to a contraction in the global economy. Yet, the magnitude of the contraction is notably larger for shocks originating from the United States compared to those from Europe.

In a Bayesian VAR model, Walerych and Wesołowski (2021) compare Fed and ECB monetary policy spillovers in emerging countries. They capture monetary policy in the form of expectations for short-term interest rates and evaluate impulse responses for prices, GDP, and bond spreads. Their results suggest that spillovers exist. Of particular interest to this thesis is that in the Central European sample - which includes Poland, the Czech Republic and Hungary - the ECB played a larger role than the Fed.

2.2 Closely related contributions

Closely related contributions, in the sense that they use GVAR models with a limited number of variables, include papers by Dees et al. (2007a), Dees et al. (2007b), Hajek and Horvath (2018) Feldkircher (2015), Benecká et al. (2020) and Chen et al. (2017). Among these, Chen et al. (2017), Hajek and Horvath (2018), and Benecká et al. (2020) use shadow policy rates for monetary policy identification. However, they do not use Bayesian GVAR models, and their data does have an earlier cut-off point than I do.

Chen et al. (2017) find that global spillovers from the Fed are generally stronger than those from the ECB, particularly in terms of output growth and inflation. Their results also align with previously presented findings that Fed policy impacts the Euro area, while ECB policy does not significantly affect the US economy. Additionally, they highlight that economies exhibit heterogeneous responses to such shocks. Of particular interest to this thesis are the impulse responses for Sweden, the United Kingdom, Poland, and the Czech Republic. In Sweden and the United Kingdom, Fed policy exerts a stronger influence than ECB policy, while in Poland

and the Czech Republic, the ECB appears to play a more dominant role.

The paper by Hajek and Horvath (2018) compares spillovers in a selection of European countries that mirrors my own sample.[1] They find spillover effects from both the Fed and the ECB, with the latter having a slightly larger impact. Similar to the mentioned papers, effects on prices dissipate quickly. Additional evidence on Fed and ECB spillovers is provided by Feldkircher (2015), who notes that both the Fed and ECB play a similarly important role in determining output in several European economies, with output declining after a monetary policy shock from either central bank. On the other hand, Benecká et al. (2020) focus solely on the effects of ECB policy, noting that a monetary policy contraction leads to decreased output and lower prices in Europe, though results vary across countries.

Regarding the Bayesian approach for GVARs, the papers by Cuaresma et al. (2016) and Feldkircher and Huber (2016) serve as points of reference. In addition, implementation of a Bayesian GVAR model in R has been done by Boeck et al. (2022), and is with some adjustments used in this thesis. Cuaresma et al. (2016) compare several priors in a GVAR setting, including the Minnesota prior mixed with the initial dummy observation prior, the sum-of-coefficients prior, and the stochastic search variable selection (SSVS) prior. The SSVS prior outperformed the other specifications in forecast evaluations. Feldkircher and Huber (2016) then utilizes a Bayesian GVAR model with an SSVS prior to present impulse responses across the world originating from different US-economy shocks. These shocks include a monetary policy shock, characterized by an increase in three-month government bond interest rates. Their results show a global decline in output, with Latin America being the most affected. In most cases, except for Latin America, short-term interest rates decline, and exchange rates depreciate globally. Inflation remains mostly unaffected, except in emerging European economies, where it falls following a contraction in US policy, although the credible intervals for these responses are large.

3 Empirical approach

3.1 Global vector autoregressions

While there are multiple methods to examine monetary policy spillovers, such as panel vector autoregressions bilateral vector autoregressions, local projections (introduced by Jordà (2005)), or event studies, the GVAR methodology introduced by Pesaran et al. (2004) offers a useful framework. It allows the representation of multiple interconnected and interdependent countries

[1] Their model, however, does only include the United States as single non-European economy, while I include other major economies.

in a single, coherent model, even in the presence of co-integration, while maintaining a relatively low number of parameters to be estimated.[2] It has also been noted by Georgiadis (2017) that a bilateral setting alone does not sufficiently account for economic integration, which can lead to less accurate forecasts.

The GVAR methodology consists of two major steps: First, the construction of country specific VARX* models that include domestic, foreign and occasionally global variables. Second, the stacking of these VARX* models into a global framework to solve the GVAR model simultaneously. The key assumption underlying the GVAR model is weak exogeneity for the foreign variables, cross sectional weak correlation, meaning that $Cov(x^*_{it}, \varepsilon_{it}) \to 0$ as $N \to \infty$, ensures that weak exogeneity is met. Presented below is the GVAR model without an intercept, trend or global variables.[3]

3.1.1 Country specific VARX* models

Following Chudik and Pesaran (2016), assume that there are N countries indexed by $i = 1, ..., N$ over a certain period of time $t = 1, 2, ..., T$. Domestic macroeconomic variables are captured in x_{it}, a $k_i \times 1$ vector, while foreign variables are presented as weighted averages in x^*_{it}, a $k^*_i \times 1$ vector. One can write down a country-specific model as follows:

$$x_{it} = \sum_{s=1}^{p} \mathbf{\Phi}_{is} x_{it-s} + \sum_{r=0}^{p*} \mathbf{\Lambda}_{ir} x^*_{it-r} + \varepsilon_{it}, \tag{3.1}$$

where $\mathbf{\Phi}_{is}$ represents a $k_i \times k_i$ coefficient matrix for the domestic variables, with $s = 1, ..., p$, whereas p denotes the number of lags. So far, this is similar to a conventional VAR model, differences arise with the third term on the right-hand side of the equation. $\mathbf{\Lambda}_{ir}$ is the coefficient matrix for the weighted foreign variables, with $r = 0, ..., p^*$, where the number of lags is denoted by p^*. Note that contemporaneous foreign variables are included in this term, so a shock to one of the variables has an immediate effect abroad. As usual, errors are captured in ε_{it}, and the associated covariance matrix is $\mathbf{\Sigma}_{\varepsilon} = E(\varepsilon_t, \varepsilon'_t\ )$. Foreign variables are weighted averages of the domestic variables in other countries and can be represented the following way:

$$x^*_{it} = \tilde{\boldsymbol{W}}'_i\ \boldsymbol{x}_t, \tag{3.2}$$

[2] Somewhat low in the sense that not every variable for each country needs to be represented individually in each model. However, the number of parameters is still larger than in a VAR that includes only domestic variables.

[3] See Chudik and Pesaran (2016) for a representation with global variables, and how one could include a deterministic trend.

with $\tilde{\boldsymbol{W}}_i$ representing the $k \times k^*$ matrix of the country-specific weights. The weights depend on the importance of one economy in another one. This importance is often being determined by using bilateral trade and/or financial flows.

3.1.2 Solving the global model

To solve the global model, one stacks the country-specific models. Specifically, the variables $x_{i,t}$ and $x^*_{i,t}$ are combined to form a $(k_i + k^*_i)$-dimensional vector. Let this new vector be $\boldsymbol{z}_{it} = \left(x'_{it}\ , x^{*'}_{it}\right)$. One can then rewrite 3.1 as:

$$\boldsymbol{A}_{i0}\boldsymbol{z}_{it} = \sum_{l=1}^{max(p,p^*)} \boldsymbol{A}_{il}\boldsymbol{z}_{it-l} + \varepsilon_{it}, \tag{3.3}$$

whereas $\boldsymbol{A}_{i0} = (\boldsymbol{I}_{k_i}, -\boldsymbol{\Lambda}_{i0})$, $\boldsymbol{A}_{il} = (\boldsymbol{\Phi}_{is}, \boldsymbol{\Lambda}_{ir})$ with $(l = 1, ..., max(p, p^*))$, and define $\boldsymbol{\Phi}_{is} = 0$ for $s > p$, as well as $\boldsymbol{\Lambda}_{ir} = 0$ for $r > p^*$. This then allows for the following vector error-correction representation:

$$\boldsymbol{\Delta} x_{it} = \boldsymbol{\Lambda}_{i0}\boldsymbol{\Delta} x^*_{it} - \boldsymbol{\Pi}_i \boldsymbol{z}_{i,t-1} + \sum_{l=1}^{max(p_i,p_i^*)} \boldsymbol{H}_{il}\boldsymbol{\Delta}\boldsymbol{z}_{i,t-1} + \varepsilon_{it}, \tag{3.4}$$

with $\boldsymbol{\Delta}$ representing the first difference operator. $\boldsymbol{\Pi}_i$ being $\boldsymbol{A}_{i0} - \sum_{l=1}^{max(p_i,p_i^*)} \boldsymbol{A}_{il}$, and $\boldsymbol{H}_{il} = -(\boldsymbol{A}_{i,l+1} + \boldsymbol{A}_{i,l+2} + ... + \boldsymbol{A}_{i,l+max(p_i,p_i^*)})$.

In order to stack the country-specific models into a global model, one utilizes $(k_i + k^*) \times k$ linking matrices which are based on the country-specific weights, also seen in 3.2. Let $\boldsymbol{E}_i$ be a $k \times k$ matrix for selecting x_{it}. These linking matrices can then be represented as: $\boldsymbol{W}_i = (\boldsymbol{E}'_i \, \tilde{\boldsymbol{W}}'_i\ )$. Then:

$$\boldsymbol{z}_{it} = \left(x'_{it}\ , x^{*'}_{it}\right)' = \boldsymbol{W}_i\boldsymbol{x}_t. \tag{3.5}$$

Using the expression in 3.5 in 3.3 one obtains:

$$\boldsymbol{A}_{i0}\boldsymbol{W}_i x_t = \sum_{l=1}^{max(p_i,p_i^*)} \boldsymbol{A}_{il}\boldsymbol{W}_i\boldsymbol{x}_{t-l} + \varepsilon_{it}, \tag{3.6}$$

and when stacking these expressions one can represent the global model as:

$$\boldsymbol{G}_0 x_t = \sum_{l=1}^{max(p_i,p_i^*)} \boldsymbol{G}_l\boldsymbol{x}_{t-l} + \boldsymbol{\varepsilon}_t, \tag{3.7}$$

with $\boldsymbol{\varepsilon}_t$ being $(\varepsilon_{1t}', \varepsilon_{2t}', ..., \varepsilon_{Nt}')$, and

$$\boldsymbol{G}_0 \boldsymbol{x}_t = \begin{pmatrix} \boldsymbol{A}_{1,l}\boldsymbol{W}_1 \\ \boldsymbol{A}_{2,l}\boldsymbol{W}_2 \\ \vdots \\ \boldsymbol{A}_{N,l}\boldsymbol{W}_N \end{pmatrix}.$$

Now $\boldsymbol{G}_0$ is a matrix depending on parameter estimates and trade weights, and given this matrix is invertible one can find a solution to the GVAR model. This is done by multiplying Equation 3.7 by $\boldsymbol{G}_0^{-1}$ from the left. This yields the following expression:

$$\boldsymbol{x}_t = \sum_{l=1}^{max(p_i, p_i^*)} \boldsymbol{F}_l \boldsymbol{x}_{t-l} + \boldsymbol{G}_0^{-1} \boldsymbol{\varepsilon}_t, \tag{3.8}$$

where $\boldsymbol{F}_l = \boldsymbol{G}_0^{-1}\boldsymbol{G}_l$. This is a $k \times k$ companion matrix. One can compute the eigenvalues of this matrix, and if they fall within the unit circle, the model is stable. This is useful in a Bayesian framework, as it allows for ensuring stability by discarding posterior draws where the eigenvalues lie outside the unit circle.

3.2 Bayesian Methods

In the Bayesian GVAR setup the priors are elicited at the country-level. Following Boeck et al. (2022); Cuaresma et al. (2016), these country-specific models as described in equation 3.1 are, for simplicity, reformulated to:

$$x_{it} = \boldsymbol{\Psi}_i' \, \boldsymbol{Z}_{it-1} + \varepsilon_{it}, \tag{3.9}$$

where $\boldsymbol{Z}_{it-1}$ captures all the domestic and foreign variables: $(x_{it-1}', ..., x_{it-p}', \; {x_{it-1}^*}', ..., {x_{it-p^*}^*}')$ with the dimension $K_i \times 1$, whereas $K_i = 1 + k_i p + k_i^*(p^* + 1)$. All the coefficient of $\boldsymbol{\Phi}$ and $\boldsymbol{\Lambda}$ are now represented together in $\boldsymbol{\Psi} = (\boldsymbol{\Phi}_{i1}, ..., \boldsymbol{\Phi}_{ip}, \boldsymbol{\Lambda}_{i0}, ..., \boldsymbol{\Lambda}_{ip^*})'$ in a $K_i \times k_i$ matrix. Here, ε_{it} once again represents the error term, with the assumption that $\varepsilon_{it} \sim \mathcal{N}(\boldsymbol{0}, \boldsymbol{\Sigma}_\varepsilon)$. Further assume that prior assumptions of the mean are captured in a vector $\underline{\boldsymbol{\Psi}}_i$.

Stochastic Search Variable Selection (SSVS) Prior

The SSVS prior is a scale mixture of two normal distributions and belongs to the family of spike and slab priors. It was introduced by George and McCulloch (1993), and adapted by George et al. (2008) for VARs. Spike and slab priors consist of two component: the spike, which is centred around the prior mean, normally 0, with a low variance, shrinks unimportant parameters towards the centre. The slab, also centred around the prior mean but with a higher variance, allows the parameters to be included into the model, little to no shrinkage is applied to these variables. The SSVS prior can be represented as follows, assuming that variables are centred around the prior mean:

$$\mathbf{\Psi}_{ij}|\delta_{ij} \sim (1-\delta_{ij})\mathcal{N}(\underline{\mathbf{\Psi}}_{ij}, \tau^2_{0,ij}) + \delta_{ij}\mathcal{N}(\underline{\mathbf{\Psi}}_{ij}, \tau^2_{1,ij}), \tag{3.10}$$

where δ_{ij} is variable taking the value 1 if a variable j is included in the country-specific model i and the value 0 if it is excluded. δ_{ij} follows a Bernoulli distribution where p is usually set to 0.5, meaning that initially each variable is equally likely to enter the model. Regarding the hyperparameters for the variances: $\tau^2_{0,ij}$ is the variance for cases where a variable does not enter the model while $\tau^2_{1,ij}$ is the variances associated with cases where a variable does enter the model. In order for this prior to work properly, one has to ensure that the chosen parameters fulfil the following condition: $\tau_{0,ij} \ll \tau_{1,ij}$. This implies that a relative uninformative prior is applied to the included variables, while the excluded variables are shrunk towards the prior mean. The selected hyperparameters are then scaled through a semi-automatic approach where the hyperparameters are set to $\tau_{0,ij} = \kappa_0 \hat{\sigma}_{\psi_{ij}}$ and $\tau_{1,ij} = \kappa_1 \hat{\sigma}_{\psi_{ij}}$. Here, $\hat{\sigma}_{\psi_{ij}}$ represents the standard error of each country-specific-model OLS estimation of ψ_{ij}. κ_0 and κ_1 are set such that $\kappa_0 \ll \kappa_1$. Estimations then rely on Markov Chain Monte Carlo (MCMC) methods to obtain posterior distribution draws. Since the conditional posteriors follow a known (normal) distribution, the Gibbs sampler, as outlined by George et al. (2008), is used to obtain draws for Ψ_{ij}. [4]

The SSVS prior offers several benefits in estimating GVAR models. While a GVAR model does limit the number of parameters that need to be estimated, one still has to include domestic, foreign, and occasionally some global variables, leading to a dense parameterization. Similar to other priors, such as the Minnesota prior (Doan et al., 1984), the SSVS prior offers additional shrinkage, alleviating the curse of dimensionality. However, additional benefits are pointed out in (Feldkircher and Huber, 2016), unlike the Minnesota prior, the shrinkage applied by the SSVS prior is not uniform across parameters due to its semi-automatic approach for each country-specific model. This means the SSVS prior offers greater flexibility and accounts for country-specific characteristics, which are likely to be present in a global sample. Another advantage is its ability to assess the importance of individual variables by examining the posterior inclusion probabilities, which can be computed by averaging δ_{ij} over the entire Markov chain.

[4] The Gibbs sampler has the advantage that convergence is faster compared to methods, such as the Metropolis-Hastings algorithm.

Table 1: Country coverage in the model

	Countries
Major economies	Euro Area (EA), United States of America (US)
CEE economies	Bulgaria (BG), Czech Republic (CZ), Hungary (HU), Poland (PL), Romania (RO)
Advanced European economies	Denmark (DK), Switzerland (CH), Norway (NO), Sweden (SE), United Kingdom (GB)
Other economies	Australia (AU), Brazil (BR), Canada (CA), Chile (CL), China (CN), Indonesia (ID), India (IN), Japan (JP), South Korea (KR), Mexico (MX), Malaysia (MY), New Zealand (NZ), Peru (PE), Philippines (PH), Russia (RU), Saudi Arabia (SA), Singapore (SG), Thailand (TH), Turkey (TR), South Africa (ZA)

Note: This table shows the covered countries. Regions in bolt are of interest to this thesis. Some of the later results are based on averages of the advanced economies in Europe and the CEE economies, which is why they are separated here.

3.3 Data

I use quarterly data from the first quarter of 2001 to the last quarter of 2019. The starting point was chosen due to limitations in the availability of data for short-term interest rates in Central and Eastern European (CEE) economies. Even if data were readily available, I would still exclude these economies due to the transition process following the fall of the Soviet regime, which resulted in abnormal variable values. The sample ends in 2019 due to similar concerns, as I want to avoid Covid-related outliers, particularly in GDP, which experienced a significant shock during that period.

My dataset includes 32 countries and one region, the Euro area, which is treated as a single entity and henceforth referred to as a country or economy. My data captures nearly 90% of the world economy and a selection these countries is shown in Table 1. While the primary focus is on how monetary policy spillovers affect European countries, other economies are included to account for global economic dynamics. This decision is also motivated by the weak exogeneity assumption, as incorporating a broader set of economies reduces the influence of any single economy, making this assumption more likely to hold.

The variable selection for the country models in this thesis is broadly consistent with some of the existing literature on spillovers in GVAR models (e.g., (Dees et al., 2007a; Feldkircher, 2015; Feldkircher and Huber, 2016; Hájek and Horváth, 2016; Hajek and Horvath, 2018)). The selected variables are presented in Table 2.

Table 2: Variables selection and descriptive statistics

Variables	Description	min	mean	max	Coverage (%)
Δ y	Quarter-on-quarter change in GDP, seasonally adjusted in percent	-11.28	0.84	11.39	100%
Δp	Quarter-on-quarter change in consumer price index, seasonally adjusted in percent	-3.20	0.84	21.37	100%
REER	Real effective exchange rate based on consumer price index, 2010=100	48.72	96.55	131.20	84%
r	short-term interest rate; 3-month bond rate in most cases; shadow rate for the Euro area and the United State, in p.a. percent	-7.72	4.69	87.36	97%
lr	long-term interest rate in form of long-term government bond yields, in p.a. percent	-0.78	3.77	12.12	47%
poil	log-price of BRENT crude oil, 2010=100	3.00	4.09	4.81	

Note: This table shows the variables that are included in the models as well as some descriptive statistics. Coverage indicates in the share of cases where I have data for the complete observation period.

Real GDP data primarily comes from the IMF IFS database and has been differenced due to stability concerns. While the GVAR model allows for co-integration, differencing helps in reducing eigenvalues and thus avoiding explosive draws that could affect the dynamics. In cases where data was unavailable in the IMF database, I relied on the Global VAR (GVAR) Database by Mohaddes and Raissi (2024).[5] The IFS database has also been used for changes in prices and the real effective exchange rate if data was not available at the IMF IFS database.

Short-term and long-term interest rates for both advanced and Central and Eastern European economies are sourced from the Austrian National Bank, while data for other economies stems from the GVAR database. The Fed shadow rate is computed following Wu and Xia (2016), and the ECB shadow rate follows the approach in Wu and Xia (2017), both of which incorporate

[5] This database also uses IMF IFS data but supplements it with data from Bloomberg and Haver Analytics in the absence of sufficient IMF data. However, this database lacks data on Central and Eastern European countries, making it only the secondary source for this thesis.

yield curve dynamics to obtain the shadow rate. The evolution of these shadow rates during the sample period is shown in Figure 1. Data for oil prices is sourced from the GVAR database.

Several weighting matrices were constructed for the country-specific models. These are based on the IMF's Directions of Trade Statistics (DOTS), which cover the entire sample period, and the IMF's Coordinated Direct Investment Survey (CDIS), available only from 2009 onward.[6] A key difference between the weights derived from CDIS and DOTS is that the former assigns even greater weights to the Euro Area and the United States, whereas the latter attributes a relatively larger role to emerging economies. However, in both datasets, the Euro Area receives the highest weights, which is particularly noteworthy given the influence these weights can have on the magnitude of spillovers. The various weighting matrices are shown in the Appendix.

The country-specific models are primarily governed by data availability. All available variables, except for oil prices, are included in each country-specific model as both domestic variables and weakly exogenous foreign variables. I follow Dees et al. (2007a) by treating oil prices as an endogenous variable in the US model, which emphasizes the significant role of the US as part of the global economy. Consequently, oil prices are treated as a foreign variable in all other country-specific models. An overview of each country-specific model can be found in Table 3.

4 Empirical results

The posterior distribution is based on 50,000 draws after a burn-in phase of 10,000 draws. To avoid memory issues, I only save every 10th draw. The hyperparameters for the SSVS prior, following Feldkircher and Huber (2016), are set to $\tau_0 = 0.1$ and $\tau_1 = 3$. Additionally, following the recommendations of George et al. (2008), κ_0 is set to 0.1 and κ_1 is set to 10, the initial inclusion probability is 0.5. For the domestic, and foreign variables I include one lagged value, and in addition to the constant terms, I add trend terms to the country-specific models. In my tests, increasing the number of lags improved the information criteria, specifically the Deviance Information Criterion (DIC) as described by Spiegelhalter et al. (2002), and led to a reduction in evidence of serial autocorrelation, which was already low to begin with. However, the improvement was minor, and increasing the number of lags also resulted in fewer stable draws and longer computation times. As a result, I use only one lag.[7]

Convergence of the MCMC chain has been verified by inspecting the in-sample fit for the various variables for each country and by using the Geweke convergence statistic (Geweke, 1991).

[6] The BIS's locational banking statistics could, in principle, serve as an alternative for constructing financial bilateral weights, but it lacks sufficient data on CEE economies.

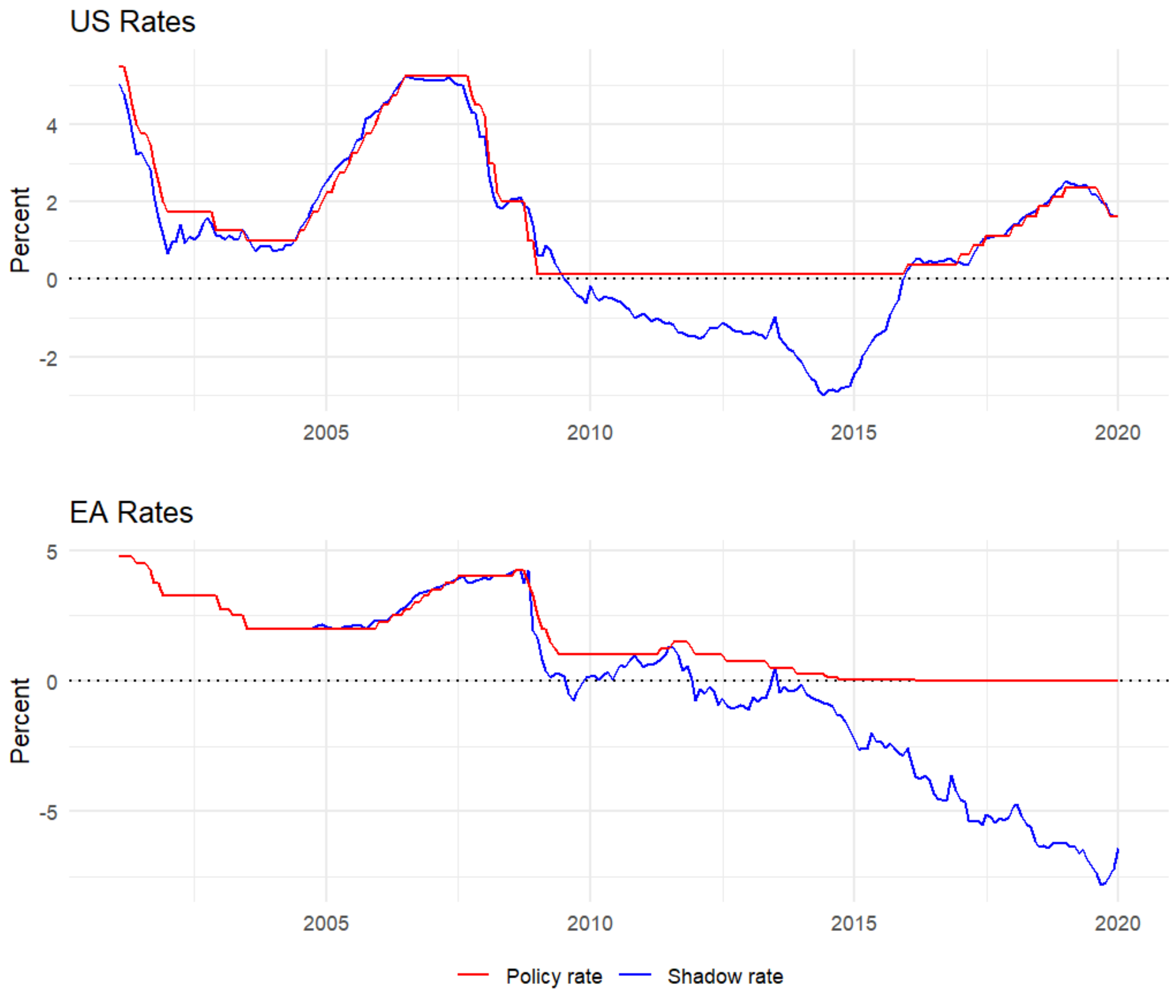
[7] GVARs with one lag are also fairly common in the literature see (Dées and Galesi, 2021; Feldkircher, 2015; Feldkircher and Huber, 2016).

