Online Appendix to “What explains international interest rate co-movement?”

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A Data

Table A.1: Data

Variable	Description
	baseline VAR variables
y	output gap; source: Oxford Economics, datastream codes AUXOGAP.R, CNXOGAP.R, EKXOGAP.R, JPXOGAP.R, KOXOGAP.R, UKXOGAP.R, USXOGAP.R
π	year-on-year inflation rate calculated from consumer prices (all items); source: IMF-IFS and Eurostat, Datastream codes AUI64...F, CNI64...F, EMCONPRCF, JPI64...F, KOI64...F, UKI64...F, USI64...F
r	quarterly average of monthly policy rates and Krippner shadow rates; sources: https://www.ljkmfa.com/ and national central banks, Datastream codes (dates of shadow rate) AUPRATE., CNB14044, EMREPO.. (02/2009-12/2019), JPPRATE. (09/1995-12/2019), KOI60B.., UKPRATE. (12/2008-10/2017), FREFEDFD (11/2008-07/2016)
q	real effective exchange rate (narrow), defined as nominal effective exchange rate times the ratio of a weighted sum of foreign price indices relative to a domestic price index; source: BIS (we are using the inverse of the data), https://www.bis.org/statistics/eer.htm
	Variables for VAR extensions
sp	stock prices, yoy growth rates; source: Thomson Reuters, Datastream codes: AUSHRPRCF, CN-SHRPRCF, EMSHRPRCF, JPSHRPRCF, KOSHRPRCF, UKSHRPRCF, USSHRPRCF
ts	term spread, long-term bond yields minus r; source (bond yields): Thomson Reuters, Datastream codes AUGBOND., CNGBOND., EMGBOND., JPGBOND., KOGBOND., UKGBOND., USGBOND.
$GDP(real)$	use to calculate *output growth* and *GDP weights*; source: OECD Quarterly National Accounts, Oxford Economics, Datastream codes: AUOEXP03D, CNOEXP03D, EKXGDSA.D, JPOEXP03D, KOOEXP03D, UKOEXP03D, USOEXP03D
	External instruments, used to cross-check with global shocks
BH2	Median of oil supply shocks identified from Baumeister and Hamilton (2019), updated to December 2022, https://sites.google.com/site/cjsbaumeister/research
Ksurp	monthly oil supply surprise shocks from Känzig (2021), updated to December 2022, https://github.com/dkaenzig/oilsupplynews
Knews	monthly oil supply news shocks from Känzig (2021), updated to December 2022, https://github.com/dkaenzig/oilsupplynews
JQ	Innovations to the financial conditions index of Jermann and Quadrini (2012) as used in Mumtaz et al. (2018)
EBP	Excess bond premium of Gilchrist and Zakrajšek (2012) as used in Mumtaz et al. (2018)
NEWS	Textual proxy for credit supply shocks, from Mumtaz et al. (2018)
SW	US Monetary policy shocks from Smets and Wouters (2007)
RR	US Romer-Romer monetary policy shocks, Romer and Romer (2004)
GKFF4	US High-frequency monetary policy shocks from Gertler and Karadi (2015)
EA BSUMP	EA High-frequency and narrative monetary policy shocks, Badinger and Schiman (2023)

B Theoretical model for identifying restrictions

Following Lubik and Schorfheide (2007), we consider a model with an international Phillips curve, IS curve, monetary policy rule, and (real) exchange rate equation, to which we add common shifts of country-specific supply and demand curves in the form of global supply and demand shocks. The set of equations for country $c \in \{1, \dots, C\}$ is given by:

$$
\begin{aligned}
y_{ct} =& \frac{\tilde{\tau}^c}{\kappa^c}\left[\mu^{c,s} + \pi_{ct} - \beta^c E[\pi_{ct+1}] + \frac{\alpha^c\beta^c}{1-\alpha^c}E[q_{ct+1}] - \frac{\alpha^c}{1-\alpha^c}q_{ct}\right] + \chi_c^{as}u_{gt}^{as} + u_{ct}^{as} && \text{(B.1)}\\
y_{ct} =& \mu^{c,d} + E[y_{ct+1}] - \tilde{\tau}^c\left(r_{ct} - E[\pi_{ct+1}]\right) + \alpha^c(2-\alpha^c)\frac{1-\tau^c}{\tau^c}E[y^*_{ct+1}] + \dots && \text{(B.2)}\\
&+ \frac{\alpha^c\tilde{\tau}^c}{1-\alpha^c}E[q_{ct+1}] + \chi_c^{ad}u_{gt}^{ad} + u_{ct}^{ad}\\
r_{ct} =& \rho^c r_{it-1} + (1-\rho^c)\left[\left(\psi^{c,1} + \psi^{c,3}\right)\pi_{ct} + \psi^{c,2}y_{ct} + \psi^{c,3}\left(q_{ct} - \pi^*_{ct}\right)\right] + \chi_c^{mp}u_{gt}^{mp} + u_{ct}^{mp} && \text{(B.3)}\\
q_{ct} =& \mu^{c,q} - \frac{1-\alpha^c}{\tilde{\tau}^c}\left(y^*_{ct} - y_{ct}\right) + u_{ct}^{er} && \text{(B.4)}
\end{aligned}
$$

with

$$
\tilde{\tau}^c = \tau^c + \alpha^c(2-\alpha^c)(1-\tau^c), \quad y^*_{ct} = \sum_{c^* \neq c} w_{cc^*}y_{c^*t}, \quad \pi^*_{ct} = \sum_{c^*\neq c} w_{cc^*}\pi_{c^*t},
$$

Equation (B.1) expresses the open economy Phillips curve. Supply depends on inflation and changes in the exchange rate. The parameter α^c, $0 < \alpha^c < 1$, measures the import share. When $\alpha^c = 0$, the model reduces to a closed economy set-up. τ^c gives the intertemporal substitution elasticity, β^c the discount factor, and κ^c the slope coefficient of the Phillips curve.

Equation (B.2) models the open economy IS curve. Demand is expressed as a function of interest rates, inflation, foreign output, and changes in the exchange rate. We substitute expectations in equations (B.1) and (B.2) with simple autoregressive forecasts, following Baumeister and Hamilton (2018). We model the expected value of a variable z as $z_{t+1|t} = c^z + \phi^z z_{t|t}$. We set the autoregressive parameter equal for all variables, as $\phi^c = 0.75$.[1] The term c^z is absorbed in the constant terms. The parameter ζ^c weights expected output in the IS curve. The Phillips and IS curve can then be expressed as

$$
\begin{aligned}
y_{ct} =& \frac{\tilde{\tau}^c}{\kappa^c}\left[\mu^{c,s} + (1-\beta^c\phi^c)\left[\pi_{ct} - \frac{\alpha^c}{1-\alpha^c}q_{ct}\right]\right] + u_{ct}^{as} && \text{(B.5)}\\
y_{ct} =& \frac{1}{1-\zeta^c\phi^c}\left[\mu^{c,d} - \tilde{\tau}^c\left(r_{ct} - \phi^c\pi_{ct}\right) + \alpha^c(2-\alpha^c)\frac{1-\tau^c}{\tau^c}(\phi^c-1)y^*_{ct} + \frac{\alpha^c\tilde{\tau}^c\phi^c}{1-\alpha^c}q_{ct}\right] + u_{ct}^{ad} && \text{(B.6)}
\end{aligned}
$$

[1]Note that Lubik and Schorfheide (2007) include in some equations expected changes in variables (as opposed to expected values of the variables). In such cases, we model the expected value of a change in variable z_{t+1}, denoted by Δz_{t+1}, as $E(\Delta z_{t+1}) = (0.75 - 1)z_t$.

The monetary policy authority sets interest rates according to the rule given in equation (B.3). The parameter $\psi^{c,1}$ captures the response of the monetary policy authority to changes in inflation, $\psi^{c,2}$ reflects the reaction to output, and $\psi^{c,3}$ to changes in the nominal exchange rate. ρ^c is a smoothing parameter, smoothing the implementation of monetary policy over time. Equation (B.4) relates changes in the exchange rate to differences in foreign and domestic output. We use that under PPP Lubik and Schorfheide (2007) express inflation as $\pi_{ct} = ex_{ct} + (1-\alpha^c)tot_{ct} + \pi^*_{ct}$ where ex_{ct} are changes in the nominal exchange rate and tot_{ct} changes in terms of trade. Thus, the real exchange rate relates to terms of trades as $tot_{ct} = -\frac{1}{1-\alpha^c}q_{ct}$.

Our coefficients in the panel SVAR model given in equations (2) to (5) are related to the structural parameters in the theoretical model in the following way:

$$\begin{aligned}
\alpha^{c,\pi} &= \frac{\tilde{\tau}^c}{\kappa^c}(1-\beta^c\phi^c), \quad \alpha^{c,q} = -\frac{\tilde{\tau}^c}{\kappa^c}(1-\beta^c\phi^c)\frac{\alpha^c}{1-\alpha^c} \\
\beta^{c,r} &= -\frac{1}{1-\zeta^c\phi^c}\tilde{\tau}^c, \quad \beta^{c,\pi} = \frac{1}{1-\zeta^c\phi^c}\tilde{\tau}^c\phi^c \\
\beta^{c,y^*} &= \frac{1}{1-\zeta^c\phi^c}\alpha^c(2-\alpha^c)\frac{1-\tau^c}{\tau^c}(\phi^c-1), \quad \beta^{c,q} = \frac{1}{1-\zeta^c\phi^c}\frac{\alpha^c\tilde{\tau}^c\phi^c}{1-\alpha^c} \\
\psi^{c,\pi} &= \psi^{c,1}+\psi^{c,3}, \quad \psi^{c,y} = \psi^{c,2}, \quad \psi^{c,q} = \psi^{c,3} \\
\theta^{c,y} &= \frac{1-\alpha^c}{\tilde{\tau}^c}.
\end{aligned}$$

C Econometric model

In this Appendix, we describe our econometric approach, and our algorithm (Metropolis-within-Gibbs) in more detail. First, we show how homogeneity restrictions simplify identification of the matrix of structural contemporaneous coefficients $\mathbf{A}$. Second, we explain the flexibility on the prior structure that we gain through hierarchical priors for structural variances $\mathbf{D}$ (Giannone et al., 2015). We can draw from the hierarchical priors using the same Metropolis-Hastings-Algorithm as the elements of $\mathbf{A}$, which simplifies our algorithm significantly. Third, we show how global shocks and their loadings can be included in the Gibbs sampler as in Korobilis (2022).