Table 3: Country-specific model set-up

Country	Domestic Variables	Foreign Variables
Euro Area	$\Delta y, r, lr, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
United States	$\Delta y, r, lr, REER, \Delta p, poil$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*$
United Kingdom	$\Delta y, r, lr, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Switzerland	$\Delta y, r, lr, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Sweden	$\Delta y, r, lr, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Norway	$\Delta y, r, lr, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Denmark	$\Delta y, r, lr, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Poland	$\Delta y, r, lr, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Czech Republic	$\Delta y, r, lr, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Hungary	$\Delta y, r, lr, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Romania	$\Delta y, r, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Bulgaria	$\Delta y, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Australia	$\Delta y, r, lr, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Brazil	$\Delta y, r, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Canada	$\Delta y, r, lr, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
China	$\Delta y, r, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Chile	$\Delta y, r, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
India	$\Delta y, r, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Indonesia	$\Delta y, r, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Japan	$\Delta y, r, lr, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
South Korea	$\Delta y, r, lr, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Malaysia	$\Delta y, r, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Mexico	$\Delta y, r, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
New Zealand	$\Delta y, r, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Peru	$\Delta y, r, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Philippines	$\Delta y, r, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
South Africa	$\Delta y, r, lr, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Singapore	$\Delta y, r, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Thailand	$\Delta y, r, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Turkey	$\Delta y, r, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$
Russia	$\Delta y, r, REER, \Delta p$	$\Delta y^*, r^*, lr^*, REER^*, \Delta p^*, poil^*$

Note: Countries that show up in bolt letters are those that are of interest in the section for the empirical results. Stars denote the weakly exogenous foreign variables.

Figure 1: Fed and ECB (Shadow) Policy Rates



Note: This figure shows the Wu-Xia shadow policy rates in blue and the central bank policy rates obtained from the BIS during the sample period in red.

This statistic compares the first 10% of the draws of the MCMC chain with the last 50% of the draws. If the chain has converged, the means of these two sections should be similar, this is tested through a Z-test. In my case, 6.5% of the Z-values are above 1.96, indicating that the vast majority of the variables converged. As mentioned, weak exogeneity is a key assumption for the GVAR model and with pairwise cross-section correlations of the residuals one can provide evidence on whether the variables are weakly exogenous. A summary of the pairwise cross-section correlation of residuals is shown in Table 4. Low values indicate weak exogeneity.

With the exception of long-term interest rates, average pairwise cross-correlations of residuals are low. The values for long-term rates, while not exceeding 20%, are higher partly due to the limited number of available observations, most of which come from advanced economies. This suggests that in the event of a shock, the results for long-term interest rates are more likely to

Table 4: Average pair-wise cross-section correlations of residuals

	r	lr	Δy	REER	Δp
<0.1	32 (100%)	13 (81%)	31 (100%)	26 (100%)	32 (100%)
0.1-0.2	0 (0%)	3 (19%)	0 (0%)	0 (0%)	0 (0%)
0.2-0.5	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
>0.5	0 (0%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)

Notes: This table shows the summary for average pair-wise cross-section correlations of residuals. Numbers in parentheses represent the share of cases.

be influenced by cross-country correlations than by the assigned weights (Dees et al., 2007a).

My model uses a mix of financial weights and trade flows. Mixed weights in the context of the GVAR model have, for example, been used in Eickmeier and Ng (2015), Cashin et al. (2017), Mohaddes and Pesaran (2017) and Feldkircher and Huber (2016). For variables such as Δy and Δp export data has been used, while for the remaining variables — $REER, r, lr$ — CDIS data has been utilized. This choice is driven by a forecasting exercise, where the weight matrices shown in Table 5 have been evaluated.

Table 5: Weights under consideration

Name	Description
Imports (DOTS)	Uses average import data as weights for all variables.
Exports (DOTS)	Uses average export data as weights for all variables.
Total trade (DOTS)	Uses average total bilateral trade flows for all variables.
Financial positions (CDIS)	Uses average financial positions for all variables.
Imports/Financial positions	Uses average import data for $\Delta y, \Delta p$; uses CDIS average financial positions for $REER, r, lr$.
Exports/Financial positions	Uses average export data for $\Delta y, \Delta p$; uses average financial positions for $REER, r, lr$.
Total trade/Financial positions	Uses average total bilateral trade data for $\Delta y, \Delta p$; uses average financial positions for $REER, r, lr$.

Note: This table shows the various weighting matrices under consideration, and for which variables these weights are used.

For these forecast evaluations, the last 10 observations in my sample have been excluded. Different weights are evaluated based on a point forecast evaluation through the root mean squared error (RMSE), a density forecast evaluation through the log-predictive score (LPS), as well as the DIC. The following variables have been of particular interest for the RMSE and LPS: Δy, Δp, and r. Table 6 shows the results. Point forecast evaluations for the different models are similar to each other, with the mixed weights showing better results for Δy and r, although forecasts for short-term interest rates fared poorly across all models. For Δp, non-mixed weights deliver more accurate forecasts. In terms of density forecast evaluations, mixed weights generally show better values than non-mixed weights. In particular, **Exports/Financial positions** performs well and dominates most of the other weights, with the exception of **Exports**, which performs better for Δp. Regarding the DIC, **Exports/Financial positions** also provides the best value, leading me to choose these weights for the complete sample.[8]

[8]Not shown in these evaluations but noteworthy for the GVAR model in general is that, in the case of some non-mixed weights, the cross-correlations of residuals are higher, particularly for lr.

Table 6: Summary of several forecasting evaluations.

Evaluated Weight	RMSE Δy	RMSE Δp	RMSE r	LPS Δy	LPS Δp	LPS r	DIC
Imports	0.365	0.187	1.369	-1.574	-1.072	-2.010	17665
Exports	0.345	0.210	1.139	-1.000	-0.747	-1.715	17416
Total trade	0.389	0.215	1.245	-1.550	-1.074	-2.015	17607
Financial positions	0.358	0.173	0.933	-1.140	-0.961	-1.667	17353
Imports/Financial positions	0.337	0.209	0.934	-1.044	-0.864	-1.618	17005
Exports/Financial positions	0.353	0.208	0.885	-0.960	-0.749	-1.598	16993
Total trade/Financial positions	0.335	0.217	0.888	-1.003	-0.850	-1.608	17027

Note: This table shows the average RMSE as well as LPS for the last 10 observations in my sample. Results of individual countries are weighted based on 2015 PPP adjusted GDP from the World Bank's World Development Indicators database. For these weights only the countries of interest have been used. DIC scores for the used models are also reported. (For the DIC scores the complete model has been evaluated.)

4.1 Posterior inclusion probabilities across countries.

As mentioned earlier, the importance of variables can be gauged through their posterior inclusion probabilities, which reflect how well a variable explains the variation of another variable. Since the countries under consideration may differ across regions, the importance of certain variables might also vary. Table 7 to Table 10 show the posterior inclusion probabilities for selected economies and regions. Since I set my initial inclusion probability to 0.5, I am mostly concerned on those posterior inclusion probabilities that are above that value.

Generally speaking, posterior inclusion probabilities are high for lagged variables if the variable is captured in levels. Concerning the lagged values for differenced series, lagged output growth seems to only be influential for output growth in the advanced European economies, and lagged values for inflation appear to strongly influence inflation only in the Central and Easter European economies. The inclusion probabilities for foreign variables are often high for their domestic counterparts. Exceptions are the posterior inclusion probabilities of foreign short-term interest rates for domestic short-term interest rates in the Euro area and the Central and Eastern European economies. Short-term interest rates in Central and Eastern Europe are not influenced strongly by any of the foreign variables. In the Euro area on the other hand, the foreign long-term interest rates seem to affect domestic short-term rates. One explanation for this would be that other short-term interest rates, with the exception of the US, do not go below the zero-lower bound while the ECB shadow rate still varies and moves far below 0. Foreign long-term interest rates which are generally higher are able to move/vary more then the foreign short-term interest rates, therefore they may be able to better explain variation in the European shadow rate than other short-term interest rates.[9] In addition, global output growth rates are

[9] In a later section I conduct a robustness test that excludes the last few years under the ZLB, in which case the posterior inclusion probability for r^* in the Euro rises to above 0.5, while other posterior inclusion probabilities remained largely unchanged. Since the EU's shadow rate was only a short amount of time and closely below 0,

also influential in the Euro area and the advanced European economies.

Since this thesis focuses on examining the effects of monetary policy spillovers - specifically, changes in r in the United States and the Euro area, as well as changes in r^* in Central and Eastern European and Advanced European economies - I also report on them in more detail. In the United States, a Fed policy shock has a significant impact on both short-term interest rates and domestic long-term rates, while other domestic variables appear to be less affected. The Euro area shows a similar pattern: as previously mentioned, lagged short-term interest rates influence domestic short-term interest rates, but the effects on other domestic variables remain limited.

In Central and Eastern European economies, foreign interest rates appear to influence the real effective exchange rate.

Also of interest are the trend terms, they are influential for interest rates in the United States, the Euro area and the Advanced European economies. In all of these countries we observe falling rates during the observation period. There is also an influential trend in output-growth for the Euro area, and in the Central and Eastern European economies, the inclusions probabilities associated with the trend for the real effective exchange rate are also high.

Table 7: Posterior Inclusion probabilities: US

Variables	r	lr	Δy	REER	Δp	poil
r_lag1	**1.000**	**0.552**	**0.321**	**0.452**	**0.313**	**0.268**
lr_lag1	**0.458**	**0.992**	**0.265**	**0.341**	**0.226**	**0.254**
Δy_lag1	**0.459**	**0.326**	**0.459**	**0.288**	**0.276**	**0.224**
REER_lag1	**0.372**	**0.494**	**0.368**	**1.000**	**0.408**	**0.367**
Δp_lag1	**0.417**	**0.395**	**0.439**	**0.392**	**0.543**	**0.259**
r*	**0.616**	**0.333**	**0.237**	**0.440**	**0.225**	**0.266**
lr*	**0.337**	**0.999**	**0.280**	**0.307**	**0.297**	**0.560**
Δy*	**0.498**	**0.413**	**0.846**	**0.623**	**0.382**	**0.382**
REER*	**0.267**	**0.299**	**0.169**	**0.653**	**0.217**	**0.184**
Δp*	**0.559**	**0.294**	**0.288**	**0.384**	**0.975**	**1.000**
r*_lag1	**0.347**	**0.246**	**0.251**	**0.279**	**0.197**	**0.381**
lr*_lag1	**0.339**	**0.871**	**0.268**	**0.321**	**0.229**	**0.235**
Δy*_lag1	**0.384**	**0.246**	**0.487**	**0.254**	**0.335**	**0.232**
REER*_lag1	**0.267**	**0.324**	**0.223**	**0.704**	**0.237**	**0.165**
Δp*_lag1	**0.360**	**0.340**	**0.431**	**0.349**	**0.427**	**0.667**
cons	**0.399**	**0.504**	**0.176**	**0.424**	**0.247**	**0.302**
trend	**0.654**	**0.291**	**0.276**	**0.563**	**0.329**	**0.336**
poil_lag1	**0.252**	**0.210**	**0.184**	**0.452**	**0.267**	**1.000**

Note: This table shows the posterior inclusion probabilities for the United States.

other short-term interest rates were able to explain variation.

Table 8: Posterior Inclusion probabilities: EA

Variables	r	lr	Δy	REER	Δp
r_lag1	**1.000**	**0.796**	**0.269**	**0.179**	**0.368**
lr_lag1	**0.256**	**1.000**	**0.304**	**0.190**	**0.204**
Δy_lag1	**0.186**	**0.286**	**0.340**	**0.141**	**0.303**
REER_lag1	**0.470**	**0.881**	**0.631**	**1.000**	**0.231**
Δp_lag1	**0.197**	**0.223**	**0.297**	**0.206**	**0.469**
r*	**0.181**	**0.182**	**0.118**	**0.116**	**0.139**
lr*	**0.587**	**1.000**	**0.415**	**0.386**	**0.219**
Δy*	**0.793**	**0.268**	**1.000**	**0.188**	**0.331**
REER*	**0.142**	**0.638**	**0.146**	**1.000**	**0.084**
Δp*	**0.245**	**0.216**	**0.404**	**0.243**	**1.000**
poil**	**0.878**	**0.254**	**0.307**	**0.218**	**0.865**
r*_lag1	**0.187**	**0.201**	**0.125**	**0.124**	**0.147**
lr*_lag1	**0.357**	**0.892**	**0.224**	**0.223**	**0.234**
Δy*_lag1	**0.172**	**0.205**	**0.641**	**0.143**	**0.702**
REER*_lag1	**0.133**	**0.455**	**0.122**	**1.000**	**0.079**
Δp*_lag1	**0.187**	**0.220**	**0.296**	**0.436**	**0.251**
poil**_lag1	**0.278**	**0.250**	**0.190**	**0.174**	**0.800**
cons	**0.233**	**0.866**	**0.111**	**0.194**	**0.088**
trend	**0.933**	**0.451**	**0.736**	**0.163**	**0.404**

Note: This table shows the posterior inclusion probabilities for the Euro area.

4.2 Impulse response functions

There are several ways to examine the transmissions of shocks with impulse response functions. Some methods, such as orthogonalized impulse responses obtained through cholesky decompositions, introduced by Sims (1980, 1986), or sign restrictions, introduced by Faust (1998) and adapted for GVARS by Eickmeier and Ng (2015)), require some judgement on how a shock is transmitted. The first method is sensitive to the ordering of variables: the first variable in a model is unaffected by shocks from other variables, the second variable is affected by shocks to both the first and second variable but unaffected by the others, and so forth. In case of sign-restrictions, one needs to postulate the direction of an effect in order to obtain the impulse responses. Following the recommendation in Chudik and Pesaran (2016), and for the purposes of this thesis, I remain agnostic and utilize Generalized Impulse Response functions (GIRFs) as outlined by Koop et al. (1996), and refined in Pesaran and Shin (1998), and Pesaran and Smith (1998). These GIRFs can be captured in $\boldsymbol{g}_{\varepsilon j}$, a $k \times 1$ vector, and this is vector is given by:

$$\boldsymbol{g}_{\varepsilon j}(h) = \frac{\boldsymbol{R}_h \boldsymbol{G}_0^{-1} \boldsymbol{\Sigma}_\varepsilon \boldsymbol{e}_j}{\sqrt{\boldsymbol{e}_j' \, \boldsymbol{\Sigma}_\varepsilon \boldsymbol{e}_j}} \tag{4.1}$$

Table 9: Posterior Inclusion probabilities: Advanced European economies

Variables	r	lr	Δy	REER	Δp
r_lag1	**1.000**	**0.476**	**0.371**	**0.445**	**0.195**
lr_lag1	**0.374**	**0.985**	**0.283**	**0.263**	**0.222**
Δy_lag1	**0.514**	**0.306**	**0.593**	**0.381**	**0.304**
REER_lag1	**0.486**	**0.590**	**0.199**	**1.000**	**0.464**
Δp_lag1	**0.256**	**0.415**	**0.495**	**0.256**	**0.371**
r*	**0.974**	**0.432**	**0.219**	**0.386**	**0.278**
lr*	**0.305**	**1.000**	**0.262**	**0.274**	**0.285**
Δy*	**0.613**	**0.344**	**0.788**	**0.449**	**0.399**
REER*	**0.385**	**0.333**	**0.102**	**0.558**	**0.241**
Δp*	**0.718**	**0.255**	**0.279**	**0.408**	**0.996**
poil**	**0.312**	**0.228**	**0.279**	**0.397**	**0.266**
r*_lag1	**0.337**	**0.281**	**0.185**	**0.253**	**0.228**
lr*_lag1	**0.250**	**0.947**	**0.339**	**0.297**	**0.232**
Δy*_lag1	**0.511**	**0.263**	**0.409**	**0.232**	**0.339**
REER*_lag1	**0.370**	**0.372**	**0.100**	**0.590**	**0.178**
Δp*_lag1	**0.367**	**0.327**	**0.273**	**0.337**	**0.366**
poil**_lag1	**0.334**	**0.447**	**0.289**	**0.346**	**0.209**
cons	**0.613**	**0.619**	**0.162**	**0.548**	**0.239**
trend	**0.923**	**0.317**	**0.233**	**0.392**	**0.341**

Note: This table shows the average posterior inclusion probabilities for the Advanced European economies group of countries including: CH, DK, SE, GB, NO. Individual posterior inclusions probabilities of countries are not weighted for these calculations.

Table 10: Posterior Inclusion probabilities: CEE

Variables	r	lr	Δy	REER	Δp
r_lag1	**1.000**	**0.573**	**0.291**	**0.573**	**0.477**
lr_lag1	**0.532**	**0.997**	**0.245**	**0.466**	**0.257**
Δy_lag1	**0.515**	**0.320**	**0.391**	**0.238**	**0.252**
REER_lag1	**0.251**	**0.297**	**0.534**	**1.000**	**0.448**
Δp_lag1	**0.728**	**0.433**	**0.444**	**0.595**	**0.784**
r*	**0.245**	**0.279**	**0.196**	**0.595**	**0.196**
lr*	**0.322**	**0.997**	**0.288**	**0.343**	**0.336**
Δy*	**0.347**	**0.490**	**0.863**	**0.850**	**0.356**
REER*	**0.142**	**0.151**	**0.244**	**0.608**	**0.226**
Δp*	**0.494**	**0.396**	**0.284**	**0.403**	**0.945**
poil**	**0.343**	**0.254**	**0.159**	**0.402**	**0.153**
r*_lag1	**0.306**	**0.231**	**0.247**	**0.342**	**0.181**
lr*_lag1	**0.318**	**0.695**	**0.197**	**0.357**	**0.205**
Δy*_lag1	**0.294**	**0.228**	**0.481**	**0.294**	**0.281**
REER*_lag1	**0.157**	**0.229**	**0.388**	**0.700**	**0.349**
Δp*_lag1	**0.436**	**0.413**	**0.567**	**0.338**	**0.557**
poil**_lag1	**0.249**	**0.210**	**0.182**	**0.374**	**0.134**
cons	**0.203**	**0.327**	**0.223**	**0.266**	**0.322**
trend	**0.293**	**0.235**	**0.202**	**0.854**	**0.318**

Note: This table shows the average posterior inclusion probabilities for the CEE group of countries including: BG, CZ, HU, PL, RO. Average values for r and lr are calculated using a subsample of these countries since lr is not available for BG and RO and r is not available for BG. Individual posterior inclusions probabilities of countries are not weighted for these calculations.

the shocks themselves are captured as jth element in $\boldsymbol{e}_j$ a $k \times 1$ vector, whereas non-shocked variables take the value 0. $\boldsymbol{R}_h$ represents $k \times k$ matrices which can be obtained recursively by $\boldsymbol{R}_h = \sum_{l=1}^{max(p,p^*)} \boldsymbol{F}_l \boldsymbol{R}_{h-l}$, where $\boldsymbol{R}_0 = \boldsymbol{I}_k$.

In this thesis I consider following shocks.[10]

1. A 100bp contraction in ECB monetary policy.

2. A 100bp contraction in Fed monetary policy.

Of particular interest are the responses of short-term interest rates, output growth, and inflation. The other two variables - long-term interest rates and the real effective exchange rate - are to this less important and shown in the Appendix. Impulse responses of long-term interest rates typically follow those of short-term interest rates, albeit at a lower level. As for the real effective exchange rate, responses are, with some exceptions in Central and Eastern European economies, where they surprisingly rise, hardly credible.

4.2.1 Short-term interest rate responses

I begin by examining the impulse responses of short-term interest rates, as these variables have the highest posterior inclusion probabilities for shocks to r or r^*. Shown in Figure 2 is the 100bp shock to ECB policy. In case of the Euro area the shock disappears relatively quickly. A credible increase in short-term rates can also be observed in the advanced European economies, in those cases the monetary policy shock also takes a longer time to dissipate. Norway in particular sees an increase of around 0.5% in the short term rate after 5 quarters, in other Scandinavian countries the responses are also large. For the Central European economies the responses are less credible and smaller. The response in the United States does not exclude 0 at the 90% credible interval. The median response however is different from the other economies in the sense that after around 5 quarter it becomes negative, indicating that monetary policy from abroad does not play a major role for the Fed.

In Figure 3, the monetary policy shock is emitted by the Fed. In the United States, the shock dissipates over time, but not as quickly as an ECB shock dissipates domestically. For the other economies, the results are less credible compared to when the shock originates from the ECB, with the responses also being smaller. In the advanced European economies, somewhat credible responses are observed in the first few quarters, though these responses remain small.

[10] Size of the shocks is large due presentation purposes.

4.2.2 GDP responses

In Figure 4 I show output-growth rate responses after a 100bp ECB monetary policy shock. As I do not use Cholesky decompositions there are no time asymmetries in the transmissions of any shock. At a first glance the responses in the first periods may seem odd, output growth rises after contractive monetary policy and only falls over time. From an econometric point of view these results are in large part driven by contemporaneous correlations, as there are no restrictions on immediate spillovers. This leads to a situation where the first non-lagged term for foreign short-term interest rates positively contribute to GDP growth while the lagged foreign short-term interests often negatively contribute to GDP growth. In addition, there are also transmission channel that go through the other domestic variables that are affected by the ECB monetary policy shock.[11] From an economic point of view the high growth rates after a 100bp shock could be explained by the fact that booming economies are those where prices are rising faster which makes monetary policy intervention likelier, and such interventions may also take some time to come into effect.

The 90% credible bands never exclude rising or falling growth rates across the regions, there are borderline cases for the United States around the 5th period where quarter-on-quarter growth rates declined by close to 0.07%, or in Sweden around the same time where output growth declined by around 0.1%. Nonetheless, the 50% credible bands often show a decline in growth rates, notable exceptions are Poland and Norway where monetary policy spillovers do not seem to have an effect.

Norway and the Czech Republic are also interesting in the regard that they highlight the country-heterogeneity of responses. While short-term interest rates in Norway are fairly sensitive to changes in short-term interest rates in the Euro area, output growth is not affected and for the Czech Republic the reverse is true. This also displays the varying degrees of importance for different transmission channels across countries.

Figure 5 shows the responses for the Fed-policy shock. Surprisingly, there is very little to report. Median responses often go below 0 but only slightly so. Two explanations for this are that the weighting matrices put a very heavy weight on the Euro area, especially for the economies of interest, both in trade and financial positions the Euro area gets assigned a larger weight, but the more pressing issue is that domestic short-term interest rates do not seem to have a strong effect on the US-economy and with that spillovers through other US-specific variables are also minimal.[12]

[11] One example is that foreign monetary policy first affects domestic monetary policy and then domestic monetary policy affects domestic GDP, such a transmission also takes some time.

[12] I re-estimated the model using only import weights, (This is the weighting matrix where the United States weights are relatively largest compared to the other weighting matrices.) and in that set-up the effects of Fed

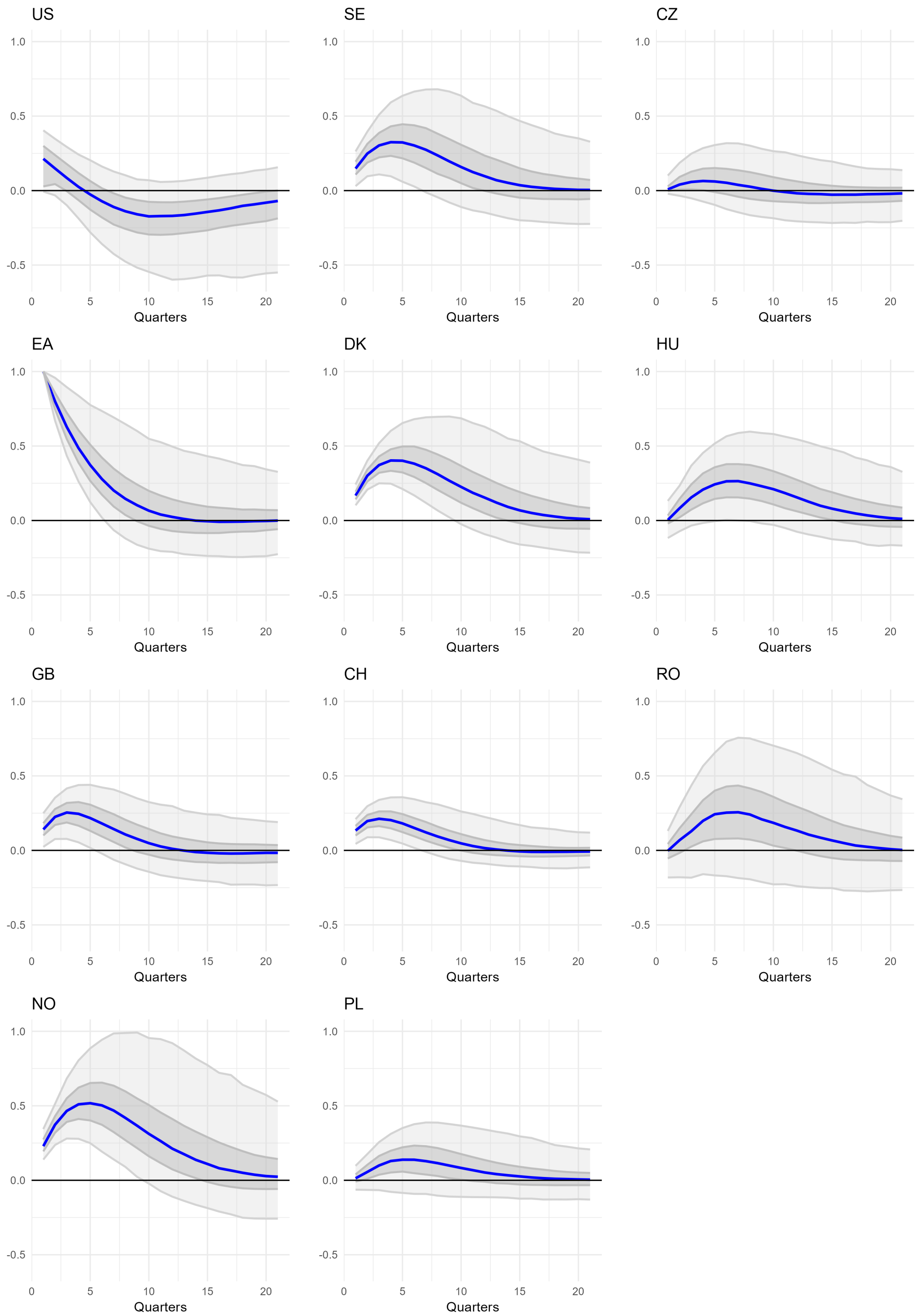
4.2.3 Inflation responses

As the results for the Fed and ECB monetary policy shocks, shown in Figure 6 and Figure 7, are fairly similar, I will report on them together. Overall, monetary policy spillovers do not seem to affect prices, with median responses for the first few periods often being positive. This contradicts the expectation that monetary policy should suppress inflation. However, such a price puzzle is somewhat common, as observed in US-VARs in Sims (1986) and Sims (1992), and in GVARs in Dees et al. (2007a) and Dees et al. (2007b). Several possible solutions could involve using sign restrictions to obtain the impulse responses, or including additional variables like commodity prices and/or the output gap (Rusnák et al., 2013). However, these suggestions are typically made for traditional single-country VARs, and obtaining the necessary data for the countries in a global model is challenging.

Another concern is that a GVAR model with only one lag may not fully capture the effects of monetary policy on inflation. Increasing the number of lags does eliminate the price puzzle, as shown in Figure 15 in the appendix, which uses the same model setup (though with fewer draws). I only report ECB responses there, as Fed responses are not visible in the plot. However, even with more lags, the responses remain overall not credible. Additionally, the issues of less stable draws and longer computation times became apparent.

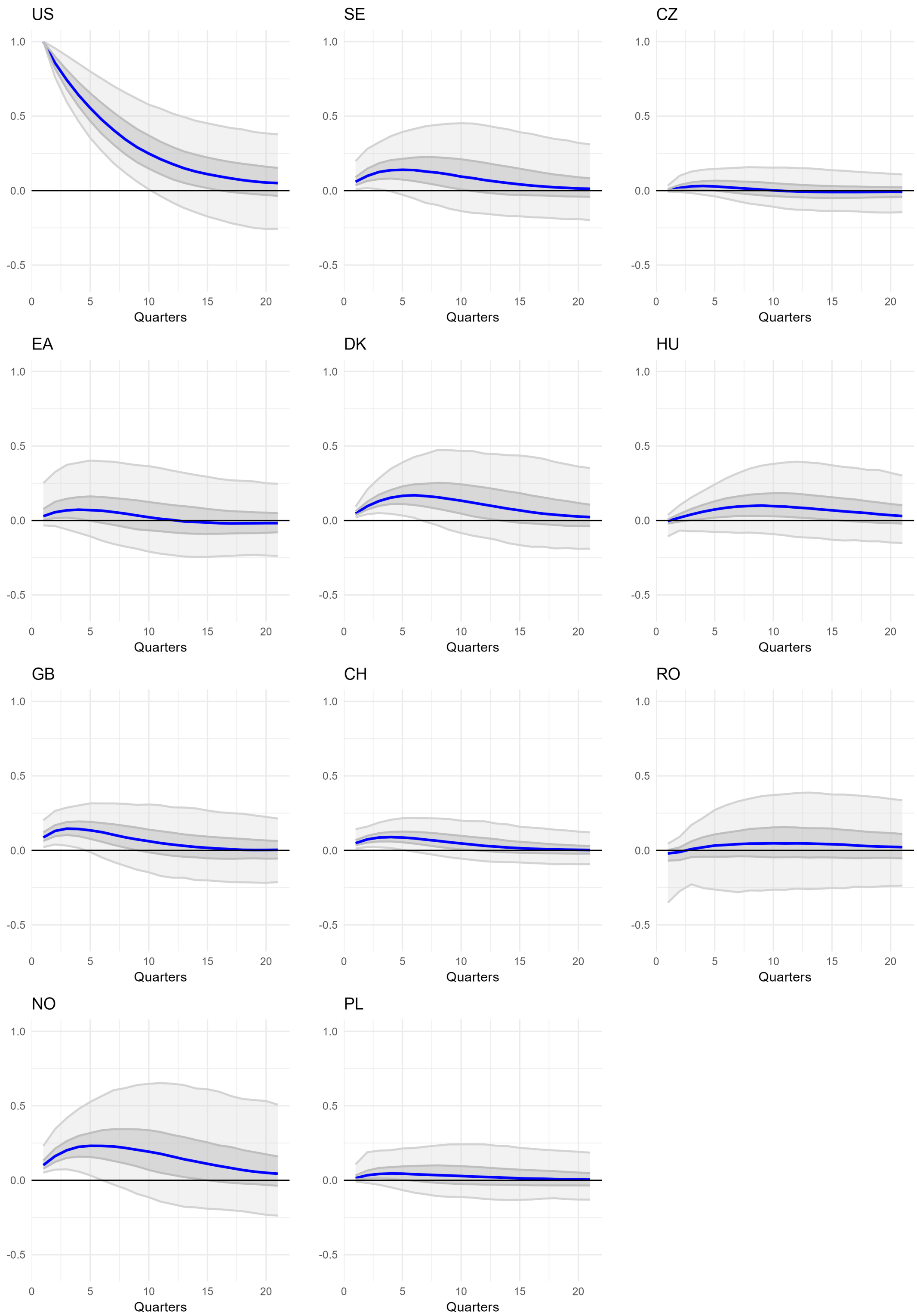
policy did increase. However, credible intervals became even larger, and the increases were only minor. Import weights also performed worse than the other weights in the forecast evaluation.

Figure 2: r impulse responses after an ECB shock



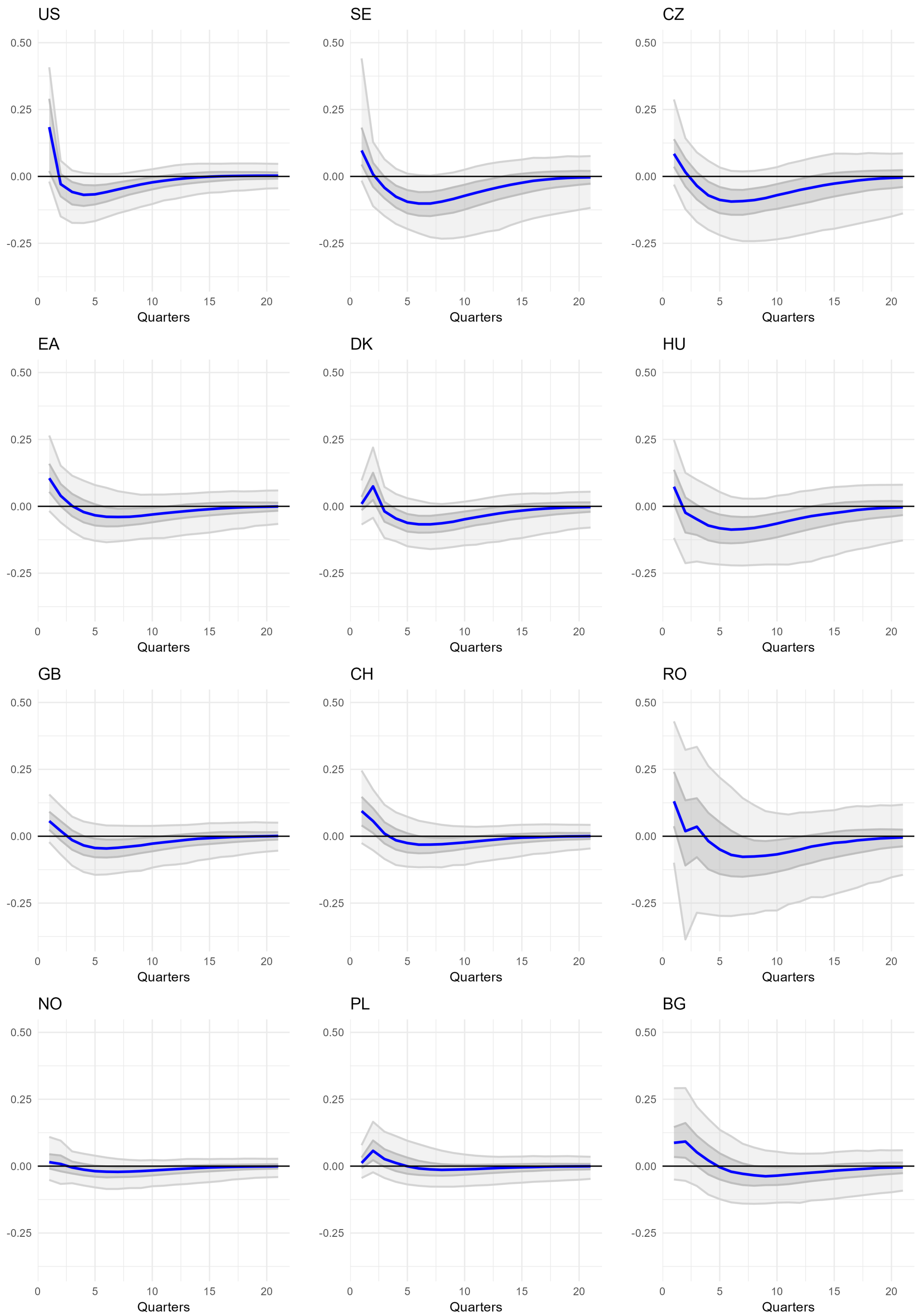
Note: Impulse responses to a 100bp contractionary monetary policy shock. The blue line indicates the median response. Grey and lightgrey areas show the credible bands for 25th and 75th as well as 5th and 95th percentiles respectively.

Figure 3: r impulse responses after a Fed shock



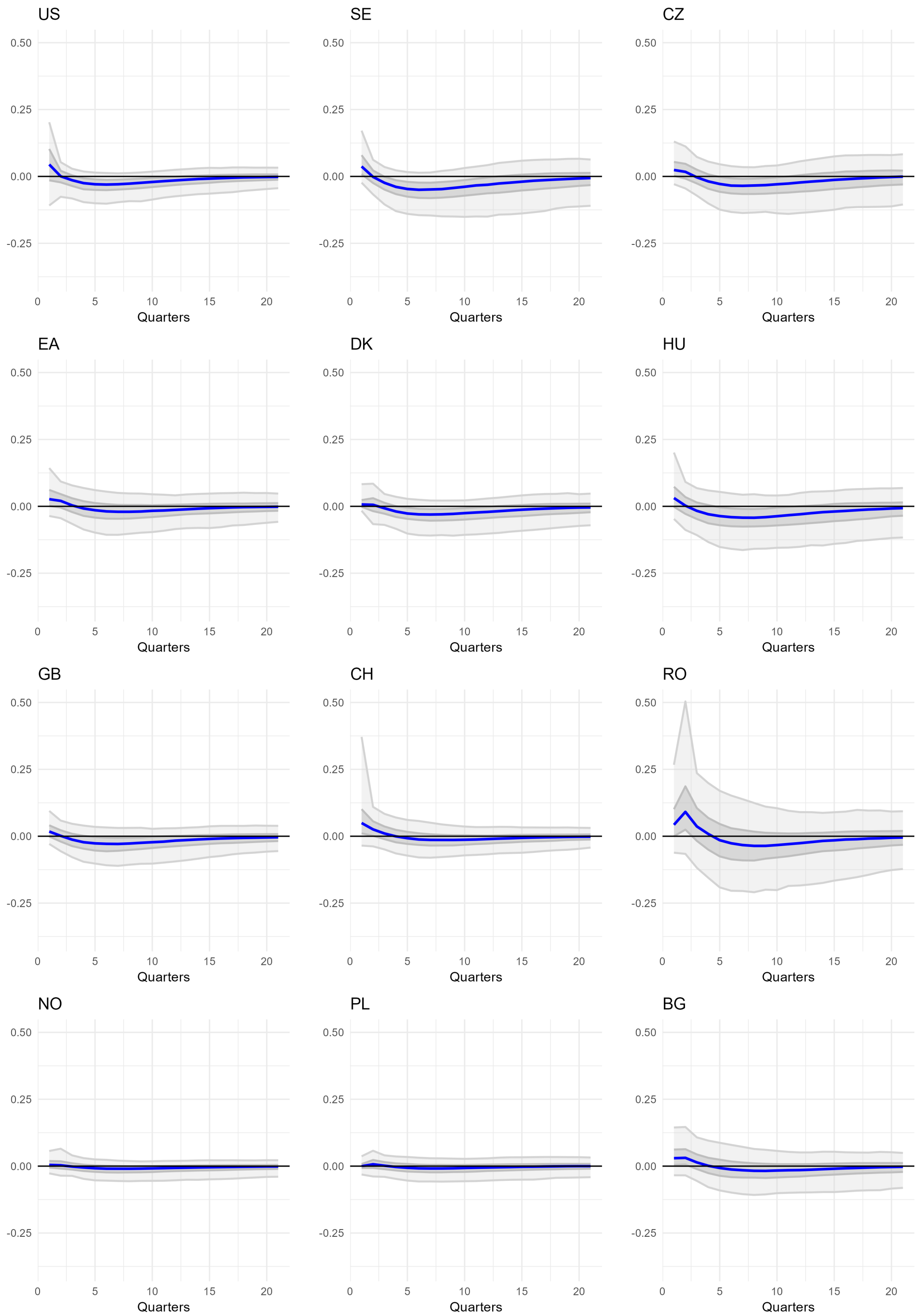
Note: Impulse responses to a 100bp contractionary monetary policy shock. The blue line indicates the median response. Grey and lightgrey areas show the credible bands for 25th and 75th as well as 5th and 95th percentiles respectively.

Figure 4: Δy impulse responses after an ECB shock



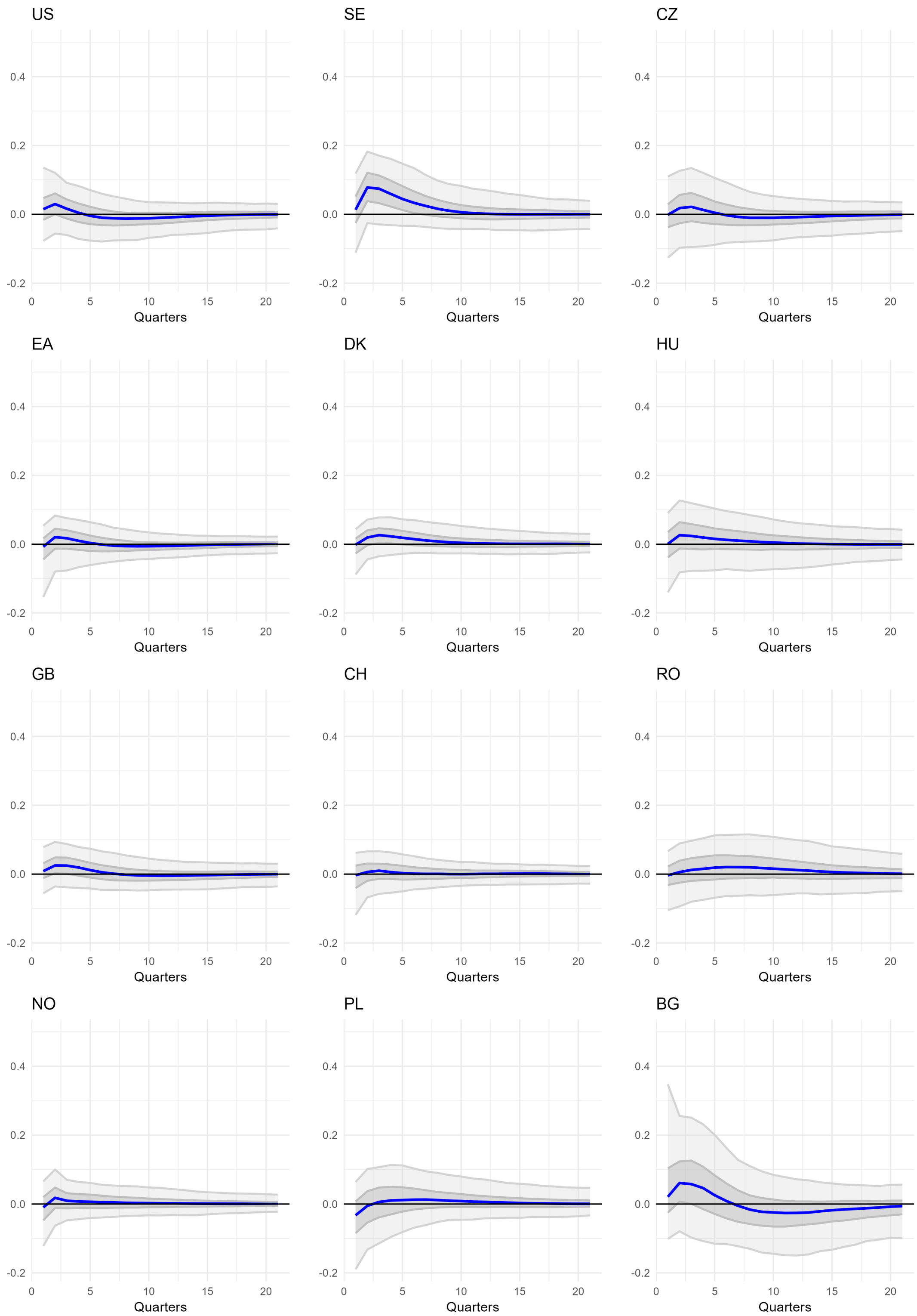
Note: Impulse responses to a 100bp contractionary monetary policy shock. The blue line indicates the median response. Grey and lightgrey areas show the credible bands for 25th and 75th as well as 5th and 95th percentiles respectively.

Figure 5: Δy impulse responses after a Fed shock



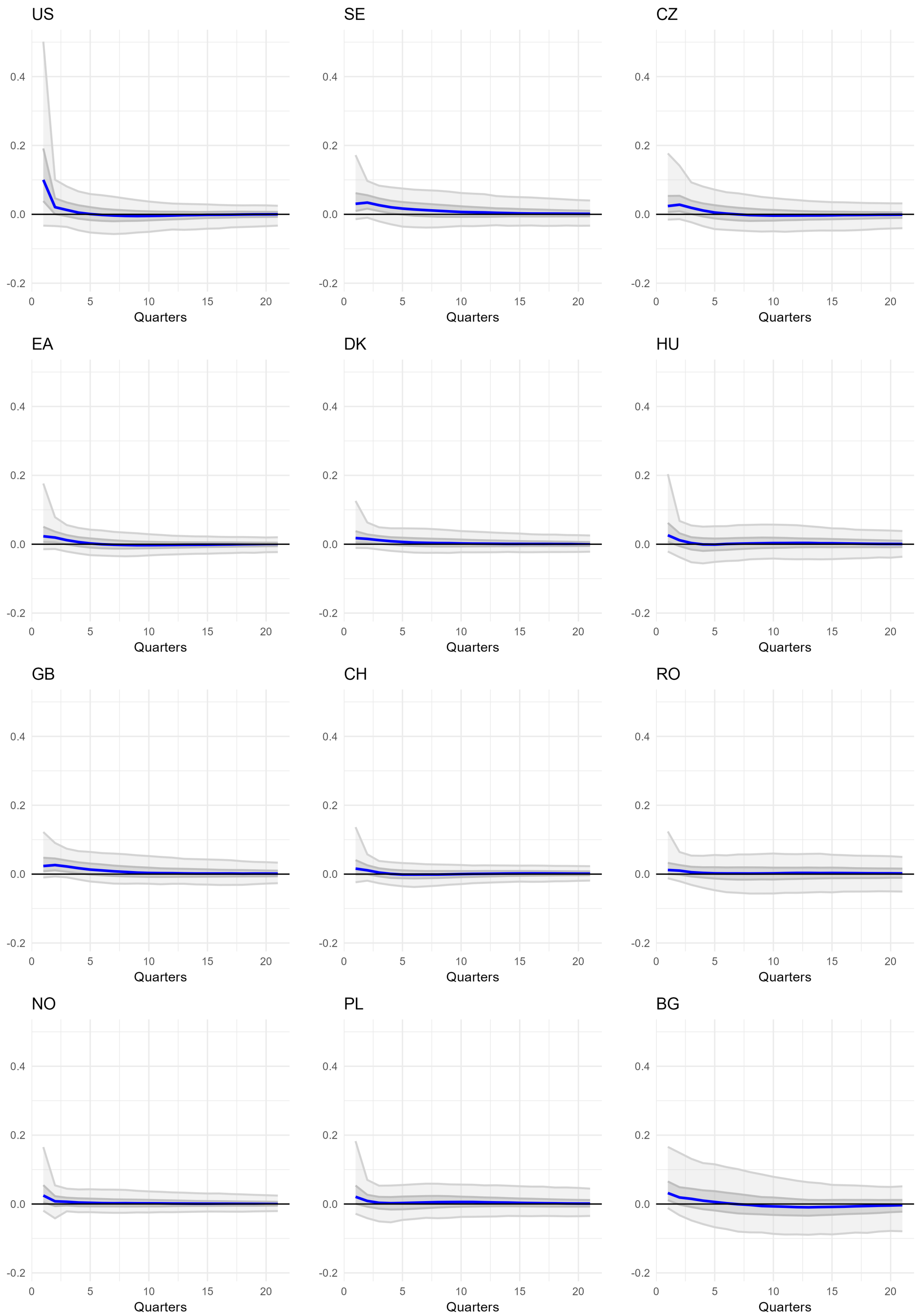
Note: Impulse responses to a 100bp contractionary monetary policy shock. The blue line indicates the median response. Grey and lightgrey areas show the credible bands for 25th and 75th as well as 5th and 95th percentiles respectively.

Figure 6: Δp impulse responses after an ECB shock



Note: Impulse responses to a 100bp contractionary monetary policy shock. The blue line indicates the median response. Grey and lightgrey areas show the credible bands for 25th and 75th as well as 5th and 95th percentiles respectively.

Figure 7: Δp impulse responses after a Fed shock



Note: Impulse responses to a 100bp contractionary monetary policy shock. The blue line indicates the median response. Grey and lightgrey areas show the credible bands for 25th and 75th as well as 5th and 95th percentiles respectively.

4.3 Forecast error variance decomposition

In addition to impulse response functions, I also provide related forecast error variance decompositions (FEVDs). These decompositions show how much each variable contributes to the variation in the other variables within all of the country-specific models.[13] Once again, emphasis is placed on the short-term interest rates, particularly those from the United States and the Euro area. Following Dees et al. (2007a), I use generalized forecast error variance decompositions (GFEVD) as the shock to obtain impulse response functions in this thesis is non-structural. The equation for the GFEVD is given by:

$$\mathcal{GFEVD}(x_{it}, \varepsilon_{jt}, h) = \frac{\sigma_{jj}^{-1} \sum_{l=0}^{h} [\boldsymbol{e}_i' \boldsymbol{F}^h \boldsymbol{G}_0^{-1} \boldsymbol{\Sigma} \boldsymbol{e}_j]^2}{\sum_{l=0}^{h} \boldsymbol{e}_i' \boldsymbol{F}^h \boldsymbol{G}_0^{-1} \boldsymbol{\Sigma} (\boldsymbol{G}_0^{-1})' \boldsymbol{F}^{h\prime} \boldsymbol{e}_i}, \tag{4.2}$$

where the only term unaccounted for thus far is σ_{jj}, which shows an element of $\boldsymbol{\Sigma}_\varepsilon$.

Since I interpret non-structural shocks, i.e., shocks that are not orthogonalized, the calculated shares from the GFEVD may exceed unity. To improve the presentation, the decompositions are scaled so that they sum to 1, following a procedure outlined by Lanne and Nyberg (2016). I present the results for short-term interest rates (Figure 8), output growth rates (Figure 9) and inflation (Figure 10).