For ease of reading, we repeat the mathematical notation. As our baseline, we estimate a Bayesian structural panel VAR with global shocks using $J = 4$ variables from a panel of $C = 7$ countries. In matrix notation, our model is

$$\begin{aligned}
\mathbf{A}\mathbf{y}_t &= \mathbf{B}\mathbf{x}_{t-1} + \chi\mathbf{u}_{gt} + \mathbf{u}_t \\
\mathbf{u}_t &\sim \mathcal{N}(\mathbf{0},\mathbf{D}), \quad \mathbf{u}_{gt} \sim \mathcal{N}(\mathbf{0},\mathbf{I}_G).
\end{aligned}$$

The model has $n = CJ$ equations, jointly indexed by subscript $c \in \{1,\ldots,C\}$ and superscript $j \in \{as, ad, mp, er\}$. Variables are indexed by $i \in \{y, \pi, r, q\}$. The $[G \times 1]$ vector

$\mathbf{u}_{gt} = (u_{gt}^{as}, u_{gt}^{ad}, u_{gt}^{mp})$ contains global supply, demand and monetary policy shocks shocks. The loadings χ_c^j for structural equation j in country c are stacked in the $[n \times G]$ loading matrix χ:

$$\chi = \left[\begin{pmatrix} \text{diag}(\chi_1) \\ \mathbf{0}_{J-G \times G} \end{pmatrix}' \quad \begin{pmatrix} \text{diag}(\chi_2) \\ \mathbf{0}_{J-G \times G} \end{pmatrix}' \quad \cdots \quad \begin{pmatrix} \text{diag}(\chi_C) \\ \mathbf{0}_{J-G \times G} \end{pmatrix}' \right]'$$
$$\text{with } \chi_c = (\chi_c^{as}, \chi_c^{ad}, \chi_c^{mp}).$$

Because the structural shocks of the model are assumed to be mutually independent (i.e., $\mathbf{D}$ is assumed to be diagonal), it is worthwhile to write down the individual structural equations. Let $\mathbf{a}_c^j$ and $\mathbf{b}_c^j$ be the $(1 \times n)$- and $(1 \times k)$- dimensional row vectors of structural coefficients (contemporaneous and lagged) in structural equation j of country c, and d_c^j the variance of the corresponding structural domestic shocks. Differentiating between equations with and without global shocks, the structural equation j in country c is

$$\mathbf{a}_c^j \mathbf{y}_t = \begin{cases} \mathbf{b}_c^j \mathbf{x}_{t-1} + \chi_c^j u_{gt}^j + u_{ct}^j, & u_{ct}^j \sim \mathcal{N}(0, d_c^j), \quad u_{gt}^j \sim \mathcal{N}(0,1) \quad, \text{if } j \in \{as, ad, mp\} \\ \mathbf{b}_c^j \mathbf{x}_{t-1} + u_{ct}^j, & u_{ct}^j \sim \mathcal{N}(0, d_c^j) \quad, \text{if } j \in \{er\} \end{cases}.$$

C.1 Identification of the global shocks

Conditional on $\mathbf{A}$, we assume that the structural shocks have a "combined" representation $\breve{u}_{ct}^j = \chi_c^j u_{gt}^j + u_{ct}^j$. To identify the latent global shocks, u_{gt}^j, and their loadings, χ_c^j, we assume the following. First, we let u_{gt}^j follow a standard normal distribution and restrict the correlation across global shocks to be zero (as done in static factor models). Second, following Korobilis (2022), we impose sign restrictions on loadings $\chi_c^j > 0$, which are used to identify economically interpretable global shocks, and make the structural factor model more explicit.

In the reduced form the combined shocks $\breve{u}_{ct}^j$ feature a full covariance matrix,

$$\mathbf{A}^{-1}\chi\chi'(\mathbf{A}^{-1})' + \mathbf{A}^{-1}\mathbf{D}(\mathbf{A}^{-1})'.$$

In order to identify global shocks in the reduced form, one would usually need sign restrictions on all reduced-form loadings $\mathbf{A}^{-1}\chi$. That requires up to $n \times G$ restrictions instead of only n restrictions on the structural model.

C.2 Homogeneity restrictions on structural contemporaneous parameters

The total number of structural contemporaneous coefficients $\mathbf{A}$ increases quadratically with the number of countries in the panel. In order to deal with the resulting curse of dimensionality in the identification of $\mathbf{A}$, we assume that the foreign coefficients in the vector $\mathbf{a}_c^j$ are identical up to a scaling constant $w_{cc'}$, which is the average trade share of foreign country c' in the total trade of country c. This homogeneity restriction means that we only have to identify posterior distributions for the J domestic and J foreign coefficients of structural equation j in country c. These coefficients can be summarized in the $[2J \times 1]$ vector $\tilde{\mathbf{a}}_c^j$.

As an example, let us look at the structural contemporaneous coefficients in the first four equations, which correspond to Australia. Combining the four row vectors into one 4×8-matrix $\tilde{\mathbf{A}}_{AU}$, our baseline model identifies

$$\tilde{\mathbf{A}}_{AU} = \begin{pmatrix} 1 & -\alpha^{AU,\pi} & 0 & \alpha^{AU,q} & 0 & 0 & 0 & 0 \\ 1 & -\beta^{AU,\pi} & -\beta^{AU,r} & -\beta^{AU,q} & -\beta^{AU,y^*} & 0 & 0 & 0 \\ -(1-\rho^{AU})\psi^{AU,y} & -(1-\rho^{AU})\psi^{AU,\pi} & 1 & -(1-\rho^{AU})\psi^{AU,q} & 0 & (1-\rho^{AU})\psi^{AU,q} & 0 & 0 \\ -\theta^{AU,y} & 0 & 0 & 1 & \theta^{AU,y} & 0 & 0 & 0 \end{pmatrix}.$$

Returning to individual equations, the full coefficient vector $\mathbf{a}_c^j$, and thereby $\mathbf{A}$, can be derived from the restricted vector $\tilde{\mathbf{a}}_c^j$ as

$$\mathbf{a}_c^j = \tilde{\mathbf{a}}_c^j \mathbf{R}_c. \tag{C.1}$$

The $2J \times n$ restriction matrix $\mathbf{R}_c$ applies the appropriate scaling and allocates coefficients to the right position in $\mathbf{a}_c^j$. It is defined as

$$\underset{(2J\times n)}{\mathbf{R}_c} = \begin{pmatrix} \mathbf{0}_{J\times J} & \cdots & \mathbf{0}_{J\times J} & \mathbf{I}_J & \mathbf{0}_{J\times J} & \cdots & \mathbf{0}_{J\times J} \\ w_{c,1}\mathbf{I}_J & \cdots & w_{c,c-1}\mathbf{I}_J & \mathbf{0}_{J\times J} & w_{c,c+1}\mathbf{I}_J & \cdots & w_{c,C}\mathbf{I}_J \end{pmatrix}.$$

C.3 Prior distributions on lag coefficients and shock variances

Let $\iota_{r,c}$ be a $[k \times 1]$-vector that is one for the first lag of interest rates from country c, and zero otherwise. Let $\mathbf{v}_1 = (1/1^2, 1/2^2, \ldots, 1/p^2)'$ be a $(p \times 1)$ vector for lag scaling, and $\mathbf{v}_2(\mathbf{s}) = (1/s^y_{AU}, 1/s^\pi_{AU}, 1/s^r_{AU}, 1/s^q_{AU}, \ldots, 1/s^q_{US})'$ a $(CJ \times 1)$ vector of inverse variances given by the $(CJ \times 1)$ vector $\mathbf{s}$. Let $\hat{\rho}^{ii'}_{cc'}$ be the correlation of residuals $\hat{\mathbf{e}}^i_{ct}$ and $\hat{\mathbf{e}}^{i'}_{c't}$ from fourth order univariate regressions of variable i (i') in country c (c'). Let finally $\mathbf{S}(\mathbf{s})$ be a prior variance-covariance matrix with entries $\mathbf{S}^{ii'}_{cc'}(\mathbf{s}) = \sqrt{s^i_c s^{i'}_{c'}}\hat{\rho}^{ii'}_{cc'}$.