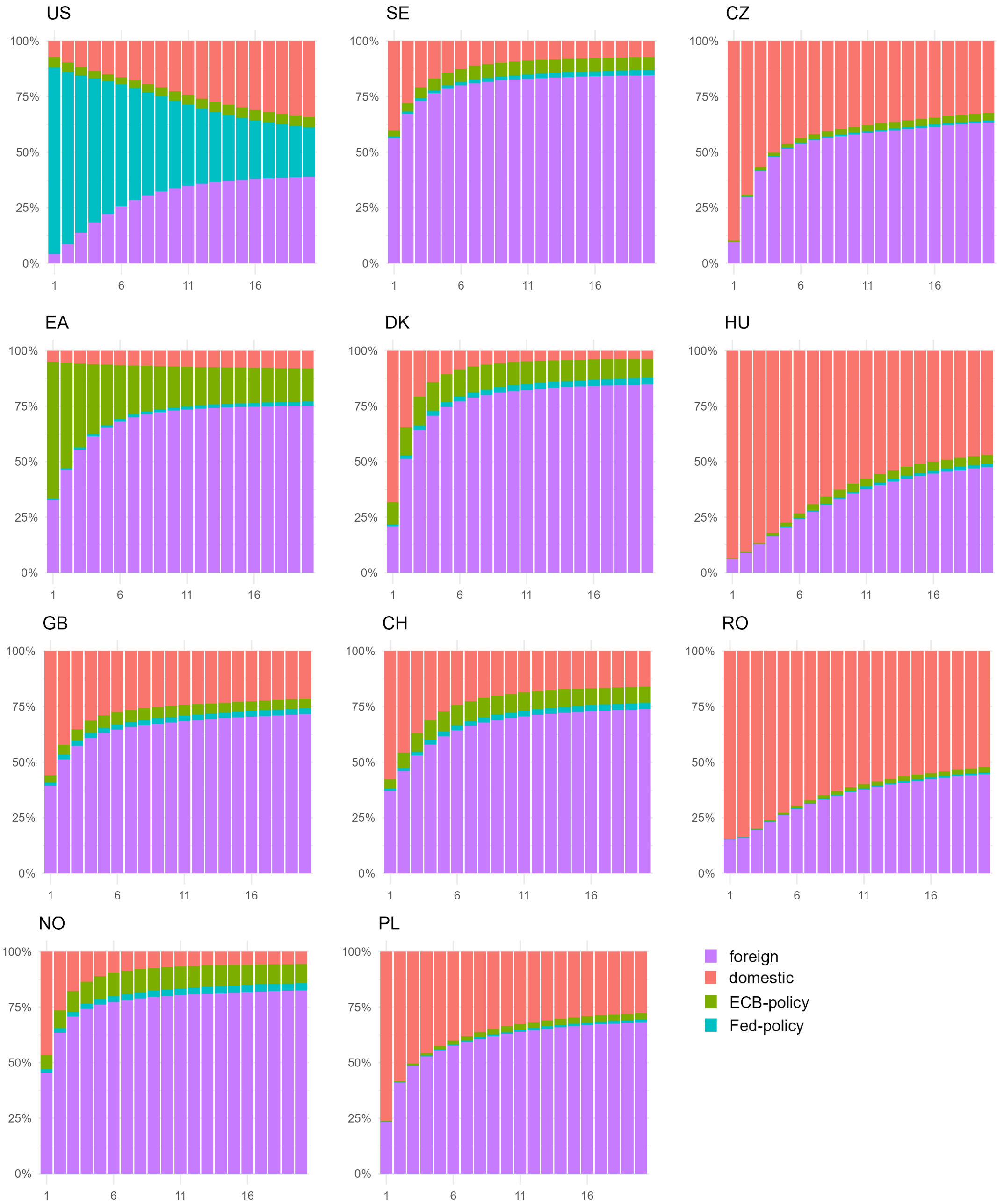
The results align with those observed in the previous subsections. ECB policy explains a significant portion of the forecast error variance for short-term interest rates in the Euro area and the advanced European economies. In some cases, such as Norway, Sweden and Denmark, the share of forecast error variance explained by ECB policy is larger in the long run than that explained by all their respective domestic variables combined. US policy, on the other hand, seems relevant only for explaining forecast error variance within the United States. For the other two variables, the role of monetary policy in explaining forecast error variance is minimal. US policy, on the other hand, only appears to explain forecast error variance within the United States. The absence of Fed-policy visibility in the plots aligns with earlier findings where there was no credible response for inflation, and the responses for output were similarly weak.

Another observation from these results is that foreign variables - beyond the direct impacts of ECB and Fed shocks - frequently play a large role in explaining domestic economic factors. The contribution of domestic versus foreign factors varies considerably across countries, which might be influenced by factors like the size of the economy as well as financial and trade integration. Financial integration could explain the more significant role of foreign variables in short-term

[13] In this sense, the FEVD is similar to the posterior inclusion probabilities. The key difference is that the FEVD quantifies the contribution of each variable to another variable over different horizons, while the posterior inclusion probability only indicates whether a variable sufficiently contributes to the variation of another variable, and is therefore not being shrunk towards the prior mean.

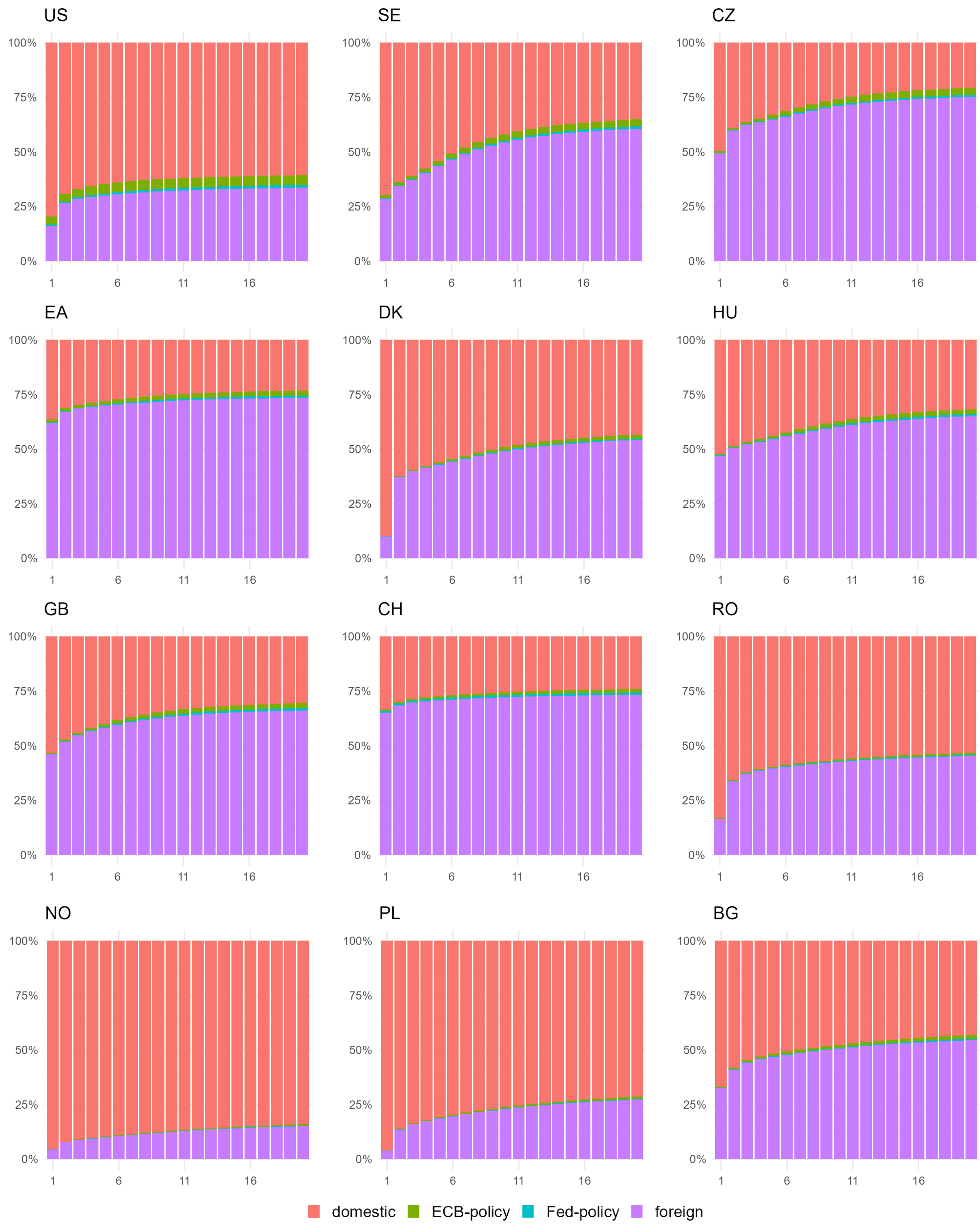
interest rates in advanced economies, while trade integration might be the key factor behind foreign influences on output growth and inflation. Additionally, it is worth noting that domestic variables in the US account for a larger share of the variance compared to the Euro area. Although the influence of domestic variables decreases in all countries over time, the reduction is more pronounced in the Euro area. This could indicate that the Euro area is more responsive to global economic changes than the United States.

Figure 8: FEVD for r



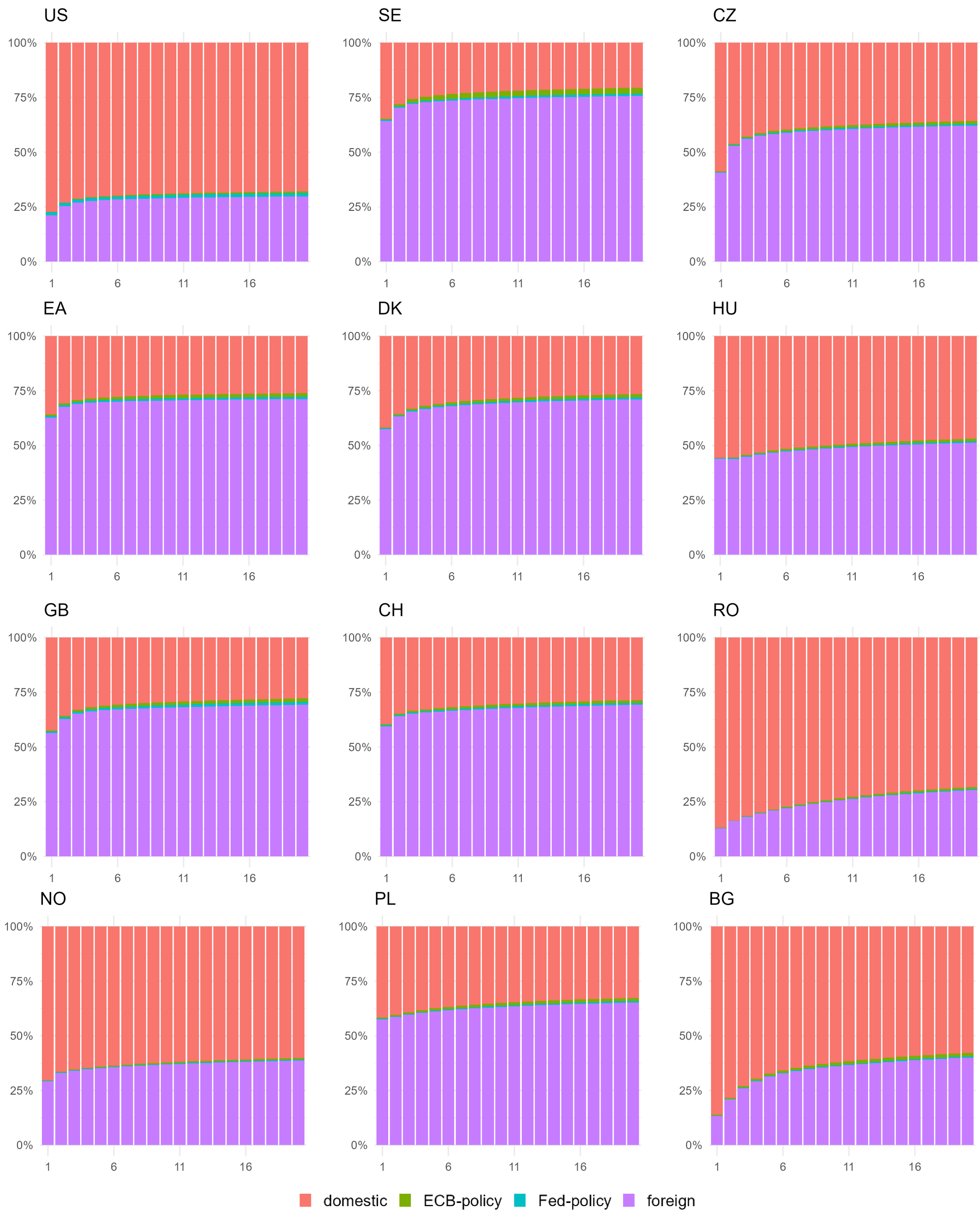
Note: This figure shows the forecast error variance decompositions for short-term interest rates in the countries of interest over a 20 period forecast horizon. In principle, "domestic" captures all the domestic variables while "foreign" captures all the foreign variables excluding Fed shadow rates and ECB shadow rates. For EA and US, the respective rate is removed from the other domestic variables.

Figure 9: FEVD for Δy



Note: This figure shows the forecast error variance decompositions for short-term interest rates in the countries of interest over a 20 period forecast horizon. In principle, ”domestic” captures all the domestic variables while ”foreign” captures all the foreign variables excluding Fed shadow rates and ECB shadow rates. For EA and US, the respective rate is removed from the other domestic variables.

Figure 10: FEVD for Δp



Note: This figure shows the forecast error variance decompositions for inflation in the countries of interest over a 20 period forecast horizon. In principle, "domestic" captures all the domestic variables while "foreign" captures all the foreign variables excluding Fed shadow rates and ECB shadow rates. For EA and US, the respective rate is removed from the other domestic variables.

5 Robustness and limitations

Some of the results, particularly regarding the strength of U.S. monetary policy spillovers, seem odd, so I performed some robustness checks. Chudik and Pesaran (2016) note that one can try using different sample periods. I have done this by using the same model while restricting my data to the period from 2001 to 2015, as some of the other papers that use shadow rates (Hajek and Horvath, 2018; Chen et al., 2017) use a similar timeframe.[14] One of the points these papers mention is that Fed policy seems to have an effect on ECB policy, while the reverse is not true.

Figure 11 first shows a 100bp ECB shock in this restricted model, in which case Fed policy, as before, is not affected, and the responses in other countries follow a similar pattern as reported previously in Figure 2. However, if we introduce a 100bp Fed policy shock, a different picture than in my main setup emerges. In Figure 12, one can see substantially larger responses across most countries. In particular, Fed policy now affects ECB policy in this limited sample.

Concerning output growth, the responses do not change much in the case of an ECB shock, as shown in Figure 13. The median responses are fairly similar to those seen previously, with one notable change being that US growth is less affected than in the full sample. The responses change once again for the Fed shock. While the credible bands (shown in the Appendix) are larger than those for the ECB shock, the median responses now indicate a stronger economic contraction after a Fed shock. Since prices exhibit a similar behaviour for both types of shocks as before, I do not plot them here.

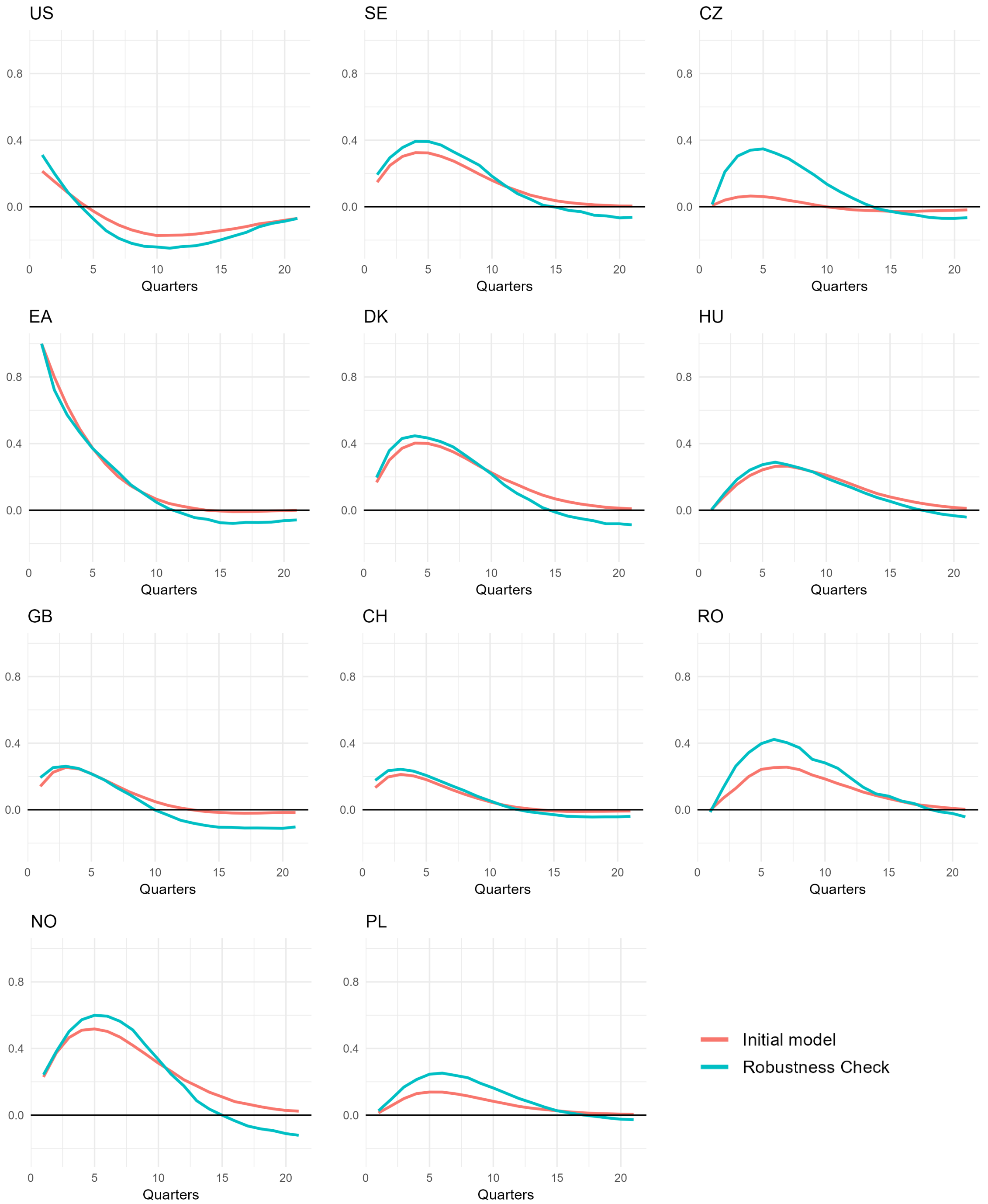
Overall, it seems that US spillovers are sensitive to the used observation period. When the sample period is restricted, the responses resemble those reported in the literature review, where US policy plays an equally large or larger role than ECB policy in the European economies. A major reason for this appears to be that, in the last few years of the sample, the ECB continued its quantitative easing policies, while the Fed began tightening its own. However, the latter did not have the negative effect on output growth that one might expect. Whether this is an anomaly or a feature of quantitative tightening is unclear.[15] The absence of a contraction leads to changes in the model where other domestic variables fail to respond to such a domestic monetary policy shock. In particular, the coefficient associated with productivity growth is economically insignificant. Therefore, the propagation of the Fed shock through other domestic variables is limited in the complete sample as well, and thus spillovers into other countries are

[14] A caveat here is that I only have quarterly data available, so only 60 observation points per series are covered. The reported papers, on the other hand, had access to monthly data.

[15] While there is a sizable body of literature on quantitative easing, to the best of my knowledge, the literature on quantitative tightening and its effects is currently underdeveloped. Du et al. (2024) provides some empirical evidence but they mostly focus on potential disruptions to financial markets and rising yields on government bonds.

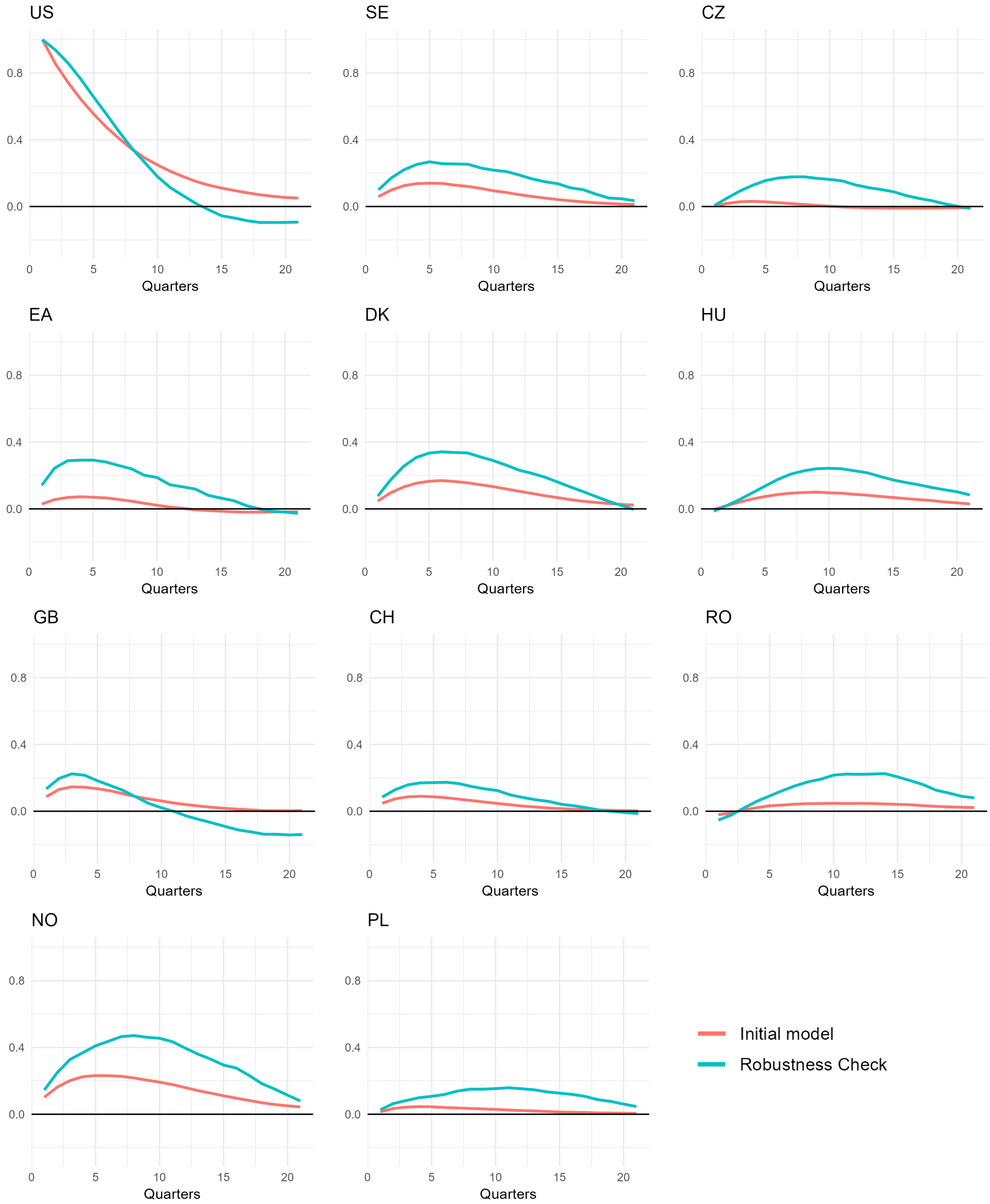
small and improbable.

Figure 11: ECB-shock median impulse response comparison for r



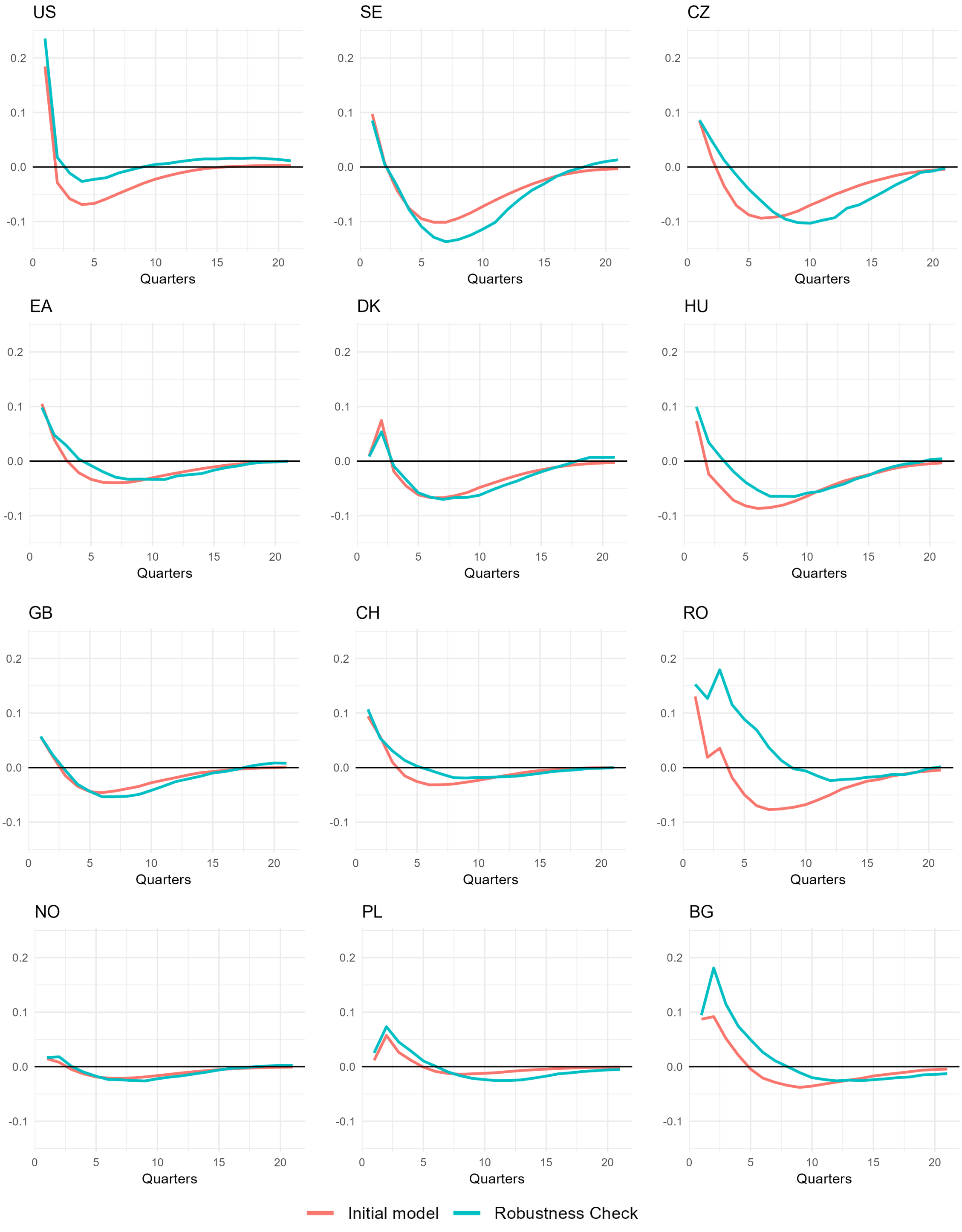
Note: Median impulse responses to a 100bp contractionary monetary policy shock. The red lines show the responses from the initial model, the turquoise lines show the model with the data from 2001 to 2015.

Figure 12: Fed-shock median impulse response comparison for r



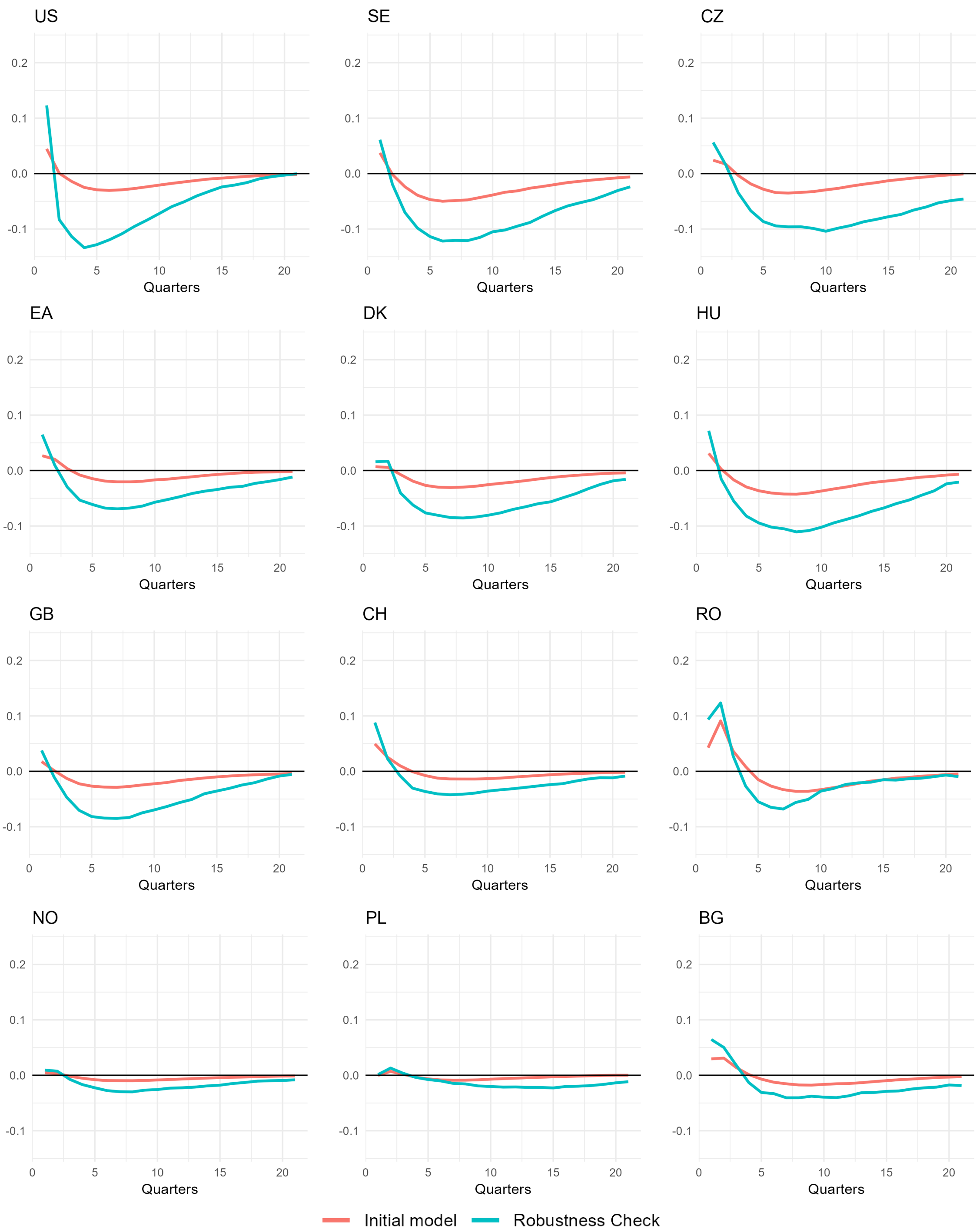
Note: Median impulse responses to a 100bp contractionary monetary policy shock. The red lines show the responses from the initial model, the turquoise lines show the model with the data from 2001 to 2015.

Figure 13: ECB-shock median impulse response comparison for Δy



Note: Median impulse responses to a 100bp contractionary monetary policy shock. The red lines show the responses from the initial model, the turquoise lines show the model with the data from 2001 to 2015.

Figure 14: Fed-shock median impulse response comparison for Δy



Note: Median impulse responses to a 100bp contractionary monetary policy shock. The red lines show the responses from the initial model, the turquoise lines show the model with the data from 2001 to 2015.

Before concluding, I want to point out some limitations of this thesis.

As alluded to previously, the data series is with only 76 observation points rather short as I decided to exclude Covid-associated outliers. But this has also the drawback of missing out on more data points in phases of monetary tightening. One method to deal with data outliers in a GVAR context is used in Feldkircher (2015) and Feldkircher and Huber (2016), where a set of dummy variables is introduced in times of abnormal values. One could also consider doing so for the outliers after 2019.[16] Having a longer time series could, in light of the robustness check done in this section, lead to different parameter estimates, and consequently different responses.

Another limitation related to data draws back to the beginning of this thesis where I mentioned that the two main channels through which monetary policy is transmitted are a trade and a financial channel. For the latter Miranda-Agrippino and Rey (2022) point out that the Fed is more influential than the ECB, but I do, by large, not account for this channel, which may also be another explanation for the surprisingly small responses after a Fed shock. Factors such as credit flows, equity prices, or market volatilities are mostly excluded from this thesis due to insufficient data in Central and Eastern European economies.[17]

A broader concern when using Global Vector Autoregressions is that, while I, like most other authors, observe some degree of country heterogeneity, I do not offer an explanation for these differences. One of the few studies that attempts to do so in a GVAR setting is done by Georgiadis (2016), who examines why certain countries are particularly sensitive to Fed monetary policy spillovers. He identifies determinants such as financial and trade integration, de jure financial openness, exchange rate regime, financial market development, labour market rigidities, industry structure and participation in global value chains. In contrast, I have only speculated that better integration and economic size might explain why spillovers are larger in some economies than in others. For instance, I did not investigate why Norway's output growth remains unaffected while its interest rates are. The main reason for this omission is that substantial additional work would be required. Georgiadis (2016) focuses only on Fed spillovers and the determinants of output spillovers. To better uncover determinants of spillover sizes one would have to investigative additional transmission channels, potentially raising data availability issues once again. Nonetheless, exploring this country heterogeneity in a GVAR setting remains an interesting avenue for future research.

[16]There are also other techniques of how one could account for Covid-related data, by including information on Covid itself (Ng, 2021), adding fat-tail errors and including surveys of professional forecasters (Bobeica and Hartwig, 2021), or by using a stochastic volatility model (Carriero et al., 2024). The first two would require more data, which is not always available for the complete sample in the GVAR, and for the stochastic volatility it would be better to have a larger number of observation points.

[17]In principle, it would have been possible to include this data solely for economies where it is available, as long as the weak exogeneity assumption holds. However, I decided against it to maintain similar country-specific models.

6 Conclusion

In this thesis, I used a Bayesian Global Vector Autoregressive model with a Stochastic Search Variable Selection prior to explore the monetary policy spillover effects of the Federal Reserve and the European Central Bank in Europe and the United States. Since monetary policy after the Great Recession was constrained by the zero lower bound, I employed the Wu-Xia shadow policy rate to capture monetary policy in both the United States and the Euro area. My complete model included data from 32 economies covering the period from 2001 to 2019. The policy spillovers were evaluated through their posterior inclusion probabilities, forecast error variance decompositions, and primarily their impulse response functions.

My estimations suggest that monetary policy spillovers exist for short-term interest rates and, to a lesser degree, for output growth rates. Monetary policy shocks are transmitted directly through changes in foreign short-term interest rates, as well as through their effects on other foreign variables. There also appears to be some country heterogeneity. Most noteworthy in this regard is that short-term interest rates in Scandinavian countries seem to be more strongly affected by Euro area spillovers than other economies. Concerning inflation, I observe weak evidence of a price puzzle, but spillover effects on prices are overall small and improbable. The findings from the impulse response functions are also supported by the forecast error variance decompositions, where monetary policy spillover effects are an important factor in explaining variance for short-term interest rates, while being a minor factor for output growth and inflation. In the long run, foreign factors often play a larger role than domestic ones. For the Scandinavian countries, ECB policy alone explains more forecast error variance over the long run than all domestic variables combined.

Between the Fed and the ECB, the latter appears to play a significantly larger role. However, Fed spillovers are highly sensitive to the selected sample period. Excluding the last four years yields results more consistent with previous literature, which finds stronger or comparable Fed spillover effects in a GVAR framework with shadow policy rates (Hajek and Horvath, 2018; Chen et al., 2017).

References

Benecká, Soňa, Ludmila Fadejeva, and Martin Feldkircher, "The impact of euro Area monetary policy on Central and Eastern Europe," *Journal of Policy Modeling*, 2020, *42* (6), 1310–1333.

Bhattarai, Saroj, Arpita Chatterjee, and Woong Yong Park, "Effects of US quantitative easing on emerging market economies," *Journal of Economic Dynamics and Control*, 2021, *122*, 104031.

Blanchard, Olivier, "Currency wars, coordination, and capital controls," *The Asian Monetary Policy Forum: Insights for Central Banking*, 2021, pp. 134–157.

Bobeica, Elena and Benny Hartwig, "The COVID-19 Shock and Challenges for Time Series Models," ECB Working Paper 2021/2558, European Central Bank May 2021.

Boeck, Maximilian, Martin Feldkircher, and Florian Huber, "BGVAR: Bayesian global vector autoregressions with shrinkage priors in R," *Journal of Statistical Software*, 2022, *104*, 1–28.

Burriel, Pablo and Alessandro Galesi, "Uncovering the heterogeneous effects of ECB unconventional monetary policies across euro area countries," *European Economic Review*, 2018, *101*, 210–229.

Carriero, Andrea, Todd E Clark, Massimiliano Marcellino, and Elmar Mertens, "Addressing COVID-19 outliers in BVARs with stochastic volatility," *Review of Economics and Statistics*, 2024, *106* (5), 1403–1417.

Cashin, Paul, Kamiar Mohaddes, and Mehdi Raissi, "China's slowdown and global financial market volatility: Is world growth losing out?," *Emerging Markets Review*, 2017, *31*, 164–175.

Ca'Zorzi, Michele, Luca Dedola, Georgios Georgiadis, Marek Jarociński, Livio Stracca, and Georg Strasser, "Monetary policy and its transmission in a globalised world," Working Paper Series 2407, European Central Bank May 2020.

Chen, Qianying, Marco Jacopo Lombardi, Alex Ross, and Feng Zhu, "Global Impact of US and Euro Area Unconventional Monetary Policies: A Comparison," BIS Working Paper 610, Bank for International Settlements February 2017.

Chudik, Alexander and M Hashem Pesaran, "Theory and practice of GVAR modelling," *Journal of Economic Surveys*, 2016, *30* (1), 165–197.

Cuaresma, Jesús Crespo, Martin Feldkircher, and Florian Huber, "Forecasting with global vector autoregressive models: A Bayesian approach," *Journal of Applied Econometrics*, 2016, *31* (7), 1371–1391.

Dedola, Luca, Georgios Georgiadis, Johannes Gräb, and Arnaud Mehl, "Does a big bazooka matter? Quantitative easing policies and exchange rates," *Journal of Monetary Economics*, 2021, *117*, 489–506.

Dées, Stéphane and Alessandro Galesi, "The Global Financial Cycle and US monetary policy in an interconnected world," *Journal of International Money and Finance*, 2021, *115*, 102395.

Dees, Stephane, Filippo di Mauro, M Hashem Pesaran, and L Vanessa Smith, "Exploring the international linkages of the euro area: a global VAR analysis," *Journal of applied econometrics*, 2007, *22* (1), 1–38.

Dees, Stephane, Sean Holly, M Hashem Pesaran, and L Vanessa Smith, "Long run macroeconomic relations in the global economy," *Economics*, 2007, *1* (1), 20070003.

Degasperi, Riccardo, Seokki Hong, and Giovanni Ricco, "The global transmission of us monetary policy," *CEPR Discussion Paper No. DP14533*, 2020.

Doan, Thomas, Robert Litterman, and Christopher Sims, "Forecasting and conditional projection using realistic prior distributions," *Econometric reviews*, 1984, *3* (1), 1–100.

Du, Wenxin, Kristin Forbes, and Matthew N Luzzetti, "Quantitative Tightening Around the Globe: What Have We Learned?," Working Paper April 2024.

Eickmeier, Sandra and Tim Ng, "How do US credit supply shocks propagate internationally? A GVAR approach," *European Economic Review*, 2015, *74*, 128–145.

Faust, Jon, "The robustness of identified VAR conclusions about money," *Carnegie-Rochester Conference Series on Public Policy*, 1998, *49*, 207–244.

Feldkircher, Martin, "A global macro model for emerging Europe," *Journal of Comparative Economics*, 2015, *43* (3), 706–726.

Feldkircher, Martin and Florian Huber, "The international transmission of US shocks—Evidence from Bayesian global vector autoregressions," *European Economic Review*, 2016, *81*, 167–188.

George, Edward I and Robert E McCulloch, "Variable selection via Gibbs sampling," *Journal of the American Statistical Association*, 1993, *88* (423), 881–889.

George, Edward I., Dongchu Sun, and Shawn Ni, "Bayesian stochastic search for VAR model restrictions," *Journal of Econometrics*, 2008, *142* (1), 553–580.

Georgiadis, Georgios, "Determinants of global spillovers from US monetary policy," *Journal of international Money and Finance*, 2016, *67*, 41–61.

Georgiadis, Georgios, "To bi, or not to bi? Differences between spillover estimates from bilateral and multilateral multi-country models," *Journal of International Economics*, 2017, *107*, 1–18.

Georgiadis, Georgios and Arnaud Mehl, "Trilemma, not dilemma: financial globalisation and Monetary policy effectiveness," *Globalization and Monetary Policy Institute Working Paper*, 2015, (222).

Gerko, Elena and Hélene Rey, "Monetary policy in the capitals of capital," *Journal of the European Economic Association*, 2017, *15* (4), 721–745.

Geweke, John, "Evaluating the accuracy of sampling-based approaches to the calculation of posterior moments," Staff Report 148, Federal Reserve Bank of Minneapolis 1991.

Gourinchas, Pierre-Oliver, "Monetary policy transmission in emerging markets: an application to Chile," *Series on Central Banking Analysis and Economic Policies no. 25*, 2018.

Hájek, Jan and Roman Horváth, "The Spillover effect of euro area on central and Southeastern European economies: a global VAR approach," *Open Economies Review*, 2016, *27*, 359–385.

Hajek, Jan and Roman Horvath, "International spillovers of (un) conventional monetary policy: The effect of the ECB and the US Fed on non-euro EU countries," *Economic Systems*, 2018, *42* (1), 91–105.

Haldane, Andrew, Matt Roberts-Sklar, Tomasz Wieladek, and Chris Young, "QE: The Story so Far," December 2016, (DP11691).

Hesse, Henning, Boris Hofmann, and James Michael Weber, "The macroeconomic effects of asset purchases revisited," *Journal of Macroeconomics*, 2018, *58*, 115–138.

Inoue, Tomoo and Tatsuyoshi Okimoto, "How does unconventional monetary policy affect the global financial markets?," *Empirical Economics*, 2022, *62* (3), 1013–1036.

Jarociński, Marek, "Central bank information effects and transatlantic spillovers," *Journal of International Economics*, 2022, *139*, 103683.

Jarociński, Marek and Peter Karadi, "Deconstructing monetary policy surprises—the role of information shocks," *American Economic Journal: Macroeconomics*, 2020, *12* (2), 1–43.

Jordà, Òscar, "Estimation and inference of impulse responses by local projections," *American economic review*, 2005, *95* (1), 161–182.

Kalemli-Ozcan, Sebnem, "U.S. Monetary Policy and International Risk Spillovers," Working Paper 26297, National Bureau of Economic Research September 2019.

Kearns, Jonathan, Andreas Schrimpf, and Fan Dora Xia, "Explaining monetary spillovers: The matrix reloaded," *Journal of Money, Credit and Banking*, 2023, *55* (6), 1535–1568.

Koop, Gary, M Hashem Pesaran, and Simon M Potter, "Impulse response analysis in nonlinear multivariate models," *Journal of econometrics*, 1996, *74* (1), 119–147.

Lanne, Markku and Henri Nyberg, "Generalized forecast error variance decomposition for linear and nonlinear multivariate models," *Oxford Bulletin of Economics and Statistics*, 2016, *78* (4), 595–603.

Miranda-Agrippino, Silvia and Giovanni Ricco, "The transmission of monetary policy shocks," *American Economic Journal: Macroeconomics*, 2021, *13* (3), 74–107.

Miranda-Agrippino, Silvia and Hélène Rey, "The global financial cycle," in "Handbook of international economics," Vol. 6, Elsevier, 2022, pp. 1–43.

Miranda-Agrippino, Silvia and Tsvetelina Nenova, "A tale of two global monetary policies," *Journal of International Economics*, 2022, *136*, 103606.

Miranda-Agrippino, Silvia, Tsvetelina Nenova, and Hélène Rey, *Global footprints of monetary policies*, CFM, Centre for Macroeconomics London, 2020.

Mohaddes, Kamiar and M Hashem Pesaran, "Oil prices and the global economy: Is it different this time around?," *Energy Economics*, 2017, *65*, 315–325.

Mohaddes, Kamiar and Mehdi Raissi, "Compilation, Revision and Updating of the Global VAR (GVAR) Database, 1979Q2-2023Q3," 2024.

Ng, Serena, "Modeling macroeconomic variations after COVID-19," Working Paper No. w29060, National Bureau of Economic Research 2021.

Obstfeld, Maurice and Kenneth Rogoff, "Global implications of self-oriented national monetary rules," *The Quarterly journal of economics*, 2002, *117* (2), 503–535.

Pesaran, H Hashem and Yongcheol Shin, "Generalized impulse response analysis in linear multivariate models," *Economics letters*, 1998, *58* (1), 17–29.

Pesaran, M Hashem and Ron P Smith, "Structural analysis of cointegrating VARs," *Journal of economic surveys*, 1998, *12* (5), 471–505.

Pesaran, M Hashem, Til Schuermann, and Scott M Weiner, "Modeling regional interdependencies using a global error-correcting macroeconometric model," *Journal of Business & Economic Statistics*, 2004, *22* (2), 129–162.

Rey, Hélène, "Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence," *Technical report. In: Proceedings - Economic Policy Symposium - Jackson Hole*, 2015.

Rusnák, Marek, Tomas Havranek, and Roman Horváth, "How to solve the price puzzle? A meta-analysis," *Journal of Money, Credit and Banking*, 2013, *45* (1), 37–70.

Sims, Christopher A, "Macroeconomics and reality," *Econometrica: journal of the Econometric Society*, 1980, pp. 1–48.

Sims, Christopher A, "Are forecasting models usable for policy analysis?," *Quarterly Review*, 1986, *10* (Win), 2–16.

Sims, Christopher A, "Interpreting the macroeconomic time series facts: The effects of monetary policy," *European economic review*, 1992, *36* (5), 975–1000.

Spiegelhalter, David J, Nicola G Best, Bradley P Carlin, and Angelika Van Der Linde, "Bayesian measures of model complexity and fit," *Journal of the royal statistical society: Series b (statistical methodology)*, 2002, *64* (4), 583–639.

Walerych, Małgorzata and Grzegorz Wesołowski, "Fed and ECB monetary policy spillovers to Emerging Market Economies," *Journal of Macroeconomics*, 2021, *70*, 103345.

Wang, Yi-Chen, Ching-Wen Wang, and Chia-Hsing Huang, "The impact of unconventional monetary policy on the tail risks of stock markets between US and Japan," *International Review of Financial Analysis*, 2015, *41*, 41–51.

Weale, Martin and Tomasz Wieladek, "What are the macroeconomic effects of asset purchases?," *Journal of monetary Economics*, 2016, *79*, 81–93.

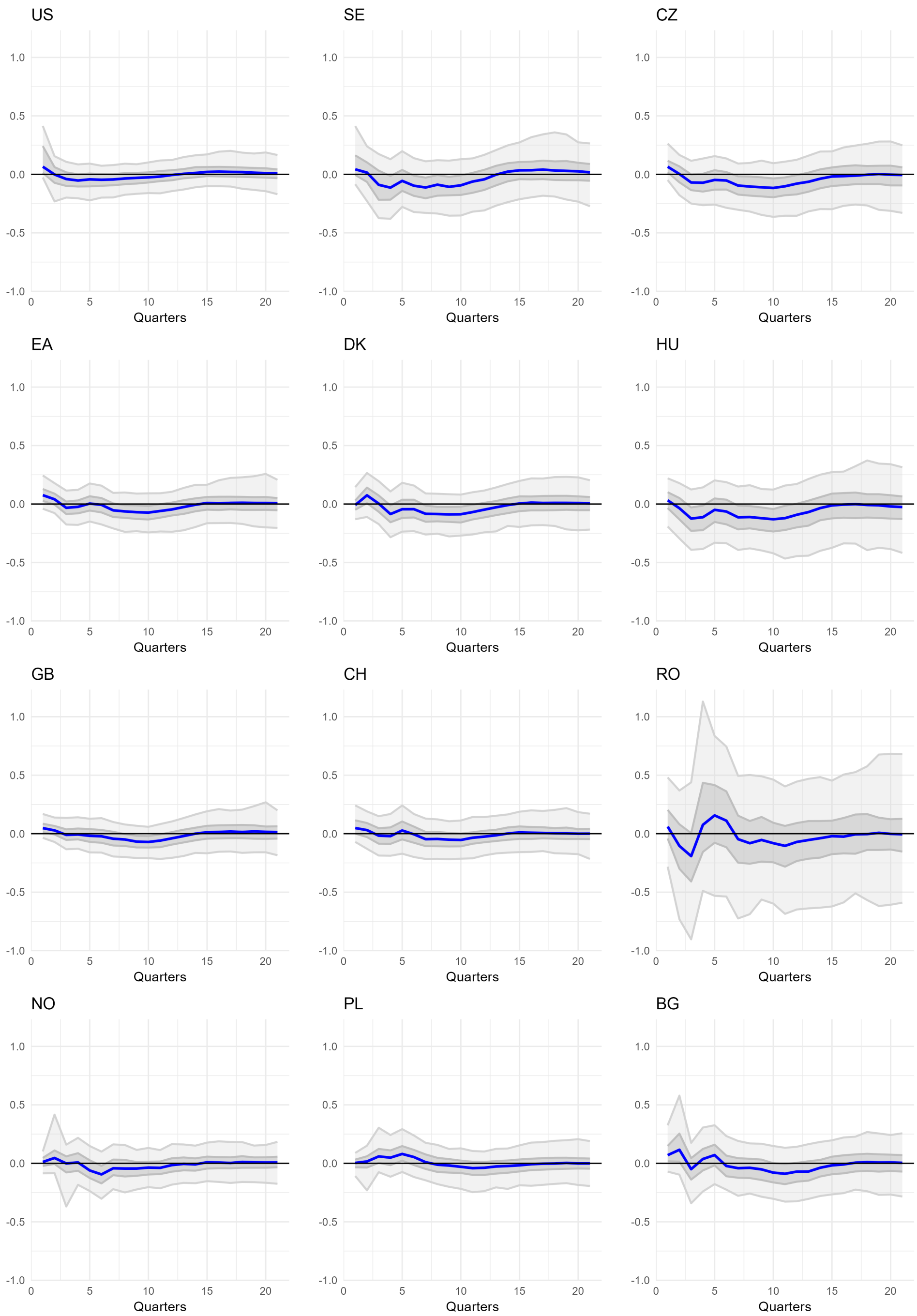
Wu, Jing Cynthia and Fan Dora Xia, "Measuring the macroeconomic impact of monetary policy at the zero lower bound," *Journal of Money, Credit and Banking*, 2016, *48* (2-3), 253–291.