Conditional on $\mathbf{A}$, we set the following prior distributions:

$$p\left(d_c^j|\mathbf{A},\mathbf{s}\right) = \gamma\left((d_c^j)^{-1};\kappa,\tau_c^j(\mathbf{A},\mathbf{s})\right) \tag{C.2}$$

$$p\left(\mathbf{b}_c^j|\mathbf{A},\lambda_0,\mathbf{s},d_c^j\right) = \phi\left(\mathbf{b};\mathbf{m}_c^j(\mathbf{A}),d_c^j\mathbf{M}_c^j(\lambda_0,\mathbf{s})\right) \tag{C.3}$$

$$p(s_c^i) = \gamma((s_c^i)^{-1};\kappa_s,\tau_{s_c^i}) \tag{C.4}$$

$$p(\lambda_0) = \gamma(\lambda_0;\kappa_{\lambda_0},\tau_{\lambda_0}) \tag{C.5}$$

with

$$\tau_c^j(\mathbf{A},\mathbf{s})) = \kappa \mathbf{a}_c^j \mathbf{S}(\mathbf{s})\, \mathbf{a}_c^{j\,\prime}$$

$$\mathbf{m}_c^j(\mathbf{A},\mathbf{s},\lambda_0) = \begin{cases} \mathbf{M}_c^j(\lambda_0,\mathbf{s}) \left[\left(\operatorname{diag}\left(\mathbf{v}_3(\lambda_0,\mathbf{s})\right)\right)^{-1} \eta\, \mathbf{a}_c^{j\,\prime} + \left(\frac{\rho_c}{V_\rho}\iota_{r,c}\right)^{\prime} \right] & j = m \\ \eta\, \mathbf{a}_c^{j\,\prime} & \text{otherwise} \end{cases}$$

$$\mathbf{M}_c^j(\lambda_0,\mathbf{s}) = \begin{cases} \left(\left(\operatorname{diag}\left(\mathbf{v}_3(\lambda_0,\mathbf{s})\right)\right)^{-1} + \operatorname{diag}\left(\frac{1}{V_\rho}\iota_{r,c}\right) \right)^{-1} & \text{if } j = m \\ \operatorname{diag}\left(\mathbf{v}_3(\lambda_0,\mathbf{s})\right) & \text{otherwise} \end{cases}$$

$$\mathbf{v}_3(\lambda_0,\mathbf{s}) = \lambda_0^2 \begin{pmatrix} \mathbf{v}_1 \otimes \left(\operatorname{diag}(\omega \otimes \mathbf{1}_{(J\times 1)})\mathbf{v}_2(\mathbf{s})\right) \\ 100^2 \times \mathbf{1}_{(2\times 1)} \end{pmatrix}$$

As in Baumeister and Hamilton (2018), the prior mean of structural lag coefficients distribution combines (a) the prior belief that the data follow an AR(1) process with AR-coefficient $\phi = 0.75$, and (b) that the central bank engages in interest-rate smoothing, as described by the structural coefficient ρ^c. We give this prior a variance of $V_\rho = 0.1$.

We increase the tightness of priors on structural lag coefficients considerably in order to deal with the curse-of-dimensionality. We do this by multiplying the prior variance of every coefficient related to a variable from country c by ω_c^2, where ω_c is the average share of GDP of country c in our sample.

We choose $\kappa_s = 0.1$. The scale $\tau_{s_c^i}$ is set to 0.05 for output gaps, inflation and interest rates, and to 2 for real effective exchange rate growth. This ensures that $\mathbf{E}(1/s_c^i) = \frac{\tau_{s_c^i}}{\kappa_{s_c^i}}$ is roughly similar to the variance of residuals $\hat{\mathbf{e}}_{ct}^i$. For λ_0, we use a gamma-distribution with mode 0.2 and standard deviation 0.4 (i.e., $\kappa_{\lambda_0} = 1.64, \tau_{\lambda_0} = 0.3125$) (Sims and Zha, 1998; Giannone et al., 2015).

C.4 Posterior distributions and algorithm

C.4.1 Posterior distributions

Out posterior sample is an extension of the Metropolis-within-Gibbs of Baumeister and Hamilton (2015) that accounts for hyperparameters for the Minnesota prior, as well as global shocks and their loadings. Two things are worthwhile to note before we develop the full sampler. First, we can sample from the known conditional posterior distributions of global shocks and loadings in the Gibbs sampler as in Korobilis (2022). Second, the sampling of hyperparameters in Giannone et al. (2015) requires a Metropolis step that uses the same likelihood kernel as the sampling of structural contemporaneous coefficients $\mathbf{A}$. That is, we can sample $(\mathbf{A}, \lambda_0, \mathbf{s})$ together in the same step, as proven in subsection C.4.2.

Let the $(T \times n)$-dimensional matrix $\mathbf{Y} = (\mathbf{y}_1, \ldots, \mathbf{y}_T)^{\prime}$ and $(T \times k)$-dimensional matrix $\mathbf{X} = (\mathbf{x}_0, \ldots, \mathbf{x}_{T-1})^{\prime}$ collect all observations. For country c and structural equation j, we construct extended data $\tilde{\mathbf{Y}}_c^j$ and $\tilde{\mathbf{X}}_c^j$ by applying two data modifications. First, we condition on $\mathbf{A}$ and hyperparameters $\lambda_0, \mathbf{s}$, and append the corresponding normal prior $\mathcal{N}(\mathbf{m}_c^j, d_c^j \mathbf{M}_c^j)$ as dummy observations (for ease of readability, we drop the dependence of $\mathbf{m}_c^j$ and $\mathbf{M}_c^j$ on $(\mathbf{A}, \lambda_0, \mathbf{s})$). Let $\mathbf{P}_c^j$ be the Cholesky factor of $(\mathbf{M}_c^j)^{-1}$, i.e. $(\mathbf{M}_c^j)^{-1} = \mathbf{P}_c^j \mathbf{P}_c^{j'}$. Second, we shift global shocks to the left-hand side of the equation such that – conditional on all other parameters of the model – structural lags and variances follow normal-inverse gamma distributions as in Baumeister and Hamilton (2018). The properly augmented data for country c and structural equation j are defined as:

$$\underset{(T+k+1)\times 1}{\tilde{\mathbf{Y}}_c^j} = \begin{pmatrix} \left(\mathbf{a}_c^j \mathbf{Y}' - \chi_c^j \mathbf{U}_{gT}^{j'}\right)' \\ \mathbf{m}_c^j \mathbf{P}_c^{j'} \end{pmatrix}, \qquad \underset{(T+k+1)\times(k+1)}{\tilde{\mathbf{X}}_c^j} = \begin{pmatrix} \mathbf{X} \\ \mathbf{P}_c^{j'} \end{pmatrix}$$

Conditional on global shocks $\mathbf{U}_{gT}$, these augmented data can be used to derive the posterior distributions of $\mathbf{A}, \tilde{\mathbf{B}}, \chi, \mathbf{D}$ just as in Baumeister and Hamilton (2015) and Giannone et al. (2015), see also the following subsection C.4.2:

$$\begin{aligned} p\left(\mathbf{A}, \lambda_0, \mathbf{s} | \mathbf{Y}_T, \chi, \mathbf{U}_{gT}\right) \propto & p(\mathbf{A}) p(\lambda_0) p(\mathbf{s}) [\det(\mathbf{A}\hat{\Omega}\mathbf{A}')]^{T/2} \\ & \prod_{c=1}^{C} \prod_{j=1}^{J} \frac{\left|\mathbf{M}_c^{j^*}\right|^{1/2}}{\left|\mathbf{M}_c^j\right|^{1/2}} \frac{(\tau_c^j)^{\kappa_c^j}}{\left(2\tau_c^{j^*}/T\right)^{\kappa_c^{j^*}}} \frac{\Gamma\left((\kappa_c^j)^*\right)}{\Gamma\left(\kappa_c^j\right)} \end{aligned} \tag{C.6}$$

$$p\left(\mathbf{D} | \mathbf{A}, \lambda_0, \mathbf{s}, \mathbf{Y}_T, \chi, \mathbf{U}_{gT}\right) = \prod_{c=1}^{C} \prod_{j=1}^{J} \gamma\left(\left(d_c^j\right)^{-1}; \kappa_c^{j^*}, \tau_c^{j^*}\right) \tag{C.7}$$

$$p\left(\mathbf{B} | \mathbf{A}, \lambda_0, \mathbf{s}, \mathbf{D}, \mathbf{Y}_T, \chi, \mathbf{U}_{gT}\right) = \prod_{c=1}^{C} \prod_{j=1}^{J} \phi\left(\mathbf{b}_c^j; \mathbf{m}_c^{j^*}, \mathbf{M}_c^{j^*}\right) \tag{C.8}$$

with

$$\begin{aligned} \kappa_c^{j^*} &= \kappa_c^j + T/2 \\ \tau_c^{j^*} &= \tau_c^j + \zeta_c^{j^*}/2 \\ \zeta_c^{j^*} &= \tilde{\mathbf{Y}}_c^{j'} \tilde{\mathbf{Y}}_c^j - \tilde{\mathbf{Y}}_c^{j'} \tilde{\mathbf{X}}_c^j \left(\tilde{\mathbf{X}}_c^{j'} \tilde{\mathbf{X}}_c^j\right)^{-1} \tilde{\mathbf{X}}_c^{j'} \tilde{\mathbf{Y}}_c^j \\ \mathbf{m}_c^{j^*} &= \left[\left(\tilde{\mathbf{X}}_c^{j'} \tilde{\mathbf{X}}_c^j\right)^{-1} \tilde{\mathbf{X}}_c^{j'} \tilde{\mathbf{Y}}_c^j\right]' \\ \mathbf{M}_c^{j^*} &= \left(\tilde{\mathbf{X}}_c^{j'} \tilde{\mathbf{X}}_c^j\right)^{-1}. \end{aligned}$$

Using Korobilis (2022), we can derive the conditional posterior distributions of global shocks and their loadings. This is particularly easy in our baseline case, where each structural equation is affected by at most one global shock.[2]

[2] A possible extension where multiple shocks load onto one equation, such as in a robustness check where global supply and demand shocks load onto exchange rates of commodity-exporting countries, are also easy to derive.

The conditional posterior distributions of loading χ_c^j depends on the correlation between global shocks $\mathbf{u}_{gt}^j$ and combined structural shocks $\check{\mathbf{u}}_{ct}^j = \left[\mathbf{a}_c^j\mathbf{Y}_T' - \mathbf{b}_c^j\mathbf{X}_T'\right]'$:

$$p(\chi_c^j|\mathbf{A},\lambda_0,\mathbf{s},\mathbf{B},\mathbf{D},\mathbf{Y}_T,\mathbf{U}_{gT}) = \mathcal{TN}_{\chi_c^j>0}\left(V_{\chi,c}^{j^*}\left(\mathbf{u}_{gt}^j\right)'\check{\mathbf{u}}_{ct}^j, d_c^j V_{\chi,c}^{j^*}\right) \tag{C.9}$$
$$V_{\chi,c}^{j^*} = \left(\left(\mathbf{u}_{gt}^j\right)'\mathbf{u}_{gt}^j + V_\chi^{-1}\right)^{-1}$$

With $\check{\mathbf{U}}_T$ the $(T\times n)$ matrix of correlated structural shocks from all equations, the posterior distribution of global shocks $\mathbf{U}_{gT}$ is given by:

$$p(U_{gT}|\mathbf{A},\lambda_0,\mathbf{s},\mathbf{B},\mathbf{D},\mathbf{Y}_T,\chi) = \mathcal{N}\left(\left(\mathbf{M}_g^*\chi'\mathbf{D}^{-1}\check{\mathbf{U}}_T'\right)',\mathbf{M}_g^*\right) \tag{C.10}$$
$$\mathbf{M}_g^* = \left(I_G + \chi'\mathbf{D}^{-1}\chi\right)^{-1}$$

C.4.2 Derivation of equation (C.6)

Considering that the prior distributions $p(\mathbf{A},\lambda_0,\mathbf{s})$ are independent, and that the prior distributions of $p(\mathbf{A},\lambda_0,\mathbf{s},\mathbf{B},\mathbf{D})$ do not depend on global shocks, we have after rearranging:

$$\begin{aligned}
&p(\mathbf{Y}_T,\mathbf{A},\lambda_0,\mathbf{s},\mathbf{B},\mathbf{D}|\chi,\mathbf{U}_{gT}) \\
&\quad= p(\mathbf{A},\lambda_0,\mathbf{s})p(\mathbf{D}|\mathbf{A},\lambda_0,\mathbf{s})p(\mathbf{B}|\mathbf{A},\lambda_0,\mathbf{s},\mathbf{D})p(\mathbf{Y}_T|\mathbf{A},\lambda_0,\mathbf{s},\mathbf{B},\mathbf{D},\chi,\mathbf{U}_{gT}) \\
&\quad= p(\mathbf{A})p(\lambda_0)p(\mathbf{s})(2\pi)^{-Tn/2}|\det(\mathbf{A})|^T \\
&\qquad\times\prod_{c=1}^C\prod_{j=1}^J\Bigg\{(d_c^j)^{-(\kappa_c^j-1)}\frac{(\tau_c^j)^{\kappa_c^j}}{\Gamma(\kappa_c^j)}\frac{\Gamma(\kappa_c^{j^*})}{(\tau_c^{j^*})^{\kappa_c^{j^*}}}\frac{(\tau_c^{j^*})^{\kappa_c^{j^*}}}{\Gamma(\kappa_c^{j^*})}(d_c^j)^{-T/2}\exp\left[-\frac{\tau_c^{j^*}}{d_c^j}\right] \\
&\qquad\times\frac{|\mathbf{M}_c^{j^*}|^{1/2}}{|\mathbf{M}_c^j|^{1/2}}\frac{1}{(2\pi)^{k/2}|d_c^j\mathbf{M}_c^{j^*}|^{1/2}}\exp\left[-\frac{\left(\mathbf{b}_c^j-\mathbf{m}_c^{j^*}\right)'\left(\mathbf{M}_c^{j^*}\right)^{-1}\left(\mathbf{b}_c^j-\mathbf{m}_c^{j^*}\right)}{2d_c^j}\right]\Bigg\} \\
&\quad= p(\mathbf{A})p(\lambda_0)p(\mathbf{s})(2\pi)^{-Tn/2}|\det(\mathbf{A})|^T \\
&\qquad\times\prod_{c=1}^C\prod_{j=1}^J\left\{\frac{|\mathbf{M}_c^{j^*}|^{1/2}}{|\mathbf{M}_c^j|^{1/2}}\frac{(\tau_c^j)^{\kappa_c^j}}{\Gamma(\kappa_c^j)}\frac{\Gamma(\kappa_c^{j^*})}{(\tau_c^{j^*})^{\kappa_c^{j^*}}}\right\}\gamma\left(\left(d_c^j\right)^{-1};\kappa_c^{j^*},\tau_c^{j^*}\right)\phi\left(\mathbf{b}_c^j;\mathbf{m}_c^{j^*},\mathbf{M}_c^{j^*}\right)
\end{aligned} \tag{C.11}$$

Equation (C.11) means that, conditional on global shocks and their loading, the posterior distribution of $(\mathbf{A},\lambda_0,\mathbf{s})$ is proportional to

$$p(\mathbf{A},\lambda_0,\mathbf{s}|\mathbf{Y}_T,\chi,\mathbf{U}_{gT}) \propto p(\mathbf{A})p(\lambda_0)p(\mathbf{s})(2\pi)^{-Tn/2}|\det(\mathbf{A})|^T\prod_{c=1}^C\prod_{j=1}^J\left\{\frac{|\mathbf{M}_c^{j^*}|^{1/2}}{|\mathbf{M}_c^j|^{1/2}}\frac{(\tau_c^j)^{\kappa_c^j}}{\Gamma(\kappa_c^j)}\frac{\Gamma(\kappa_c^{j^*})}{(\tau_c^{j^*})^{\kappa_c^{j^*}}}\right\}.$$

Equation (C.6) can be obtained after removing some constants and multiplying with $|\hat{\Omega}_T|^{T/2}$, where $\hat{\Omega}_T$ is the variance-covariance matrix of reduced-form errors, which does not depend on any of the model parameters:

$$p(\mathbf{A}, \lambda_0, \mathbf{s}|\mathbf{Y}_T, \chi, \mathbf{U}_{gT}) \propto p(\mathbf{A})p(\lambda_0)p(\mathbf{s})|\det(\mathbf{A}\hat{\Omega}_T\mathbf{A})|^T \prod_{c=1}^{C}\prod_{j=1}^{J}\left\{\frac{|\mathbf{M}_c^{j*}|^{1/2}}{|\mathbf{M}_c^{j}|^{1/2}}\frac{(\tau_c^j)^{\kappa_c^j}}{\Gamma(\kappa_c^j)}\frac{\Gamma(\kappa_c^{j*})}{(2\tau_c^{j*}/T)^{\kappa_c^{j*}}}\right\}.$$

C.4.3 Drawing from the posterior distribution

We use a Metropolis-within-Gibbs to generate draws from the posterior distributions in the following sequence:

1. Draw $(\mathbf{A}, \lambda_0, \mathbf{s})$ from $p(\mathbf{A}, \lambda_0, \mathbf{s}|\mathbf{Y}_T, \chi, \mathbf{U}_{gT})$, equation (C.6), in a Metropolis-Hastings step evaluated for $C+1$ parameter blocks, namely C random blocks for coefficients in $\mathbf{A}$, followed by a single block for hyperparameters $(\lambda_0, \mathbf{s})$.

2. For every country c and structural equation j, ...

   (a) ... draw $(d_c^j)^{-1}$ from $p\left(\mathbf{D}|\mathbf{A}, \lambda_0, \mathbf{s}, \mathbf{Y}_T, \chi, \mathbf{U}_{gT}\right)$, equation (C.7).

   (b) ... draw $\mathbf{b}_c^j$ jointly from $p\left(\mathbf{B}|\mathbf{A}, \lambda_0, \mathbf{s}, \mathbf{D}, \mathbf{Y}_T, \chi, \mathbf{U}_{gT}\right)$, equation (C.8).

   (c) ... calculate combined structural shocks $\check{\mathbf{u}}_t = \mathbf{A}\mathbf{y}_t - \mathbf{B}\mathbf{x}_{t-1}$.

3. Draw χ from $p(\chi|\mathbf{A}, \lambda_0, \mathbf{s}, \mathbf{D}, \mathbf{B}, \mathbf{Y}_T, \mathbf{U}_{gT})$, equation (C.9).

4. Draw $\mathbf{U}_{gT}$ from $p(\mathbf{U}_{gt}|\mathbf{A}, \lambda_0, \mathbf{s}, \mathbf{D}, \mathbf{B}, \mathbf{Y}_T, \chi)$, equations (C.10).

Following Baumeister and Hamilton (2015), we calculate the mode of the posterior likelihood $p(\mathbf{A}, \lambda_0, \mathbf{s}|\mathbf{Y}_T, \mathbf{0}_{n\times G}, \mathbf{U}_{gT})$, albeit at loadings of zero. We take the parameters $(\mathbf{A}, \lambda_0, \mathbf{s})$ at the mode as initial draws, and their Hessian as the most promising search direction for the Metropolis-Hastings steps.

Because of global shocks, we want to fine-tune this initial draw further. Thus, we run a pre-sampling such that we obtain twice as many draws as the number of free parameters of $\mathbf{A}$ after 400'000 burn-in and thinning of 500 draws (total chain length of baseline model: 484'000 draws). Taking the median retained draw as starting point, and the variance-covariance of the retained draws as search direction, the main algorithm keeps a total of 20'000 retained draws after a burn-in of 200,000 draws and thinning of 50 draws (total chain length: 1'200'000). For the prior distribution and robustness checks, we reduce the number of retained draws to 5'000. This "thins" out posterior distributions of structural coefficients, but does not materially affect the quantile-based results for forecast-error-variance decompositions and impulse-response-functions. We adapt the step-size during the burn-in phase to achieve an acceptance probability of 30% for the Metropolis-Hastings step.