Wu, Jing Cynthia and Fan Dora Xia, "Time-varying lower bound of interest rates in Europe," *Chicago Booth Research Paper*, 2017, (17-06).

A Appendix

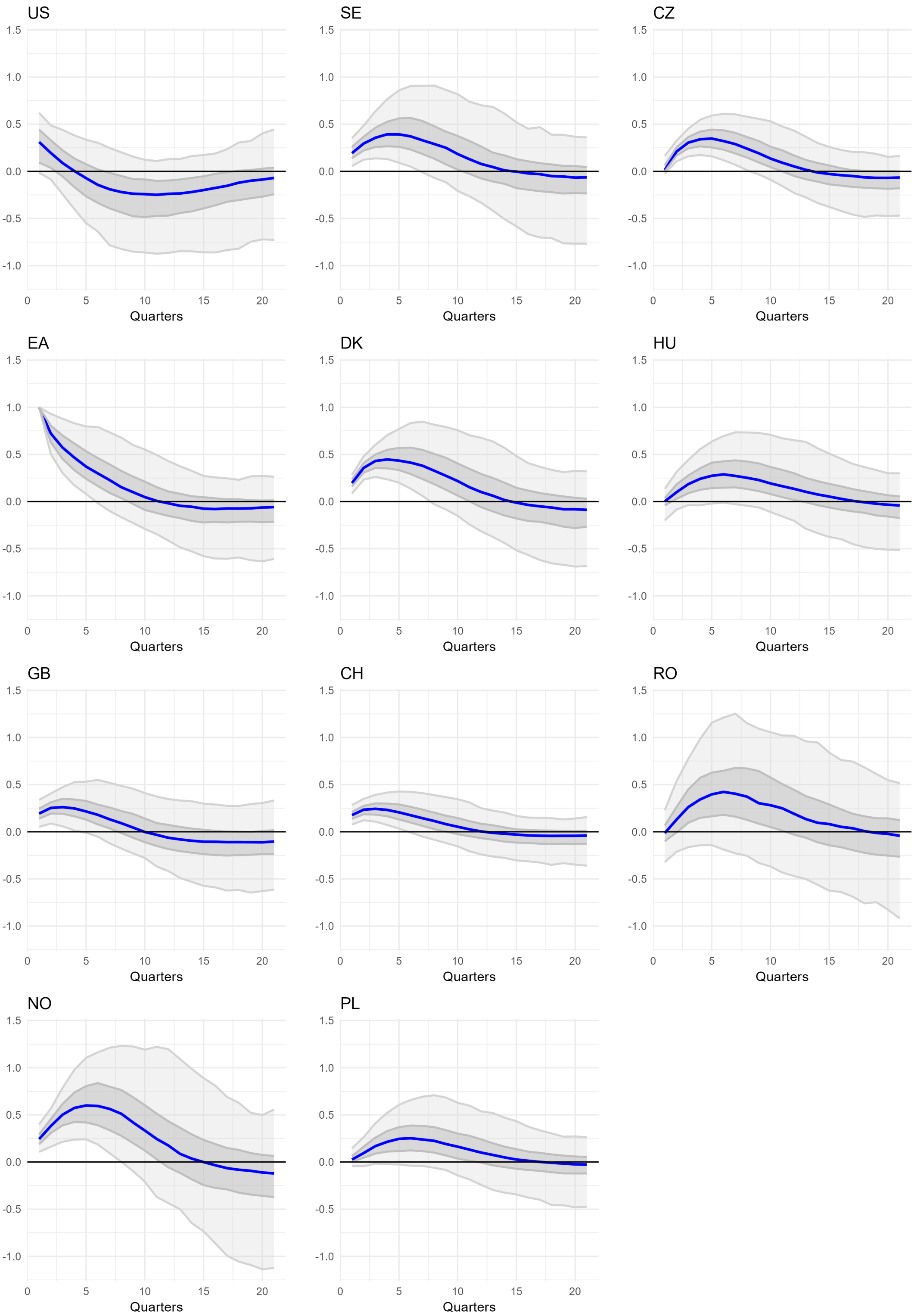
A.1 Robustness check plots

Figure 15: GVAR(4) inflation responses after an ECB-shock



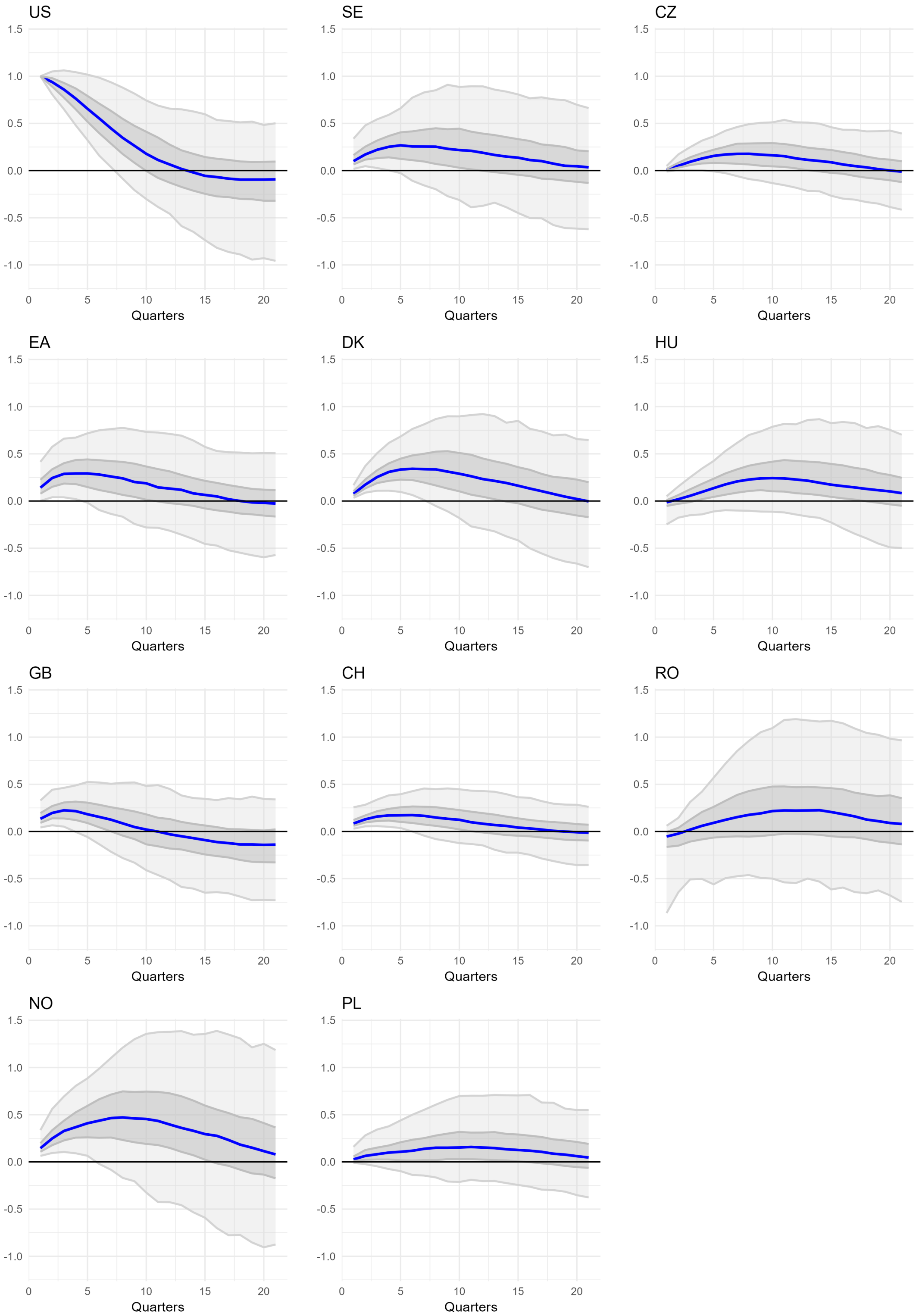
Note: Impulse responses to a 100bp contractionary monetary policy shock. The blue line indicates the median response. Grey and light grey areas show the credible bands for 25th and 75th as well as 5th and 95th percentiles, respectively. The used model includes 4 domestic and foreign variables.

Figure 16: r impulse responses after an ECB shock (limited sample)



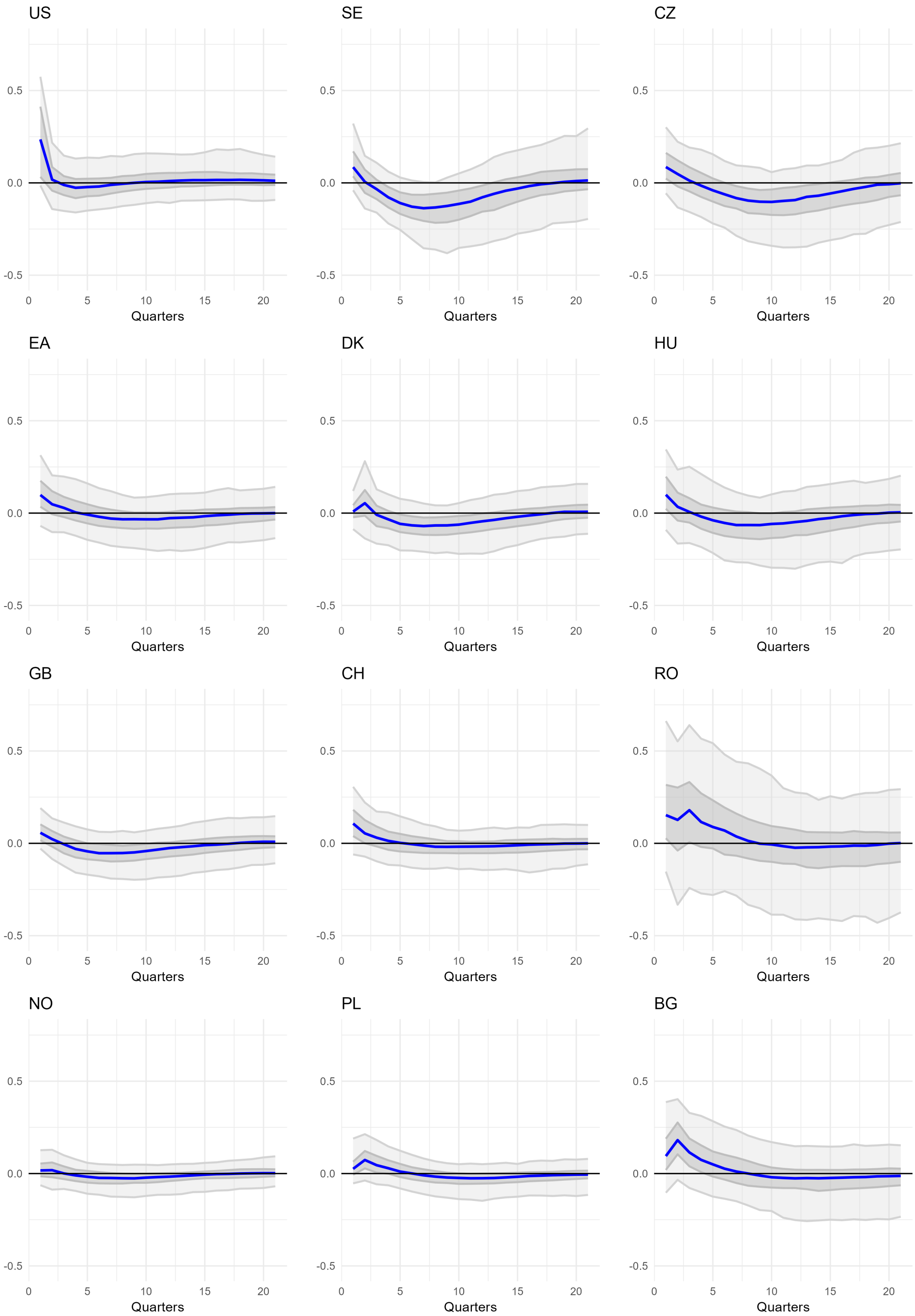
Note: Impulse responses to a 100bp contractionary monetary policy shock. The blue line indicates the median response. Grey and light grey areas show the credible bands for 25th and 75th as well as 5th and 95th percentiles, respectively.

Figure 17: r impulse responses after a Fed shock (limited sample)



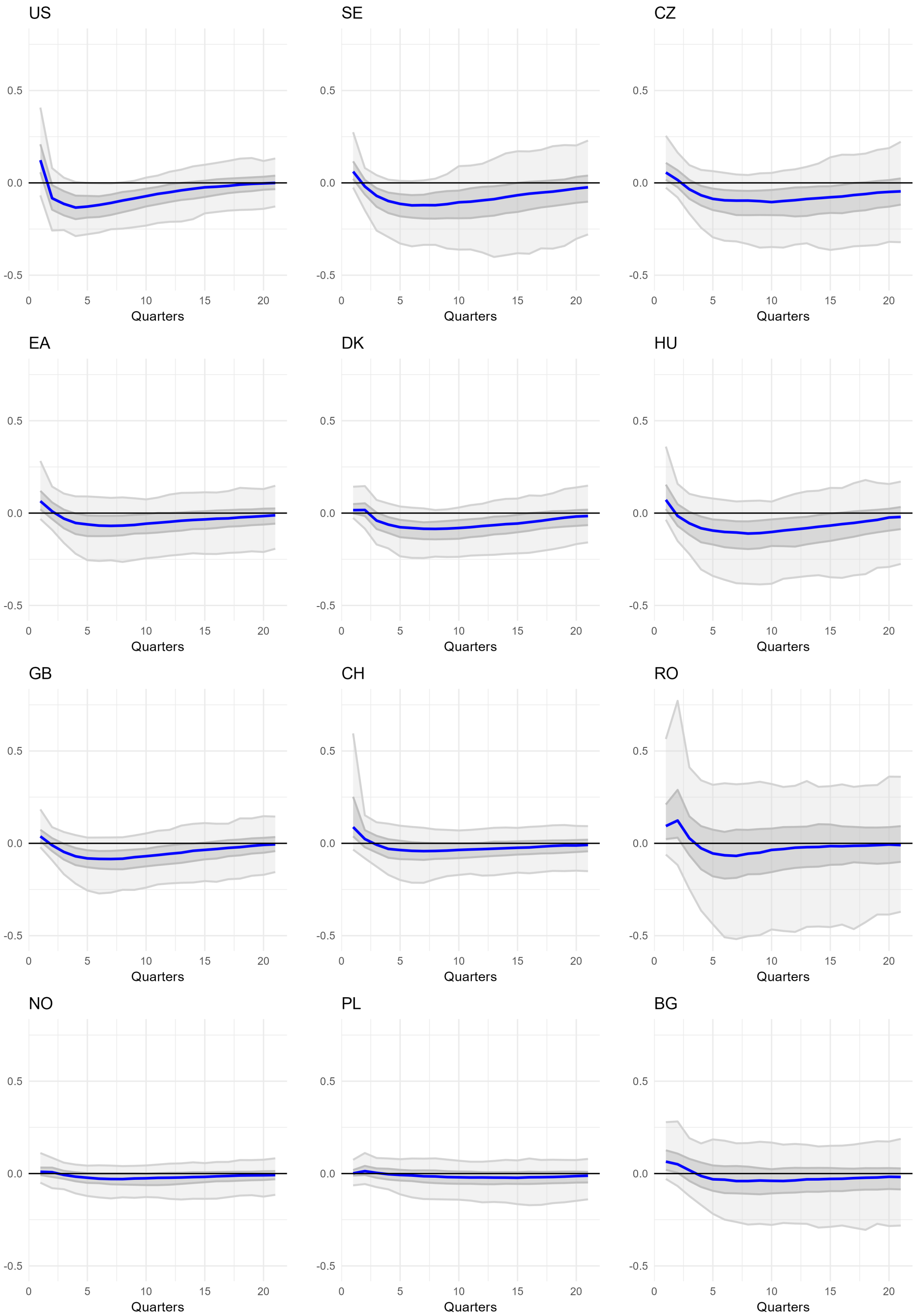
Note: Impulse responses to a 100bp contractionary monetary policy shock. The blue line indicates the median response. Grey and light grey areas show the credible bands for 25th and 75th as well as 5th and 95th percentiles, respectively.

Figure 18: Δy impulse responses after an ECB shock (limited sample)



Note: Impulse responses to a 100bp contractionary monetary policy shock. The blue line indicates the median response. Grey and light grey areas show the credible bands for 25th and 75th as well as 5th and 95th percentiles, respectively.

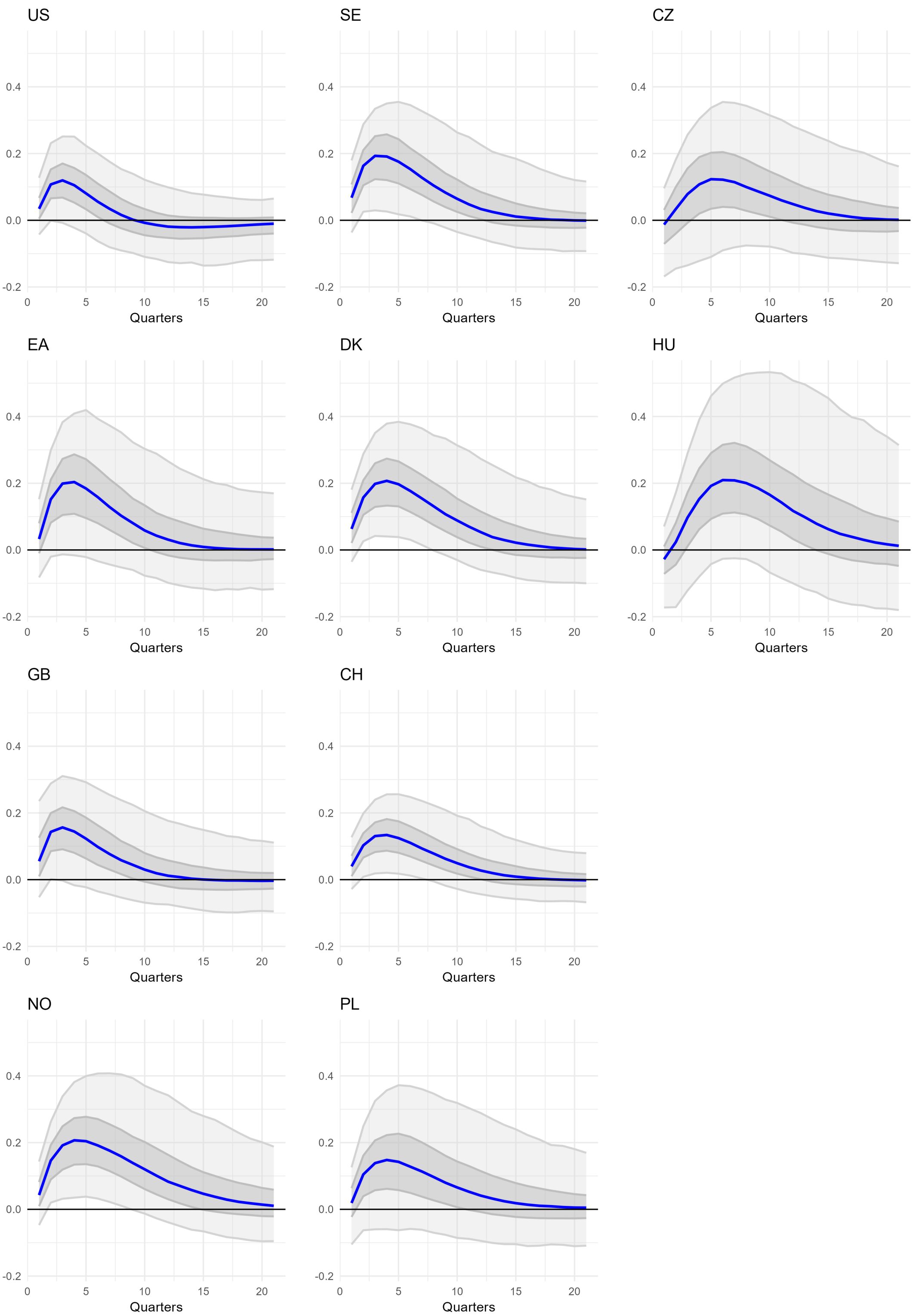
Figure 19: Δy impulse responses after a Fed shock (limited sample)



Note: Impulse responses to a 100bp contractionary monetary policy shock. The blue line indicates the median response. Grey and light grey areas show the credible bands for 25th and 75th as well as 5th and 95th percentiles, respectively.