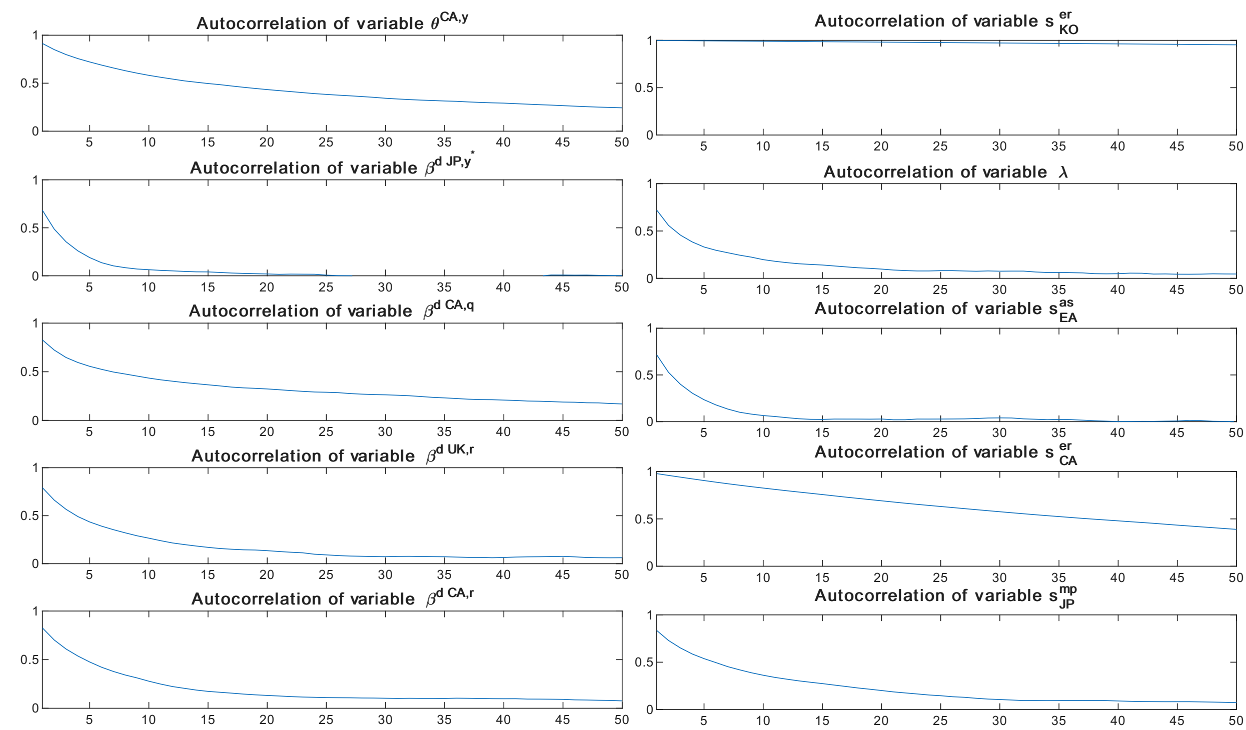
C.5 Convergence statistics

Figure C.1 and C.2 plot the autocorrelation across draws (after burn-in) and all draws for the four chains exemplary for the coefficients which have the weakest convergence statistics according to Geweke (1992) test for equality in means. These coefficients have by far the lowest p-values, mostly between 0.01 and 0.05. Across the 106 coefficients drawn in the Metropolis-Hastings step, only 10 have a p-value below 0.05, which is only marginally larger than the share one would expect from multiple testing.

We see that the autocorrelation and trace plots for structural contemporaneous coefficients $\mathbf{A}$ is well behaved. Some of the prior variances $\mathbf{s}$, however, are be correlated across retained draws. We set the same hyperparameters for countries in all prior distributions.

Figure C.1: Autocorrelations of draws

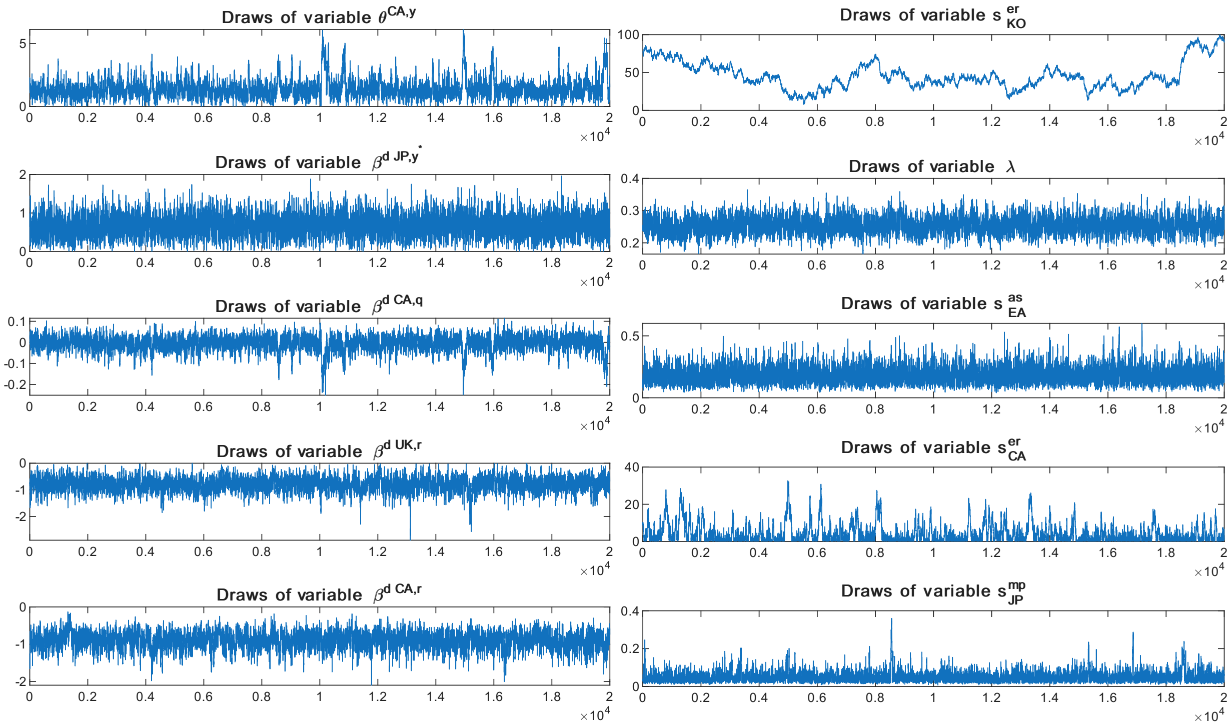
(a) A | **(b) $\mathbf{s}, \lambda$**



NOTES: The plots show the autocorrelation across draws (after burn-in) of the structural parameters in $\mathbf{A}$ (left subplot) and hyperparameters $(\mathbf{s}, \lambda)$ (right subplot) with the weakest convergence statistics.

Figure C.2: Trace plot of draws

(a) A **(b) s, λ**



NOTES: Trace plots of the structural parameters in **A** (left subplot) and hyperparameters (**s**, λ) (right subplot) with the weakest convergence statistics.

D Further results

D.1 Forecast error variance and correlation decompositions in the baseline model

The first three figures D.1 to D.3 show the forecast error variance decomposition of country-specific variables (in subplots) to domestic (dom) and foreign (for) supply, demand, monetary policy and exchange rate shocks and global (glob) supply, demand and monetary policy shocks over 20 quarters. Figure D.4 shows the decomposition of the forecast error correlation between country-specific and US interest rates.

Figure D.1: Forecast error variance decomposition of output gaps

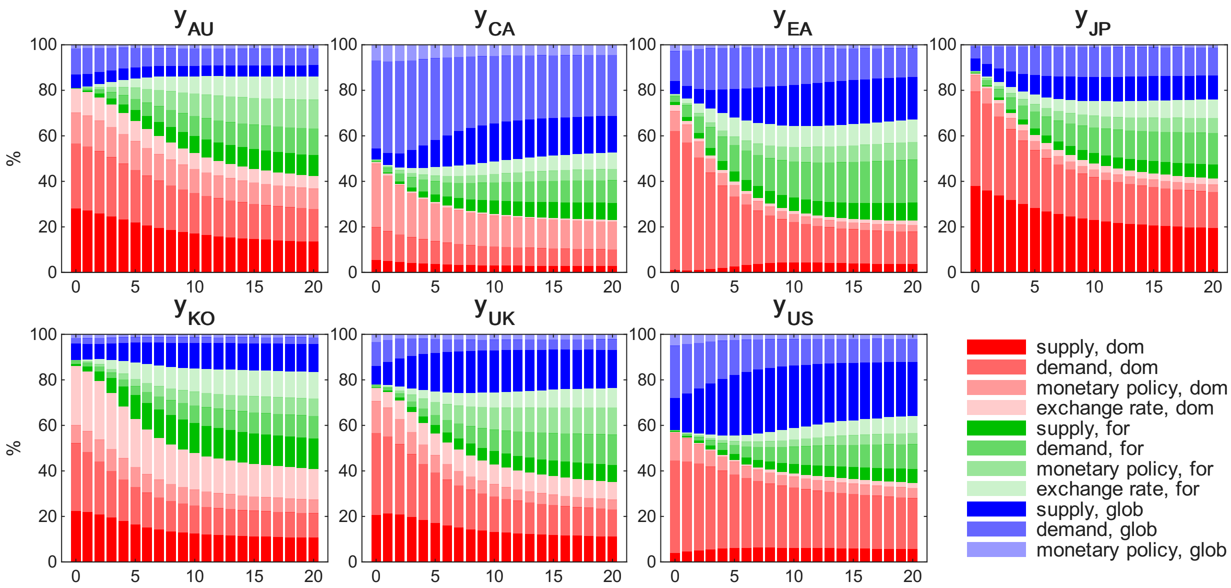


Figure D.2: Forecast error variance decomposition of inflation

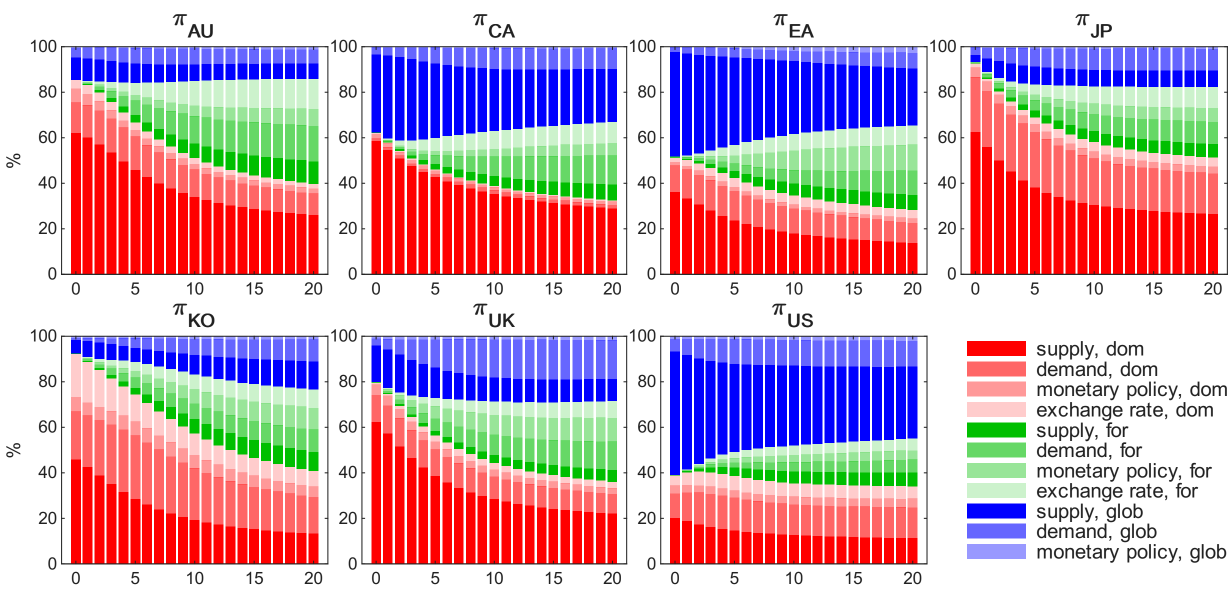


Figure D.3: Forecast error variance decomposition of exchange rate growth

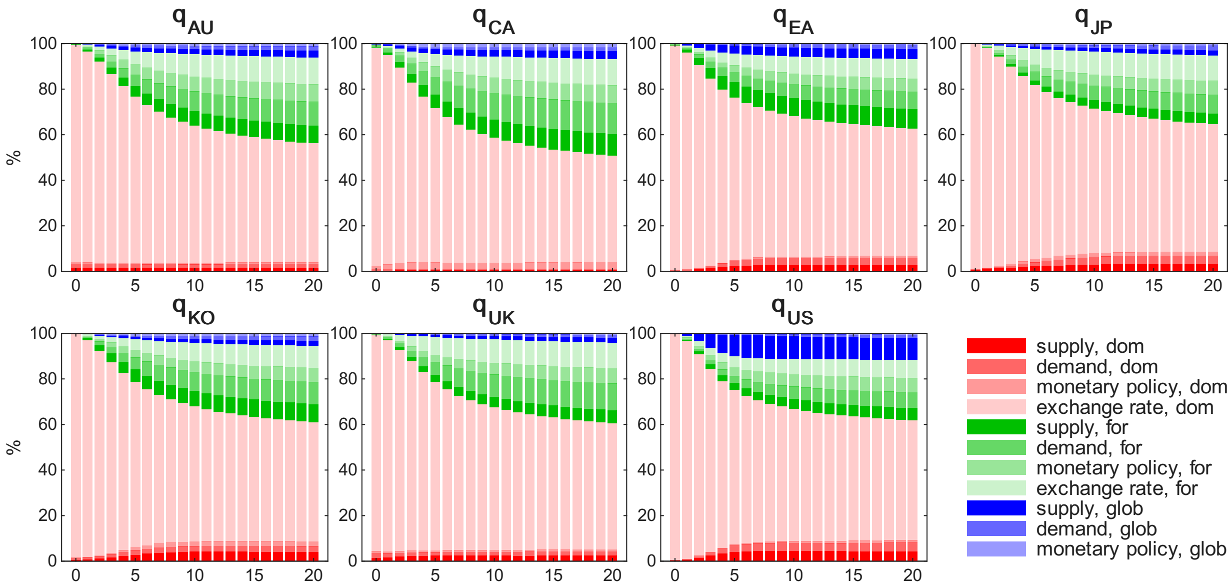


Figure D.4: Forecast error correlation decomposition between US and country-specific interest rates

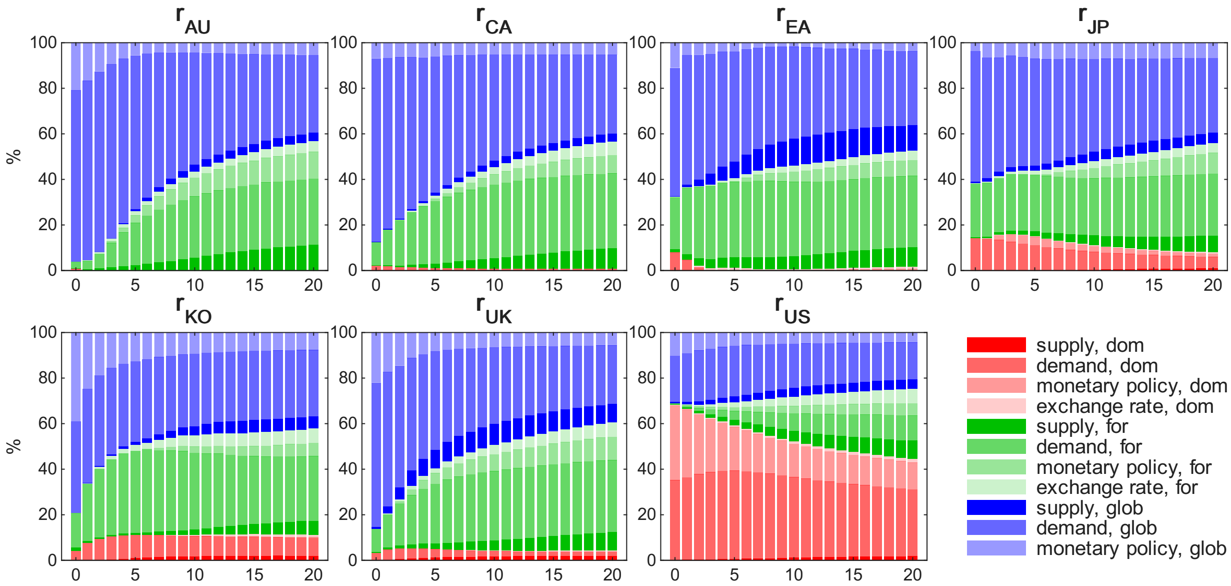


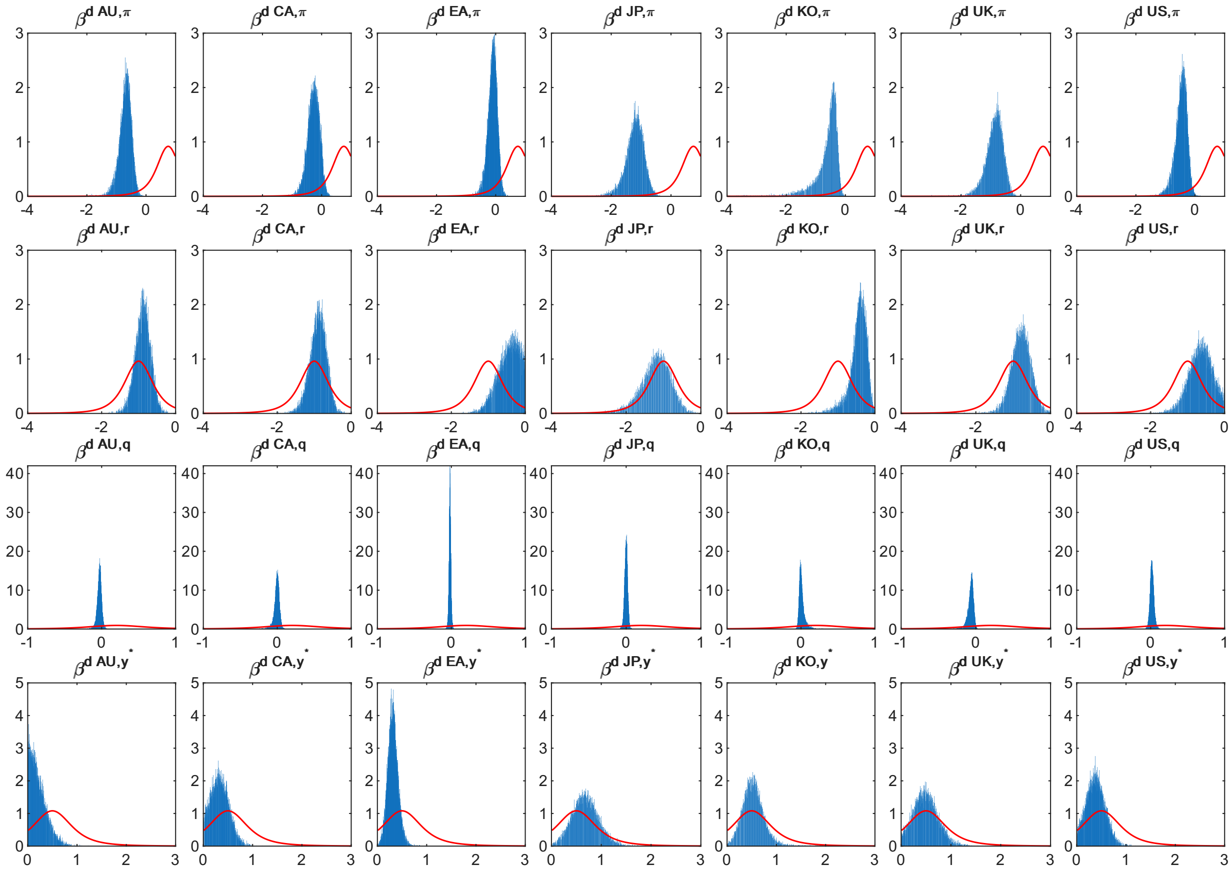
Table D.1: Decomposition of correlations of interest rates, $H = 20$