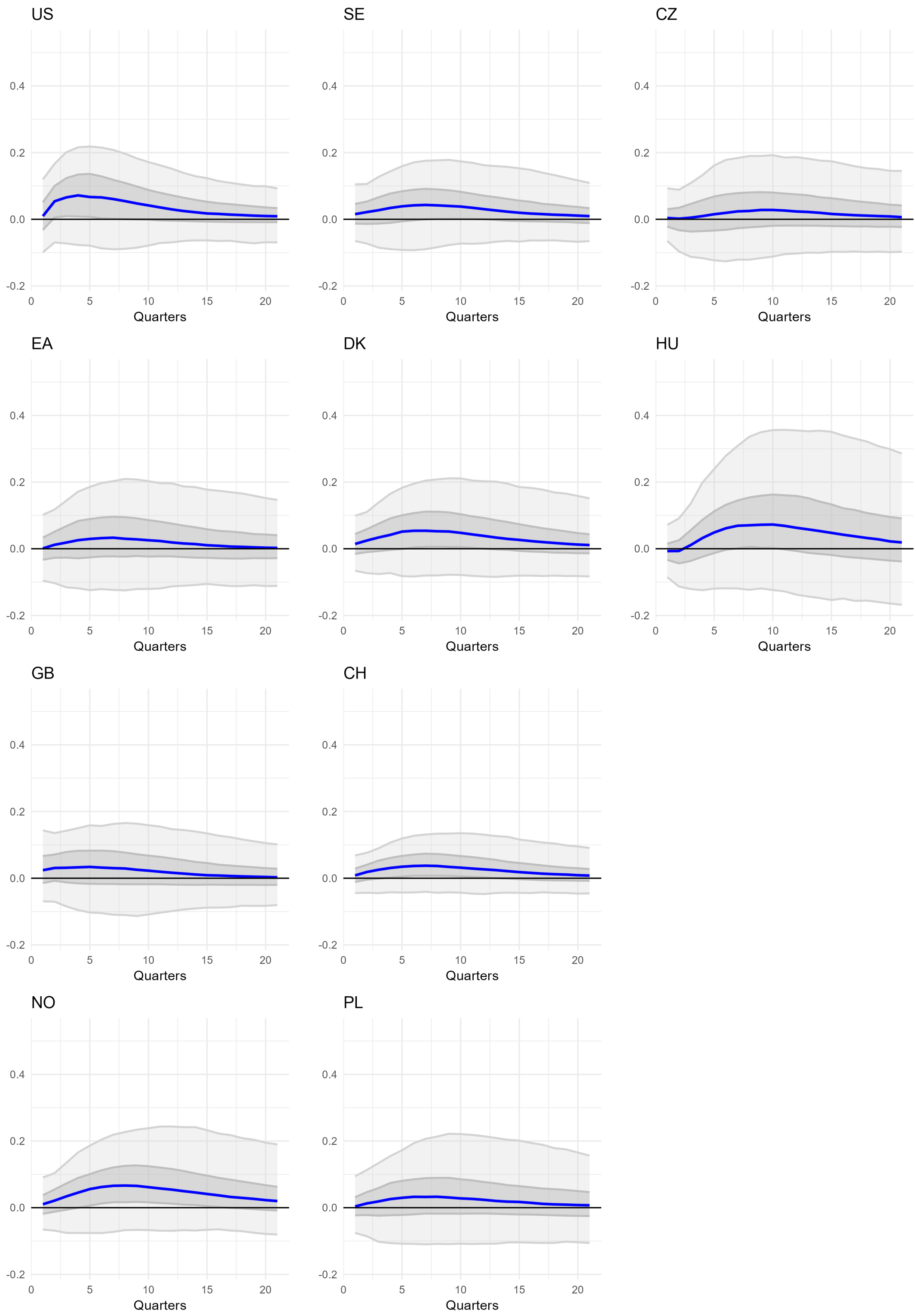
A.2 Complete sample Impulse responses for REER and lr

Figure 20: lr impulse responses after an ECB shock (limited sample)



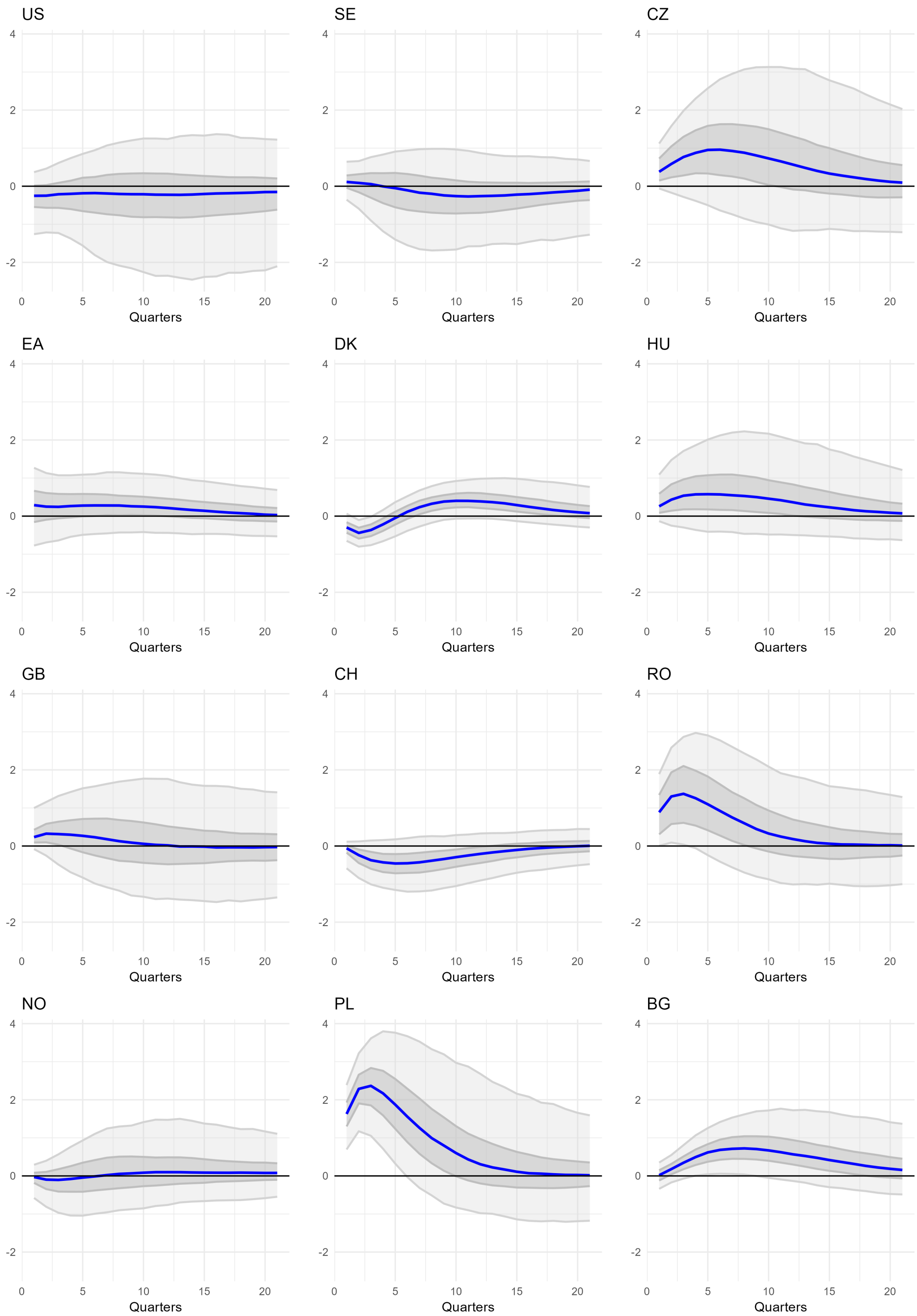
Note: Impulse responses to a 100bp contractionary monetary policy shock. The blue line indicates the median response. Grey and light grey areas show the credible bands for 25th and 75th as well as 5th and 95th percentiles, respectively.

Figure 21: lr impulse responses after a Fed shock (limited sample)



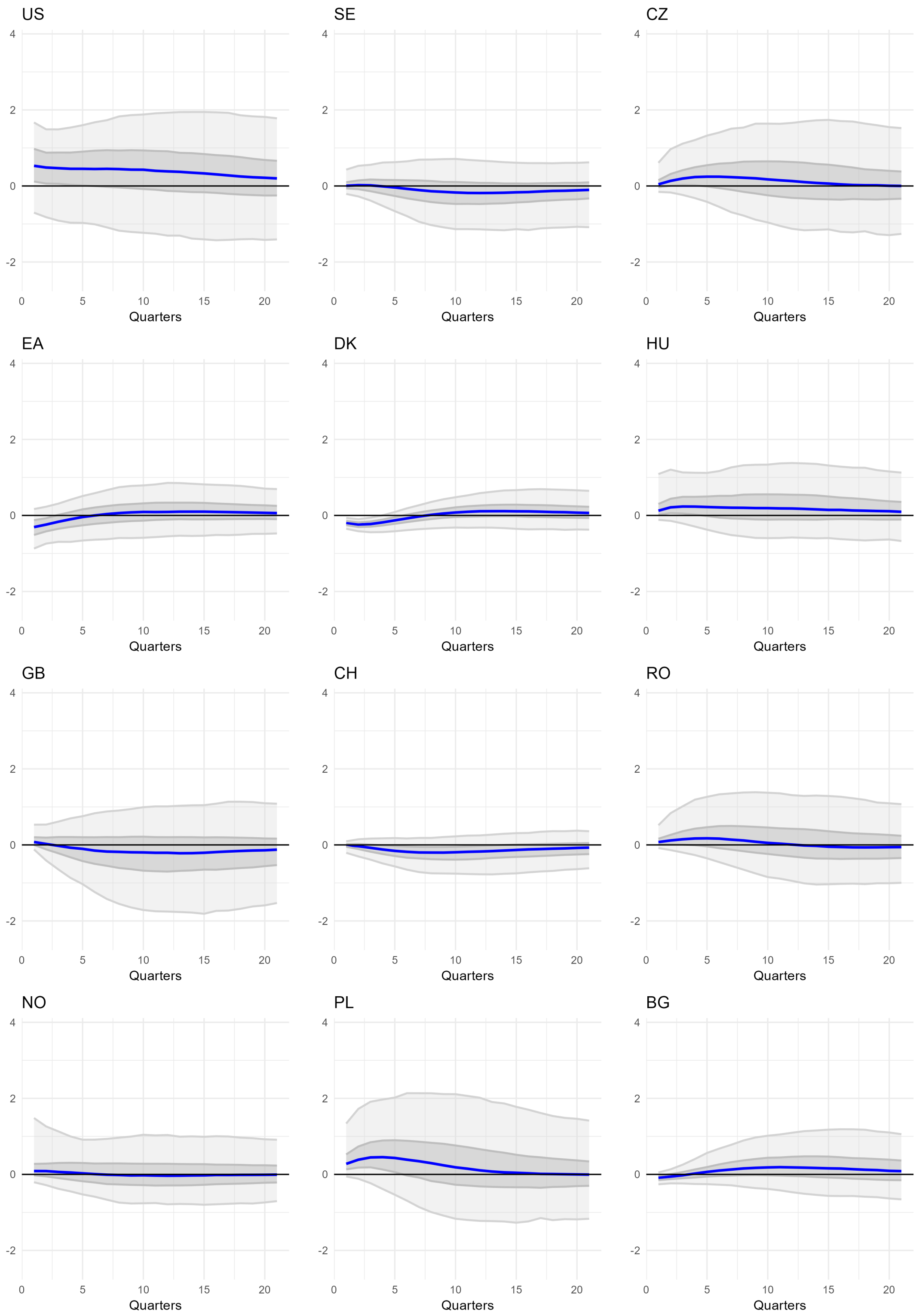
Note: Impulse responses to a 100bp contractionary monetary policy shock. The blue line indicates the median response. Grey and light grey areas show the credible bands for 25th and 75th as well as 5th and 95th percentiles, respectively.

Figure 22: REER impulse responses after an ECB shock (limited sample)



Note: Impulse responses to a 100bp contractionary monetary policy shock. The blue line indicates the median response. Grey and light grey areas show the credible bands for 25th and 75th as well as 5th and 95th percentiles, respectively.

Figure 23: REER impulse responses after a Fed shock (limited sample)



Note: Impulse responses to a 100bp contractionary monetary policy shock. The blue line indicates the median response. Grey and light grey areas show the credible bands for 25th and 75th as well as 5th and 95th percentiles, respectively.

A.3 Weight matrices

CDIS weights

	AU	BG	BR	CA	CH	CL	CN	CZ	DK	EA	GB	HU	ID	IN	JP	KR	MX	MY	NO	NZ	PE	PH	PL	RO	RU	SA	SE	SG	TH	TR	US	ZA
AU	0.000	0.000	0.006	0.046	0.020	0.002	0.043	0.000	0.003	0.122	0.184	0.000	0.006	0.002	0.091	0.005	0.001	0.016	0.001	0.069	0.000	0.001	0.000	0.000	0.001	0.001	0.003	0.045	0.005	0.000	0.320	0.005
BG	0.001	0.000	0.000	0.001	0.032	0.000	0.003	0.017	0.008	0.723	0.061	0.029	0.000	0.000	0.002	0.003	0.000	0.000	0.005	0.000	0.000	0.000	0.005	0.011	0.051	0.000	0.005	0.000	0.000	0.016	0.027	0.000
BR	0.006	0.000	0.000	0.021	0.007	0.021	0.003	0.000	0.006	0.620	0.040	0.002	0.000	0.000	0.041	0.006	0.018	0.000	0.008	0.001	0.003	0.000	0.000	0.000	0.000	0.000	0.007	0.003	0.000	0.000	0.186	0.001
CA	0.025	0.000	0.020	0.000	0.025	0.012	0.016	0.000	0.001	0.204	0.094	0.007	0.002	0.003	0.020	0.003	0.011	0.001	0.004	0.001	0.007	0.001	0.002	0.000	0.002	0.000	0.004	0.003	0.000	0.001	0.528	0.002
CH	0.009	0.000	0.004	0.022	0.000	0.001	0.010	0.002	0.006	0.622	0.057	0.030	0.001	0.004	0.009	0.002	0.004	0.002	0.002	0.000	0.000	0.001	0.004	0.001	0.013	0.001	0.008	0.012	0.001	0.001	0.168	0.002
CL	0.011	0.000	0.106	0.151	0.019	0.000	0.002	0.000	0.002	0.346	0.052	0.000	0.000	0.000	0.015	0.002	0.023	0.000	0.007	0.000	0.048	0.000	0.001	0.000	0.000	0.000	0.007	0.000	0.000	0.000	0.209	0.001
CN	0.042	0.000	0.003	0.029	0.017	0.000	0.000	0.000	0.005	0.216	0.032	0.001	0.009	0.002	0.193	0.089	0.001	0.010	0.004	0.002	0.001	0.003	0.001	0.000	0.005	0.004	0.014	0.170	0.010	0.001	0.128	0.008
CZ	0.000	0.004	0.000	0.002	0.040	0.000	0.003	0.000	0.006	0.822	0.026	0.004	0.000	0.001	0.010	0.014	0.000	0.000	0.002	0.000	0.000	0.000	0.020	0.006	0.006	0.000	0.010	0.001	0.000	0.001	0.021	0.000
DK	0.009	0.000	0.007	0.007	0.045	0.001	0.015	0.004	0.000	0.380	0.100	0.003	0.001	0.003	0.021	0.001	0.003	0.004	0.062	0.001	0.000	0.000	0.014	0.002	0.004	0.001	0.187	0.038	0.002	0.002	0.080	0.002
EA	0.010	0.002	0.027	0.041	0.115	0.003	0.015	0.011	0.009	0.000	0.248	0.014	0.002	0.005	0.020	0.005	0.015	0.002	0.008	0.001	0.001	0.001	0.012	0.005	0.034	0.003	0.031	0.019	0.002	0.007	0.325	0.006
GB	0.022	0.000	0.006	0.024	0.032	0.001	0.006	0.001	0.006	0.523	0.000	0.001	0.003	0.009	0.026	0.004	0.007	0.002	0.005	0.001	0.000	0.000	0.003	0.000	0.007	0.001	0.015	0.012	0.002	0.003	0.266	0.012
HU	0.001	0.003	0.004	0.058	0.178	0.000	0.000	0.002	0.003	0.560	0.018	0.000	0.000	0.000	0.004	0.017	0.006	0.000	0.002	0.000	0.000	0.000	0.005	0.004	0.003	0.000	0.002	0.005	0.000	0.000	0.123	0.000
ID	0.014	0.000	0.000	0.014	0.010	0.000	0.049	0.000	0.000	0.198	0.068	0.000	0.000	0.001	0.103	0.019	0.000	0.060	0.001	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.353	0.012	0.001	0.094	0.000
IN	0.004	0.000	0.001	0.007	0.062	0.000	0.003	0.000	0.002	0.234	0.174	0.000	0.001	0.000	0.087	0.023	0.001	0.002	0.001	0.000	0.000	0.004	0.001	0.000	0.005	0.001	0.008	0.171	0.002	0.000	0.206	0.002
JP	0.048	0.000	0.022	0.013	0.013	0.002	0.080	0.001	0.005	0.192	0.083	0.001	0.019	0.014	0.000	0.026	0.005	0.011	0.001	0.003	0.000	0.010	0.001	0.000	0.001	0.004	0.005	0.050	0.039	0.001	0.348	0.004
KR	0.025	0.000	0.012	0.017	0.010	0.001	0.176	0.005	0.001	0.174	0.055	0.012	0.015	0.016	0.131	0.000	0.006	0.016	0.004	0.002	0.004	0.006	0.004	0.000	0.007	0.003	0.007	0.049	0.007	0.002	0.232	0.001
MX	0.001	0.000	0.029	0.047	0.023	0.008	0.001	0.000	0.002	0.366	0.064	0.004	0.000	0.001	0.013	0.004	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000	0.000	0.000	0.004	0.002	0.000	0.000	0.427	0.000
MY	0.056	0.000	0.001	0.040	0.038	0.000	0.023	0.000	0.009	0.145	0.064	0.000	0.077	0.016	0.106	0.028	0.000	0.000	0.004	0.001	0.000	0.003	0.001	0.000	0.001	0.003	0.005	0.275	0.021	0.005	0.069	0.011
NO	0.003	0.001	0.015	0.011	0.015	0.002	0.009	0.001	0.071	0.407	0.068	0.003	0.000	0.001	0.004	0.004	0.000	0.002	0.000	0.000	0.001	0.000	0.007	0.000	0.003	0.000	0.183	0.054	0.006	0.004	0.120	0.001
NZ	0.594	0.000	0.003	0.017	0.006	0.000	0.007	0.000	0.003	0.090	0.055	0.000	0.001	0.001	0.040	0.011	0.001	0.002	0.001	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.001	0.048	0.001	0.000	0.115	0.001
PE	0.003	0.000	0.028	0.191	0.017	0.137	0.017	0.000	0.003	0.282	0.029	0.000	0.000	0.000	0.004	0.031	0.038	0.000	0.007	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.007	0.003	0.000	0.000	0.198	0.008
PH	0.018	0.000	0.000	0.005	0.051	0.000	0.030	0.000	0.003	0.297	0.022	0.003	0.004	0.009	0.239	0.031	0.001	0.010	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.002	0.138	0.015	0.000	0.118	0.001
PL	0.000	0.000	0.000	0.003	0.037	0.001	0.002	0.013	0.017	0.791	0.042	0.008	0.000	0.001	0.005	0.005	0.000	0.000	0.009	0.000	0.000	0.000	0.000	0.003	0.005	0.000	0.017	0.001	0.000	0.001	0.036	0.000
RO	0.001	0.006	0.000	0.002	0.040	0.000	0.003	0.017	0.006	0.836	0.020	0.017	0.000	0.000	0.004	0.001	0.000	0.000	0.003	0.000	0.000	0.000	0.006	0.000	0.001	0.000	0.007	0.001	0.000	0.008	0.020	0.000
RU	0.001	0.005	0.000	0.003	0.039	0.000	0.005	0.004	0.002	0.826	0.038	0.002	0.000	0.002	0.003	0.003	0.000	0.000	0.002	0.000	0.000	0.000	0.002	0.000	0.000	0.000	0.016	0.010	0.001	0.012	0.024	0.001
SA	0.006	0.000	0.000	0.005	0.019	0.000	0.037	0.000	0.002	0.567	0.060	0.000	0.000	0.003	0.080	0.021	0.000	0.006	0.001	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.003	0.012	0.001	0.022	0.150	0.002
SE	0.005	0.000	0.006	0.010	0.026	0.002	0.016	0.003	0.073	0.522	0.099	0.001	0.000	0.003	0.010	0.004	0.002	0.001	0.074	0.000	0.001	0.000	0.005	0.001	0.011	0.000	0.000	0.001	0.002	0.002	0.117	0.001
SG	0.034	0.000	0.001	0.012	0.031	0.000	0.122	0.000	0.010	0.208	0.054	0.001	0.064	0.052	0.081	0.017	0.001	0.067	0.016	0.006	0.000	0.007	0.000	0.000	0.007	0.001	0.001	0.000	0.033	0.000	0.173	0.000
TH	0.020	0.000	0.001	0.017	0.018	0.000	0.039	0.000	0.004	0.135	0.046	0.000	0.015	0.007	0.357	0.016	0.001	0.031	0.002	0.000	0.000	0.004	0.000	0.000	0.002	0.001	0.004	0.183	0.000	0.001	0.094	0.001
TR	0.001	0.001	0.001	0.001	0.027	0.000	0.005	0.002	0.002	0.718	0.071	0.000	0.001	0.002	0.009	0.004	0.000	0.007	0.003	0.000	0.000	0.000	0.001	0.002	0.059	0.009	0.004	0.003	0.001	0.000	0.066	0.000
US	0.030	0.000	0.010	0.093	0.056	0.004	0.014	0.001	0.004	0.454	0.159	0.005	0.002	0.005	0.071	0.010	0.016	0.002	0.008	0.002	0.001	0.001	0.002	0.000	0.003	0.002	0.011	0.031	0.002	0.001	0.000	0.001
ZA	0.031	0.000	0.002	0.008	0.017	0.001	0.222	0.000	0.001	0.299	0.300	0.000	0.000	0.003	0.018	0.001	0.000	0.007	0.000	0.000	0.003	0.000	0.003	0.000	0.006	0.001	0.003	0.002	0.000	0.000	0.070	0.000

Note: This table shows the weights calculated with the CDIS data. The values in the columns show how large of an total investment share a specific economy has in another economy (rows). (The rows add up to 1.)

Export weights

	AU	BG	BR	CA	CH	CL	CN	CZ	DK	EA	GB	HU	ID	IN	JP	KR	MX	MY	NO	NZ	PE	PH	PL	RO	RU	SA	SE	SG	TH	TR	US	ZA
AU	0.000	0.000	0.003	0.010	0.014	0.003	0.183	0.002	0.006	0.168	0.037	0.001	0.023	0.013	0.096	0.048	0.005	0.044	0.002	0.040	0.001	0.003	0.003	0.000	0.000	0.002	0.012	0.074	0.049	0.003	0.147	0.006
BG	0.002	0.000	0.008	0.004	0.013	0.013	0.039	0.026	0.005	0.499	0.020	0.035	0.003	0.005	0.003	0.006	0.001	0.002	0.001	0.000	0.009	0.001	0.030	0.071	0.105	0.002	0.006	0.001	0.001	0.075	0.012	0.001
BR	0.006	0.000	0.000	0.013	0.014	0.023	0.157	0.002	0.004	0.226	0.020	0.001	0.008	0.023	0.031	0.042	0.024	0.006	0.004	0.000	0.008	0.001	0.003	0.001	0.012	0.017	0.008	0.009	0.010	0.003	0.236	0.004
CA	0.004	0.000	0.006	0.000	0.008	0.003	0.061	0.001	0.002	0.075	0.017	0.001	0.002	0.005	0.025	0.012	0.024	0.002	0.006	0.001	0.005	0.001	0.002	0.000	0.001	0.011	0.004	0.003	0.004	0.002	0.708	0.001
CH	0.003	0.001	0.006	0.005	0.000	0.002	0.014	0.010	0.004	0.628	0.092	0.004	0.002	0.004	0.019	0.003	0.003	0.002	0.003	0.000	0.012	0.001	0.007	0.002	0.035	0.001	0.008	0.007	0.013	0.009	0.090	0.007
CL	0.005	0.000	0.091	0.013	0.005	0.000	0.190	0.001	0.003	0.152	0.015	0.001	0.003	0.010	0.036	0.041	0.032	0.003	0.002	0.002	0.028	0.001	0.002	0.000	0.001	0.001	0.007	0.001	0.009	0.003	0.253	0.001
CN	0.064	0.001	0.037	0.016	0.016	0.017	0.000	0.002	0.003	0.157	0.018	0.002	0.019	0.014	0.147	0.135	0.005	0.028	0.003	0.006	0.008	0.007	0.002	0.001	0.034	0.056	0.006	0.046	0.025	0.002	0.110	0.008
CZ	0.001	0.003	0.001	0.001	0.013	0.000	0.052	0.000	0.007	0.660	0.023	0.030	0.001	0.002	0.013	0.011	0.001	0.002	0.006	0.000	0.000	0.001	0.086	0.009	0.035	0.000	0.010	0.003	0.005	0.006	0.014	0.001
DK	0.002	0.001	0.004	0.004	0.012	0.002	0.059	0.014	0.000	0.524	0.051	0.008	0.002	0.007	0.007	0.009	0.001	0.002	0.055	0.001	0.001	0.000	0.036	0.002	0.020	0.000	0.123	0.003	0.005	0.010	0.028	0.002
EA	0.005	0.006	0.019	0.010	0.059	0.006	0.124	0.055	0.024	0.000	0.123	0.034	0.007	0.018	0.039	0.021	0.008	0.010	0.032	0.001	0.003	0.004	0.058	0.017	0.085	0.015	0.037	0.015	0.009	0.025	0.115	0.008
GB	0.010	0.001	0.006	0.021	0.024	0.001	0.070	0.012	0.014	0.525	0.000	0.007	0.003	0.013	0.026	0.010	0.003	0.004	0.052	0.002	0.001	0.001	0.018	0.004	0.017	0.004	0.019	0.009	0.006	0.015	0.093	0.007
HU	0.000	0.004	0.002	0.002	0.011	0.000	0.060	0.045	0.007	0.610	0.021	0.000	0.001	0.003	0.020	0.017	0.003	0.004	0.001	0.000	0.000	0.002	0.053	0.030	0.059	0.000	0.009	0.006	0.004	0.008	0.018	0.001
ID	0.043	0.000	0.015	0.013	0.005	0.002	0.267	0.001	0.001	0.085	0.009	0.000	0.000	0.038	0.141	0.087	0.001	0.069	0.001	0.006	0.001	0.006	0.001	0.000	0.006	0.037	0.006	0.000	0.077	0.002	0.066	0.004
IN	0.041	0.000	0.012	0.010	0.048	0.007	0.183	0.002	0.002	0.146	0.027	0.001	0.040	0.000	0.034	0.045	0.009	0.032	0.001	0.002	0.003	0.001	0.002	0.001	0.023	0.149	0.007	0.045	0.019	0.003	0.086	0.012
JP	0.067	0.000	0.011	0.018	0.013	0.013	0.240	0.001	0.004	0.104	0.015	0.001	0.044	0.008	0.000	0.057	0.005	0.038	0.003	0.005	0.003	0.019	0.001	0.000	0.021	0.087	0.005	0.032	0.040	0.001	0.133	0.010
KR	0.045	0.000	0.009	0.010	0.007	0.011	0.228	0.001	0.002	0.105	0.015	0.001	0.029	0.011	0.164	0.000	0.005	0.021	0.004	0.003	0.003	0.007	0.001	0.001	0.030	0.095	0.004	0.041	0.011	0.001	0.126	0.004
MX	0.002	0.000	0.014	0.016	0.005	0.006	0.078	0.001	0.001	0.099	0.006	0.001	0.002	0.006	0.033	0.029	0.000	0.005	0.000	0.001	0.001	0.001	0.001	0.000	0.003	0.000	0.003	0.004	0.005	0.001	0.669	0.001
MY	0.024	0.000	0.008	0.004	0.007	0.001	0.188	0.001	0.001	0.081	0.013	0.001	0.047	0.023	0.097	0.044	0.001	0.000	0.001	0.004	0.000	0.012	0.001	0.000	0.004	0.018	0.003	0.260	0.061	0.001	0.085	0.004
NO	0.002	0.000	0.010	0.026	0.011	0.001	0.034	0.009	0.084	0.370	0.065	0.003	0.001	0.004	0.016	0.026	0.001	0.002	0.000	0.000	0.001	0.000	0.037	0.006	0.012	0.000	0.214	0.008	0.003	0.006	0.049	0.002
NZ	0.261	0.000	0.002	0.013	0.007	0.002	0.121	0.002	0.005	0.127	0.031	0.001	0.014	0.010	0.083	0.039	0.003	0.034	0.001	0.000	0.001	0.002	0.002	0.000	0.004	0.006	0.007	0.061	0.034	0.003	0.119	0.003
PE	0.003	0.001	0.076	0.019	0.005	0.065	0.176	0.001	0.002	0.117	0.008	0.001	0.005	0.020	0.030	0.036	0.047	0.004	0.001	0.003	0.000	0.001	0.002	0.000	0.012	0.004	0.007	0.002	0.011	0.006	0.288	0.002
PH	0.017	0.000	0.007	0.007	0.004	0.002	0.228	0.001	0.002	0.072	0.008	0.000	0.046	0.014	0.143	0.091	0.001	0.041	0.001	0.007	0.001	0.000	0.001	0.000	0.007	0.031	0.002	0.085	0.060	0.001	0.113	0.001
PL	0.001	0.002	0.002	0.002	0.011	0.001	0.060	0.046	0.014	0.620	0.029	0.020	0.002	0.004	0.009	0.018	0.001	0.002	0.011	0.000	0.000	0.000	0.000	0.007	0.073	0.006	0.022	0.001	0.002	0.010	0.018	0.001
RO	0.001	0.028	0.005	0.002	0.012	0.000	0.050	0.029	0.005	0.585	0.023	0.081	0.001	0.005	0.005	0.008	0.001	0.001	0.002	0.000	0.000	0.000	0.046	0.000	0.038	0.000	0.006	0.001	0.002	0.046	0.013	0.001
RU	0.003	0.003	0.017	0.005	0.013	0.002	0.180	0.019	0.008	0.475	0.025	0.013	0.004	0.009	0.042	0.038	0.001	0.004	0.004	0.001	0.000	0.000	0.037	0.005	0.000	0.000	0.015	0.003	0.004	0.023	0.039	0.001
SA	0.017	0.001	0.024	0.010	0.025	0.001	0.144	0.003	0.007	0.276	0.048	0.002	0.014	0.058	0.065	0.056	0.002	0.010	0.001	0.004	0.000	0.001	0.004	0.003	0.006	0.000	0.014	0.000	0.020	0.026	0.146	0.004
SE	0.002	0.001	0.004	0.003	0.012	0.002	0.040	0.016	0.095	0.555	0.061	0.009	0.001	0.004	0.013	0.006	0.001	0.003	0.057	0.000	0.001	0.000	0.037	0.003	0.023	0.001	0.000	0.001	0.004	0.008	0.033	0.002
SG	0.023	0.001	0.009	0.004	0.021	0.000	0.156	0.001	0.002	0.109	0.024	0.001	0.055	0.038	0.098	0.062	0.003	0.124	0.005	0.003	0.000	0.017	0.002	0.000	0.008	0.062	0.004	0.000	0.041	0.002	0.124	0.002
TH	0.029	0.000	0.010	0.005	0.017	0.002	0.179	0.001	0.002	0.083	0.014	0.001	0.034	0.019	0.217	0.046	0.002	0.077	0.002	0.004	0.001	0.015	0.001	0.000	0.006	0.051	0.004	0.096	0.000	0.001	0.075	0.003
TR	0.003	0.014	0.008	0.006	0.022	0.002	0.087	0.010	0.005	0.437	0.041	0.010	0.007	0.021	0.017	0.031	0.001	0.007	0.005	0.000	0.000	0.000	0.016	0.018	0.121	0.022	0.011	0.003	0.006	0.000	0.063	0.003
US	0.005	0.000	0.014	0.188	0.015	0.005	0.172	0.002	0.004	0.168	0.035	0.001	0.008	0.018	0.081	0.033	0.154	0.013	0.004	0.002	0.003	0.005	0.002	0.001	0.006	0.017	0.007	0.015	0.013	0.003	0.000	0.004
ZA	0.020	0.001	0.021	0.007	0.010	0.001	0.158	0.006	0.004	0.312	0.055	0.005	0.011	0.046	0.049	0.021	0.003	0.011	0.002	0.002	0.001	0.002	0.006	0.002	0.002	0.089	0.015	0.014	0.027	0.008	0.081	0.000