	AU	CA	EA	JP	KO	UK	US
				domestic			
group agg	-0.02	0.01	-0.01	0.10	0.12	**0.06**	**0.44**
	[-0.29,0.10]	[-0.03,0.09]	[-0.30,0.19]	[-0.03,0.32]	[-0.09,0.39]	[0.00,0.19]	[0.28,0.61]
supply, dom	0.00	0.00	-0.02	0.01	0.02	0.02	**0.02**
	[-0.03,0.03]	[-0.00,0.01]	[-0.16,0.04]	[-0.03,0.11]	[-0.03,0.12]	[-0.00,0.10]	[0.00,0.08]
demand, dom	-0.01	0.01	-0.01	0.05	0.08	0.02	**0.29**
	[-0.16,0.07]	[-0.01,0.06]	[-0.12,0.09]	[-0.01,0.19]	[-0.05,0.27]	[-0.01,0.11]	[0.10,0.46]
mon. pol., dom	-0.01	-0.00	0.01	0.01	0.00	0.00	**0.12**
	[-0.12,0.04]	[-0.03,0.04]	[-0.08,0.14]	[-0.05,0.16]	[-0.04,0.06]	[-0.01,0.04]	[0.02,0.32]
er, dom	0.00	0.00	0.01	0.01	0.01	0.01	**0.02**
	[-0.02,0.03]	[-0.00,0.04]	[-0.11,0.13]	[-0.04,0.10]	[-0.04,0.10]	[-0.01,0.07]	[0.00,0.11]
				foreign			
group agg	**0.57**	**0.56**	**0.51**	**0.47**	0.45	**0.55**	**0.30**
	[0.05,0.85]	[0.28,0.79]	[0.15,0.88]	[0.14,0.75]	[-0.06,0.82]	[0.33,0.77]	[0.15,0.50]
supply, for	0.11	**0.09**	0.09	0.07	0.06	**0.08**	**0.08**
	[-0.03,0.32]	[0.01,0.21]	[-0.02,0.24]	[-0.02,0.21]	[-0.14,0.24]	[0.01,0.20]	[0.02,0.17]
demand, for	**0.29**	**0.33**	**0.31**	**0.27**	**0.28**	**0.32**	**0.11**
	[0.00,0.63]	[0.12,0.54]	[0.08,0.65]	[0.04,0.51]	[0.04,0.62]	[0.11,0.51]	[0.03,0.22]
mon. pol., for	0.12	0.08	0.07	0.09	0.06	**0.10**	**0.05**
	[-0.08,0.36]	[-0.01,0.26]	[-0.10,0.31]	[-0.06,0.31]	[-0.21,0.27]	[0.01,0.27]	[0.01,0.13]
er, for	0.05	0.06	0.04	0.04	0.06	0.06	**0.06**
	[-0.32,0.28]	[-0.03,0.21]	[-0.23,0.21]	[-0.16,0.23]	[-0.17,0.30]	[-0.01,0.22]	[0.02,0.17]
				global			
group agg	**0.45**	**0.43**	**0.49**	**0.43**	**0.43**	**0.39**	**0.25**
	[0.20,1.12]	[0.20,0.69]	[0.15,1.00]	[0.15,0.80]	[0.12,0.88]	[0.16,0.61]	[0.10,0.45]
supply, glob	0.04	0.03	0.11	0.04	0.05	0.08	**0.04**
	[-0.11,0.22]	[-0.01,0.18]	[-0.16,0.36]	[-0.04,0.21]	[-0.07,0.28]	[-0.02,0.24]	[0.00,0.17]
demand, glob	**0.34**	**0.35**	**0.32**	**0.33**	**0.29**	**0.26**	**0.16**
	[0.05,0.99]	[0.08,0.60]	[0.03,0.77]	[0.04,0.64]	[0.02,0.68]	[0.04,0.47]	[0.02,0.35]
mon. pol., glob	0.08	**0.05**	0.07	0.07	0.08	**0.06**	**0.04**
	[-0.01,0.38]	[0.00,0.23]	[-0.00,0.38]	[-0.00,0.30]	[-0.01,0.37]	[0.00,0.24]	[0.00,0.20]

Note: Contributions relate to correlation between the interest rate of country c and the global interest rate at horizon $H = 20$. We first report aggregates for domestic, foreign and global shocks before breaking them down into different types of shocks. We report the mode of the decomposition (scaled such that they sum up to 1) together with 95% credibility sets. Correlations where the 95% credibility sets do not contain zero are marked in bold.

D.2 Structural contemporaneous coefficients

Figure D.5: Posterior distributions of structural contemporaneous coefficients, supply and demand equation



NOTES: The histograms show the posterior distribution of structural contemporaneous coefficients in the demand equation together with the prior distribution (red line).

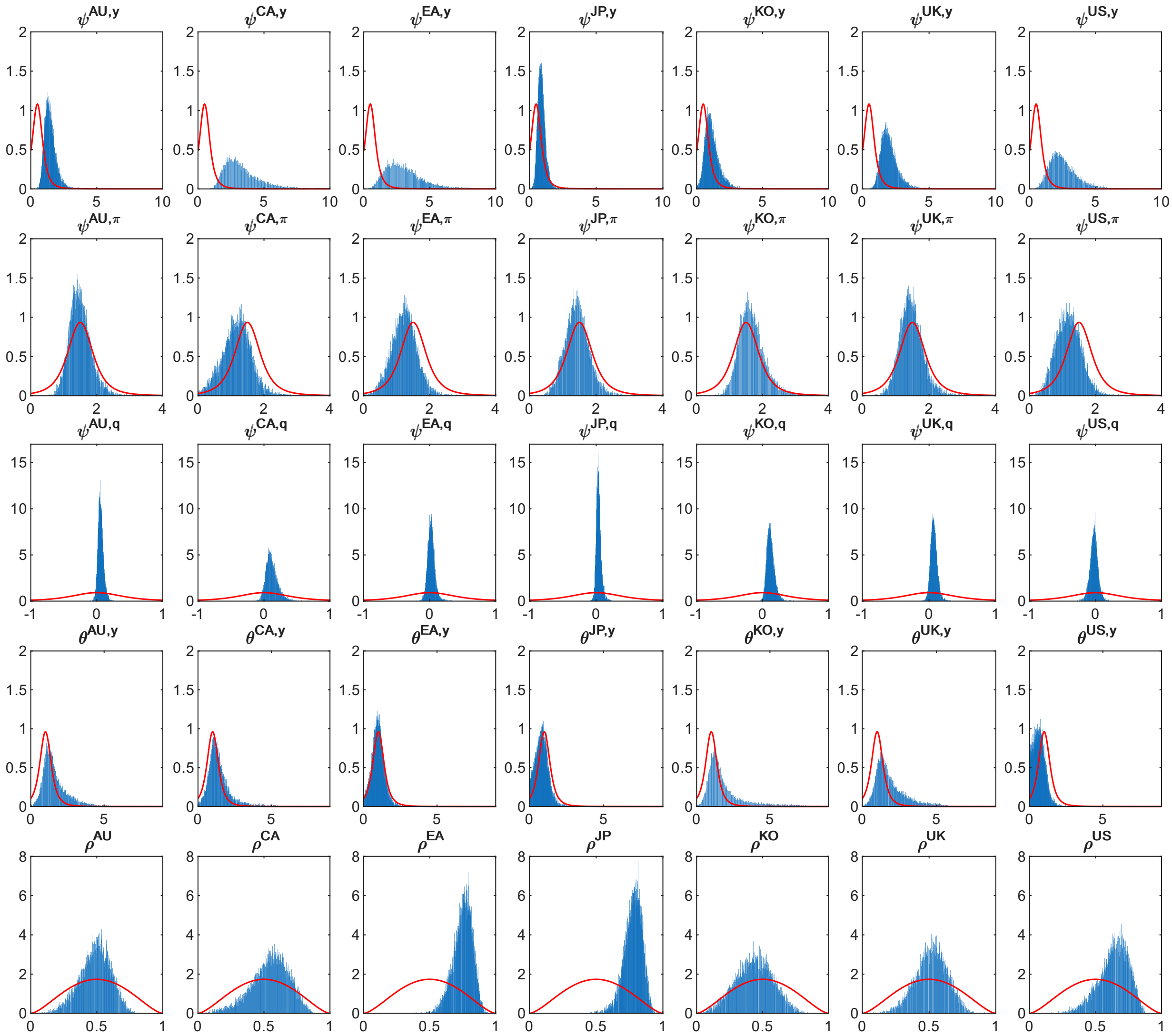
Table D.2: Prior and posterior mean and credibility set of structural contemporaneous coefficients