Note: This table shows the weights calculated with the DOTS export data. The values in the columns show how large of an export share a specific economy has in another economy (rows). (The rows add up to 1.)

Import weights

	AU	BG	BR	CA	CH	CL	CN	CZ	DK	EA	GB	HU	ID	IN	JP	KR	MX	MY	NO	NZ	PE	PH	PL	RO	RU	SA	SE	SG	TH	TR	US	ZA
AU	0.000	0.000	0.006	0.009	0.003	0.002	0.322	0.000	0.001	0.049	0.032	0.000	0.024	0.052	0.215	0.093	0.004	0.021	0.001	0.030	0.001	0.006	0.001	0.000	0.003	0.010	0.002	0.022	0.025	0.004	0.054	0.007
BG	0.002	0.000	0.003	0.006	0.010	0.001	0.028	0.014	0.005	0.566	0.025	0.014	0.002	0.005	0.004	0.006	0.003	0.001	0.003	0.000	0.001	0.002	0.021	0.086	0.026	0.006	0.007	0.011	0.002	0.107	0.030	0.003
BR	0.004	0.001	0.000	0.021	0.007	0.031	0.249	0.001	0.002	0.214	0.026	0.001	0.010	0.019	0.050	0.026	0.034	0.009	0.007	0.001	0.013	0.002	0.004	0.003	0.020	0.015	0.004	0.008	0.011	0.010	0.186	0.010
CA	0.005	0.000	0.006	0.000	0.003	0.002	0.040	0.000	0.001	0.045	0.032	0.000	0.003	0.006	0.027	0.011	0.023	0.002	0.005	0.001	0.001	0.001	0.001	0.000	0.003	0.003	0.001	0.003	0.002	0.003	0.769	0.002
CH	0.010	0.001	0.011	0.014	0.000	0.001	0.087	0.005	0.004	0.457	0.057	0.003	0.002	0.074	0.031	0.010	0.007	0.007	0.004	0.001	0.001	0.001	0.005	0.002	0.009	0.011	0.006	0.019	0.020	0.020	0.115	0.004
CL	0.009	0.002	0.058	0.027	0.006	0.000	0.258	0.000	0.003	0.168	0.016	0.000	0.003	0.027	0.115	0.064	0.032	0.003	0.002	0.001	0.020	0.001	0.002	0.000	0.008	0.003	0.004	0.002	0.005	0.006	0.153	0.002
CN	0.027	0.001	0.017	0.032	0.006	0.008	0.000	0.006	0.004	0.181	0.035	0.005	0.016	0.030	0.109	0.052	0.037	0.019	0.005	0.004	0.004	0.007	0.008	0.002	0.024	0.011	0.005	0.025	0.021	0.012	0.280	0.009
CZ	0.003	0.005	0.003	0.003	0.015	0.000	0.016	0.000	0.009	0.687	0.047	0.028	0.001	0.003	0.005	0.004	0.006	0.001	0.006	0.000	0.000	0.001	0.057	0.014	0.023	0.003	0.014	0.002	0.001	0.013	0.027	0.004
DK	0.011	0.001	0.006	0.014	0.010	0.002	0.032	0.010	0.000	0.437	0.081	0.007	0.002	0.005	0.027	0.008	0.005	0.002	0.054	0.002	0.001	0.001	0.028	0.004	0.015	0.006	0.133	0.006	0.003	0.008	0.077	0.003
EA	0.007	0.003	0.008	0.009	0.033	0.002	0.037	0.021	0.011	0.531	0.073	0.014	0.002	0.008	0.016	0.010	0.009	0.004	0.007	0.001	0.001	0.001	0.028	0.009	0.017	0.006	0.019	0.008	0.003	0.015	0.080	0.005
GB	0.015	0.001	0.007	0.024	0.042	0.002	0.035	0.008	0.012	0.530	0.000	0.005	0.002	0.013	0.018	0.012	0.006	0.005	0.012	0.002	0.001	0.001	0.013	0.004	0.012	0.009	0.022	0.014	0.005	0.014	0.143	0.009
HU	0.004	0.010	0.003	0.005	0.011	0.000	0.025	0.039	0.008	0.613	0.045	0.000	0.001	0.002	0.010	0.005	0.008	0.001	0.004	0.001	0.000	0.000	0.039	0.055	0.026	0.005	0.013	0.004	0.001	0.014	0.045	0.004
ID	0.031	0.000	0.008	0.008	0.004	0.001	0.139	0.001	0.002	0.101	0.014	0.001	0.000	0.068	0.169	0.072	0.008	0.052	0.001	0.004	0.001	0.020	0.002	0.001	0.008	0.009	0.001	0.099	0.039	0.009	0.120	0.005
IN	0.016	0.001	0.024	0.018	0.008	0.003	0.102	0.002	0.004	0.207	0.054	0.002	0.020	0.000	0.035	0.033	0.019	0.023	0.003	0.002	0.004	0.006	0.006	0.003	0.015	0.029	0.005	0.048	0.018	0.029	0.241	0.021
JP	0.027	0.000	0.009	0.022	0.006	0.003	0.233	0.003	0.001	0.110	0.023	0.003	0.021	0.013	0.000	0.087	0.027	0.029	0.003	0.004	0.002	0.013	0.002	0.001	0.014	0.012	0.004	0.035	0.052	0.006	0.230	0.006
KR	0.020	0.000	0.015	0.017	0.002	0.005	0.351	0.004	0.002	0.093	0.014	0.004	0.018	0.026	0.077	0.000	0.034	0.020	0.003	0.003	0.003	0.013	0.007	0.001	0.017	0.014	0.003	0.041	0.018	0.013	0.156	0.004
MX	0.005	0.000	0.011	0.067	0.002	0.005	0.022	0.001	0.000	0.051	0.007	0.001	0.001	0.007	0.012	0.007	0.000	0.001	0.000	0.001	0.004	0.000	0.001	0.000	0.002	0.002	0.000	0.004	0.001	0.002	0.780	0.001
MY	0.035	0.000	0.007	0.011	0.002	0.001	0.197	0.002	0.001	0.084	0.018	0.002	0.033	0.032	0.098	0.040	0.028	0.000	0.001	0.005	0.001	0.013	0.002	0.001	0.006	0.005	0.002	0.163	0.047	0.006	0.152	0.004
NO	0.003	0.000	0.005	0.028	0.003	0.001	0.022	0.001	0.047	0.443	0.209	0.000	0.001	0.006	0.015	0.017	0.002	0.002	0.000	0.000	0.000	0.000	0.014	0.001	0.008	0.001	0.097	0.008	0.002	0.006	0.055	0.001
NZ	0.217	0.000	0.002	0.019	0.003	0.003	0.183	0.000	0.004	0.090	0.044	0.000	0.021	0.016	0.096	0.041	0.014	0.023	0.002	0.000	0.002	0.015	0.001	0.000	0.005	0.016	0.002	0.022	0.018	0.002	0.129	0.006
PE	0.004	0.003	0.039	0.077	0.045	0.044	0.235	0.000	0.003	0.166	0.013	0.000	0.002	0.021	0.060	0.042	0.018	0.001	0.007	0.001	0.000	0.002	0.001	0.000	0.003	0.000	0.005	0.001	0.004	0.002	0.199	0.001
PH	0.010	0.000	0.005	0.016	0.004	0.001	0.258	0.002	0.001	0.100	0.019	0.004	0.009	0.006	0.141	0.048	0.028	0.037	0.001	0.002	0.000	0.000	0.002	0.000	0.004	0.003	0.001	0.087	0.038	0.002	0.168	0.002
PL	0.003	0.005	0.003	0.007	0.010	0.001	0.013	0.066	0.018	0.614	0.063	0.029	0.001	0.003	0.005	0.003	0.004	0.001	0.014	0.000	0.000	0.000	0.000	0.019	0.033	0.004	0.030	0.002	0.001	0.016	0.028	0.004
RO	0.002	0.037	0.004	0.006	0.009	0.001	0.022	0.022	0.004	0.592	0.044	0.053	0.001	0.006	0.008	0.008	0.005	0.001	0.009	0.000	0.000	0.000	0.025	0.000	0.025	0.006	0.007	0.002	0.001	0.061	0.035	0.004
RU	0.001	0.012	0.007	0.004	0.005	0.000	0.101	0.016	0.004	0.461	0.030	0.019	0.004	0.012	0.044	0.030	0.003	0.002	0.005	0.001	0.001	0.002	0.052	0.010	0.000	0.003	0.018	0.010	0.007	0.065	0.068	0.001
SA	0.003	0.000	0.011	0.010	0.001	0.000	0.148	0.000	0.000	0.127	0.010	0.000	0.019	0.092	0.166	0.117	0.002	0.011	0.000	0.002	0.000	0.012	0.002	0.000	0.001	0.000	0.001	0.051	0.027	0.010	0.158	0.021
SE	0.013	0.001	0.010	0.013	0.011	0.003	0.039	0.008	0.078	0.450	0.071	0.006	0.005	0.010	0.016	0.010	0.007	0.004	0.069	0.002	0.002	0.001	0.029	0.003	0.017	0.008	0.000	0.007	0.005	0.012	0.081	0.007
SG	0.060	0.000	0.006	0.007	0.008	0.000	0.153	0.003	0.002	0.112	0.028	0.003	0.107	0.045	0.051	0.049	0.011	0.125	0.002	0.008	0.000	0.032	0.003	0.000	0.003	0.005	0.001	0.000	0.043	0.002	0.125	0.006
TH	0.053	0.000	0.009	0.015	0.013	0.003	0.184	0.004	0.003	0.097	0.023	0.003	0.043	0.024	0.125	0.026	0.022	0.057	0.002	0.007	0.002	0.024	0.003	0.001	0.008	0.013	0.003	0.053	0.000	0.007	0.160	0.012
TR	0.006	0.018	0.006	0.011	0.018	0.003	0.027	0.008	0.010	0.515	0.099	0.008	0.005	0.012	0.006	0.006	0.006	0.002	0.007	0.001	0.002	0.001	0.020	0.030	0.046	0.023	0.013	0.006	0.003	0.000	0.075	0.006
US	0.021	0.000	0.023	0.204	0.013	0.009	0.093	0.002	0.002	0.174	0.047	0.001	0.007	0.017	0.067	0.038	0.158	0.015	0.004	0.003	0.006	0.007	0.003	0.001	0.010	0.014	0.004	0.030	0.011	0.009	0.000	0.006
ZA	0.013	0.000	0.008	0.010	0.019	0.001	0.250	0.002	0.002	0.221	0.112	0.001	0.006	0.072	0.080	0.023	0.005	0.008	0.004	0.001	0.001	0.001	0.003	0.001	0.006	0.008	0.004	0.006	0.011	0.017	0.105	0.000

Note: This table shows the weights calculated with the DOTS import data. The values in the columns show how large of an import share a specific economy has in another economy (rows). (The rows add up to 1.)

Total trade weights

	AU	BG	BR	CA	CH	CL	CN	CZ	DK	EA	GB	HU	ID	IN	JP	KR	MX	MY	NO	NZ	PE	PH	PL	RO	RU	SA	SE	SG	TH	TR	US	ZA
AU	0.000	0.000	0.005	0.010	0.008	0.002	0.257	0.001	0.003	0.104	0.034	0.001	0.023	0.034	0.160	0.072	0.004	0.032	0.001	0.035	0.001	0.004	0.002	0.000	0.002	0.006	0.007	0.047	0.036	0.003	0.097	0.007
BG	0.002	0.000	0.006	0.005	0.011	0.008	0.034	0.021	0.005	0.529	0.022	0.026	0.003	0.005	0.004	0.006	0.002	0.002	0.002	0.000	0.005	0.001	0.026	0.077	0.071	0.003	0.006	0.006	0.002	0.089	0.020	0.002
BR	0.006	0.001	0.000	0.020	0.013	0.032	0.241	0.002	0.004	0.133	0.027	0.002	0.010	0.024	0.048	0.039	0.034	0.008	0.007	0.001	0.012	0.002	0.004	0.002	0.019	0.019	0.007	0.010	0.012	0.008	0.245	0.008
CA	0.004	0.000	0.006	0.000	0.005	0.003	0.050	0.001	0.002	0.059	0.025	0.000	0.003	0.005	0.026	0.011	0.023	0.002	0.006	0.001	0.003	0.001	0.001	0.000	0.002	0.007	0.002	0.003	0.003	0.002	0.741	0.001
CH	0.007	0.001	0.009	0.010	0.000	0.002	0.052	0.008	0.004	0.535	0.076	0.004	0.002	0.040	0.026	0.007	0.005	0.005	0.003	0.001	0.007	0.001	0.006	0.002	0.022	0.006	0.007	0.013	0.017	0.015	0.105	0.006
CL	0.008	0.002	0.081	0.023	0.007	0.000	0.254	0.001	0.003	0.105	0.017	0.000	0.004	0.022	0.090	0.060	0.036	0.003	0.002	0.001	0.026	0.001	0.002	0.000	0.005	0.002	0.006	0.002	0.008	0.005	0.220	0.002
CN	0.041	0.001	0.025	0.026	0.010	0.011	0.000	0.004	0.004	0.172	0.029	0.004	0.017	0.024	0.123	0.083	0.025	0.022	0.004	0.005	0.005	0.007	0.006	0.002	0.028	0.028	0.005	0.033	0.022	0.009	0.218	0.009
CZ	0.002	0.004	0.002	0.002	0.014	0.000	0.033	0.000	0.008	0.675	0.036	0.029	0.001	0.003	0.009	0.007	0.004	0.002	0.006	0.000	0.000	0.001	0.071	0.011	0.029	0.002	0.012	0.003	0.003	0.010	0.021	0.003
DK	0.006	0.001	0.005	0.009	0.011	0.002	0.045	0.012	0.000	0.481	0.066	0.007	0.002	0.006	0.017	0.009	0.003	0.002	0.055	0.002	0.001	0.001	0.032	0.003	0.018	0.003	0.128	0.004	0.004	0.009	0.053	0.002
EA	0.010	0.007	0.018	0.015	0.065	0.005	0.102	0.050	0.025	0.000	0.140	0.032	0.006	0.018	0.036	0.021	0.014	0.009	0.024	0.002	0.002	0.003	0.059	0.019	0.060	0.014	0.039	0.016	0.008	0.028	0.144	0.010
GB	0.012	0.001	0.006	0.022	0.031	0.001	0.056	0.010	0.013	0.528	0.000	0.006	0.003	0.013	0.023	0.011	0.004	0.005	0.036	0.002	0.001	0.001	0.016	0.004	0.015	0.006	0.020	0.011	0.006	0.014	0.113	0.008
HU	0.002	0.007	0.002	0.003	0.011	0.000	0.042	0.042	0.007	0.611	0.033	0.000	0.001	0.003	0.015	0.011	0.006	0.003	0.003	0.000	0.000	0.001	0.046	0.043	0.042	0.003	0.011	0.005	0.003	0.011	0.032	0.003
ID	0.033	0.000	0.010	0.009	0.004	0.001	0.174	0.001	0.001	0.057	0.011	0.001	0.000	0.052	0.146	0.072	0.005	0.054	0.001	0.005	0.001	0.014	0.002	0.000	0.007	0.018	0.003	0.168	0.049	0.006	0.091	0.004
IN	0.035	0.001	0.019	0.014	0.036	0.006	0.165	0.003	0.003	0.091	0.041	0.002	0.035	0.000	0.038	0.044	0.014	0.031	0.002	0.002	0.003	0.004	0.004	0.002	0.022	0.112	0.006	0.051	0.021	0.014	0.163	0.017
JP	0.045	0.000	0.010	0.020	0.009	0.007	0.236	0.002	0.002	0.107	0.019	0.002	0.031	0.011	0.000	0.074	0.017	0.033	0.003	0.005	0.002	0.016	0.002	0.001	0.017	0.045	0.004	0.034	0.047	0.003	0.187	0.008
KR	0.033	0.000	0.013	0.015	0.004	0.009	0.310	0.003	0.002	0.053	0.015	0.003	0.024	0.020	0.123	0.000	0.022	0.022	0.003	0.003	0.003	0.011	0.005	0.001	0.024	0.054	0.003	0.043	0.016	0.008	0.150	0.004
MX	0.003	0.000	0.013	0.044	0.003	0.006	0.048	0.001	0.001	0.074	0.006	0.001	0.001	0.006	0.022	0.017	0.000	0.003	0.000	0.001	0.003	0.001	0.001	0.000	0.002	0.001	0.001	0.004	0.003	0.001	0.730	0.001
MY	0.032	0.000	0.008	0.008	0.005	0.001	0.200	0.002	0.001	0.051	0.016	0.002	0.040	0.030	0.101	0.043	0.018	0.000	0.001	0.005	0.001	0.013	0.002	0.000	0.005	0.011	0.003	0.211	0.055	0.004	0.129	0.004
NO	0.002	0.000	0.007	0.027	0.006	0.001	0.027	0.004	0.061	0.416	0.156	0.001	0.001	0.005	0.015	0.020	0.001	0.002	0.000	0.000	0.000	0.000	0.022	0.003	0.010	0.001	0.140	0.008	0.003	0.006	0.053	0.001
NZ	0.239	0.000	0.002	0.016	0.005	0.002	0.153	0.001	0.005	0.109	0.038	0.001	0.018	0.013	0.090	0.040	0.009	0.028	0.001	0.000	0.002	0.009	0.002	0.000	0.005	0.011	0.004	0.041	0.026	0.002	0.124	0.004
PE	0.004	0.002	0.056	0.053	0.028	0.054	0.213	0.001	0.003	0.147	0.011	0.000	0.003	0.021	0.048	0.041	0.031	0.002	0.004	0.002	0.000	0.001	0.001	0.000	0.007	0.002	0.006	0.001	0.007	0.004	0.243	0.001
PH	0.014	0.000	0.006	0.011	0.004	0.001	0.242	0.001	0.001	0.085	0.013	0.002	0.029	0.010	0.143	0.071	0.014	0.039	0.001	0.004	0.001	0.000	0.001	0.000	0.006	0.018	0.002	0.086	0.050	0.002	0.139	0.002
PL	0.002	0.004	0.003	0.004	0.010	0.001	0.038	0.055	0.016	0.619	0.045	0.024	0.001	0.004	0.007	0.011	0.002	0.001	0.012	0.000	0.000	0.000	0.000	0.013	0.055	0.005	0.026	0.001	0.002	0.013	0.023	0.002
RO	0.001	0.032	0.005	0.004	0.011	0.000	0.038	0.026	0.005	0.589	0.032	0.069	0.001	0.005	0.006	0.008	0.003	0.001	0.005	0.000	0.000	0.000	0.037	0.000	0.032	0.003	0.007	0.001	0.002	0.053	0.023	0.002
RU	0.002	0.009	0.011	0.004	0.008	0.001	0.130	0.017	0.006	0.467	0.028	0.017	0.004	0.011	0.043	0.033	0.003	0.003	0.005	0.001	0.001	0.001	0.047	0.008	0.000	0.002	0.017	0.007	0.006	0.050	0.058	0.001
SA	0.007	0.000	0.015	0.010	0.009	0.001	0.147	0.001	0.002	0.172	0.021	0.001	0.017	0.082	0.136	0.098	0.002	0.010	0.000	0.003	0.000	0.009	0.002	0.001	0.002	0.000	0.005	0.038	0.025	0.015	0.154	0.016
SE	0.008	0.001	0.007	0.009	0.011	0.002	0.040	0.012	0.086	0.500	0.067	0.008	0.003	0.007	0.015	0.008	0.004	0.003	0.063	0.001	0.001	0.001	0.033	0.003	0.020	0.005	0.000	0.004	0.004	0.010	0.058	0.005
SG	0.038	0.001	0.007	0.005	0.016	0.000	0.154	0.002	0.002	0.110	0.025	0.002	0.076	0.041	0.079	0.057	0.006	0.125	0.004	0.005	0.000	0.023	0.002	0.000	0.006	0.039	0.003	0.000	0.042	0.002	0.124	0.004
TH	0.043	0.000	0.010	0.010	0.015	0.003	0.182	0.003	0.002	0.091	0.019	0.002	0.039	0.022	0.167	0.035	0.013	0.066	0.002	0.005	0.002	0.020	0.002	0.001	0.007	0.030	0.004	0.073	0.000	0.004	0.122	0.008
TR	0.004	0.016	0.007	0.008	0.020	0.002	0.064	0.009	0.007	0.468	0.063	0.009	0.006	0.018	0.013	0.021	0.003	0.005	0.006	0.001	0.001	0.001	0.017	0.023	0.092	0.022	0.012	0.004	0.005	0.000	0.068	0.004
US	0.011	0.000	0.018	0.195	0.014	0.007	0.141	0.002	0.003	0.171	0.040	0.001	0.008	0.018	0.076	0.035	0.156	0.014	0.004	0.002	0.004	0.006	0.002	0.001	0.008	0.016	0.006	0.021	0.012	0.006	0.000	0.004
ZA	0.017	0.001	0.014	0.009	0.015	0.001	0.208	0.004	0.003	0.265	0.086	0.002	0.008	0.060	0.065	0.022	0.004	0.010	0.003	0.002	0.001	0.001	0.004	0.001	0.004	0.047	0.009	0.010	0.018	0.012	0.094	0.000

Note: This table shows the weights calculated with the DOTS for imports and exports data. The values in the columns show how large of a trade share a specific economy has in another economy (rows). (The rows add up to 1.)