	prior		posterior			prior		posterior	
	mean	95% cs	mean	95% cs		mean	95% cs	mean	95% cs
$\alpha^{s\,AU,\pi}$	2.02	[0.85,3.29]	2.04	[1.16,3.14]	$\alpha^{s\,CA,\pi}$	2.02	[0.85,3.29]	5.77	[1.95,25.31]
$\alpha^{s\,AU,q}$	-0.50	[-1.79,0.79]	-0.12	[-0.22,-0.05]	$\alpha^{s\,CA,q}$	-0.50	[-1.79,0.79]	0.05	[-0.13,0.33]
$\beta^{d\,AU,\pi}$	0.75	[-0.53,2.03]	-0.70	[-1.16,-0.35]	$\beta^{d\,CA,\pi}$	0.75	[-0.53,2.03]	-0.27	[-0.71,0.08]
$\beta^{d\,AU,r}$	-1.07	[-2.31,-0.17]	-0.89	[-1.32,-0.49]	$\beta^{d\,CA,r}$	-1.07	[-2.31,-0.17]	-0.90	[-1.38,-0.49]
$\beta^{d\,AU,q}$	0.20	[-1.09,1.49]	-0.03	[-0.09,0.02]	$\beta^{d\,CA,q}$	0.20	[-1.09,1.49]	-0.01	[-0.09,0.05]
$\beta^{d\,AU,y^*}$	0.67	[0.05,1.99]	0.22	[0.01,0.62]	$\beta^{d\,CA,y^*}$	0.67	[0.05,1.99]	0.33	[0.03,0.71]
$\psi^{AU,y}$	0.67	[0.05,1.99]	1.46	[0.81,2.42]	$\psi^{CA,y}$	0.67	[0.05,1.99]	3.43	[1.53,7.62]
$\psi^{AU,\pi}$	1.54	[0.47,2.79]	1.49	[0.93,2.24]	$\psi^{CA,\pi}$	1.54	[0.47,2.79]	1.18	[0.31,2.05]
$\psi^{AU,q}$	-0.00	[-1.29,1.29]	0.06	[-0.01,0.15]	$\psi^{CA,q}$	-0.00	[-1.29,1.29]	0.12	[-0.03,0.34]
$\theta^{AU,y}$	1.07	[0.19,2.33]	1.64	[0.51,3.97]	$\theta^{CA,y}$	1.07	[0.19,2.33]	1.41	[0.35,3.48]
ρ^{AU}	0.50	[0.13,0.87]	0.49	[0.24,0.69]	ρ^{CA}	0.50	[0.13,0.87]	0.55	[0.23,0.79]

Table D.2: Prior and posterior mean and credibility set of structural contemporaneous coefficients

	prior		posterior			prior		posterior	
	mean	95% cs	mean	95% cs		mean	95% cs	mean	95% cs
$\alpha^{s\,EA,\pi}$	2.02	[0.85,3.29]	2.60	[1.73,4.47]	$\alpha^{s\,JP,\pi}$	2.02	[0.85,3.29]	2.17	[1.33,3.38]
$\alpha^{s\,EA,q}$	-0.50	[-1.79,0.79]	-0.06	[-0.11,-0.02]	$\alpha^{s\,JP,q}$	-0.50	[-1.79,0.79]	0.04	[-0.01,0.09]
$\beta^{d\,EA,\pi}$	0.75	[-0.53,2.03]	-0.11	[-0.46,0.17]	$\beta^{d\,JP,\pi}$	0.75	[-0.53,2.03]	-1.21	[-1.92,-0.69]
$\beta^{d\,EA,r}$	-1.07	[-2.31,-0.17]	-0.46	[-1.09,-0.03]	$\beta^{d\,JP,r}$	-1.07	[-2.31,-0.17]	-1.21	[-2.13,-0.51]
$\beta^{d\,EA,q}$	0.20	[-1.09,1.49]	-0.02	[-0.04,0.01]	$\beta^{d\,JP,q}$	0.20	[-1.09,1.49]	-0.00	[-0.04,0.04]
$\beta^{d\,EA,y^*}$	0.67	[0.05,1.99]	0.31	[0.12,0.53]	$\beta^{d\,JP,y^*}$	0.67	[0.05,1.99]	0.68	[0.18,1.23]
$\psi^{EA,y}$	0.67	[0.05,1.99]	3.10	[1.02,7.06]	$\psi^{JP,y}$	0.67	[0.05,1.99]	0.91	[0.44,1.57]
$\psi^{EA,\pi}$	1.54	[0.47,2.79]	1.23	[0.48,2.00]	$\psi^{JP,\pi}$	1.54	[0.47,2.79]	1.43	[0.77,2.20]
$\psi^{EA,q}$	-0.00	[-1.29,1.29]	0.02	[-0.07,0.14]	$\psi^{JP,q}$	-0.00	[-1.29,1.29]	0.04	[-0.02,0.11]
$\theta^{EA,y}$	1.07	[0.19,2.33]	0.95	[0.17,1.82]	$\theta^{JP,y}$	1.07	[0.19,2.33]	0.82	[0.08,1.75]
ρ^{EA}	0.50	[0.13,0.87]	0.75	[0.59,0.87]	ρ^{JP}	0.50	[0.13,0.87]	0.78	[0.63,0.89]
$\alpha^{s\,KO,\pi}$	2.02	[0.85,3.29]	1.41	[0.36,2.55]	$\alpha^{s\,UK,\pi}$	2.02	[0.85,3.29]	2.50	[1.58,4.60]
$\alpha^{s\,KO,q}$	-0.50	[-1.79,0.79]	-0.14	[-0.22,-0.07]	$\alpha^{s\,UK,q}$	-0.50	[-1.79,0.79]	-0.01	[-0.10,0.06]
$\beta^{d\,KO,\pi}$	0.75	[-0.53,2.03]	-0.64	[-1.84,-0.20]	$\beta^{d\,UK,\pi}$	0.75	[-0.53,2.03]	-0.88	[-1.56,-0.39]
$\beta^{d\,KO,r}$	-1.07	[-2.31,-0.17]	-0.45	[-1.09,-0.12]	$\beta^{d\,UK,r}$	-1.07	[-2.31,-0.17]	-0.79	[-1.33,-0.28]
$\beta^{d\,KO,q}$	0.20	[-1.09,1.49]	0.01	[-0.04,0.12]	$\beta^{d\,UK,q}$	0.20	[-1.09,1.49]	-0.07	[-0.16,-0.01]
$\beta^{d\,KO,y^*}$	0.67	[0.05,1.99]	0.53	[0.15,1.02]	$\beta^{d\,UK,y^*}$	0.67	[0.05,1.99]	0.50	[0.06,1.01]
$\psi^{KO,y}$	0.67	[0.05,1.99]	1.16	[0.35,2.47]	$\psi^{UK,y}$	0.67	[0.05,1.99]	2.01	[1.08,3.53]
$\psi^{KO,\pi}$	1.54	[0.47,2.79]	1.67	[1.01,2.60]	$\psi^{UK,\pi}$	1.54	[0.47,2.79]	1.47	[0.83,2.25]
$\psi^{KO,q}$	-0.00	[-1.29,1.29]	0.12	[0.03,0.25]	$\psi^{UK,q}$	-0.00	[-1.29,1.29]	0.07	[-0.02,0.18]
$\theta^{KO,y}$	1.07	[0.19,2.33]	1.94	[0.51,6.34]	$\theta^{UK,y}$	1.07	[0.19,2.33]	1.87	[0.56,4.79]
ρ^{KO}	0.50	[0.13,0.87]	0.44	[0.16,0.71]	ρ^{UK}	0.50	[0.13,0.87]	0.52	[0.27,0.74]
$\alpha^{s\,US,\pi}$	2.02	[0.85,3.29]	2.13	[1.46,3.02]					
$\alpha^{s\,US,q}$	-0.50	[-1.79,0.79]	-0.08	[-0.15,-0.03]					
$\beta^{d\,US,\pi}$	0.75	[-0.53,2.03]	-0.47	[-0.94,-0.15]					
$\beta^{d\,US,r}$	-1.07	[-2.31,-0.17]	-0.65	[-1.33,-0.08]					
$\beta^{d\,US,q}$	0.20	[-1.09,1.49]	0.02	[-0.03,0.07]					
$\beta^{d\,US,y^*}$	0.67	[0.05,1.99]	0.39	[0.05,0.77]					
$\psi^{US,y}$	0.67	[0.05,1.99]	2.57	[0.99,5.25]					
$\psi^{US,\pi}$	1.54	[0.47,2.79]	1.18	[0.50,1.94]					
$\psi^{US,q}$	-0.00	[-1.29,1.29]	-0.02	[-0.14,0.09]					
$\theta^{US,y}$	1.07	[0.19,2.33]	0.65	[0.04,1.45]					
ρ^{US}	0.50	[0.13,0.87]	0.64	[0.38,0.82]					

Figure D.6: Posterior distributions of structural contemporaneous coefficients, monetary policy rule and exchange rate equation

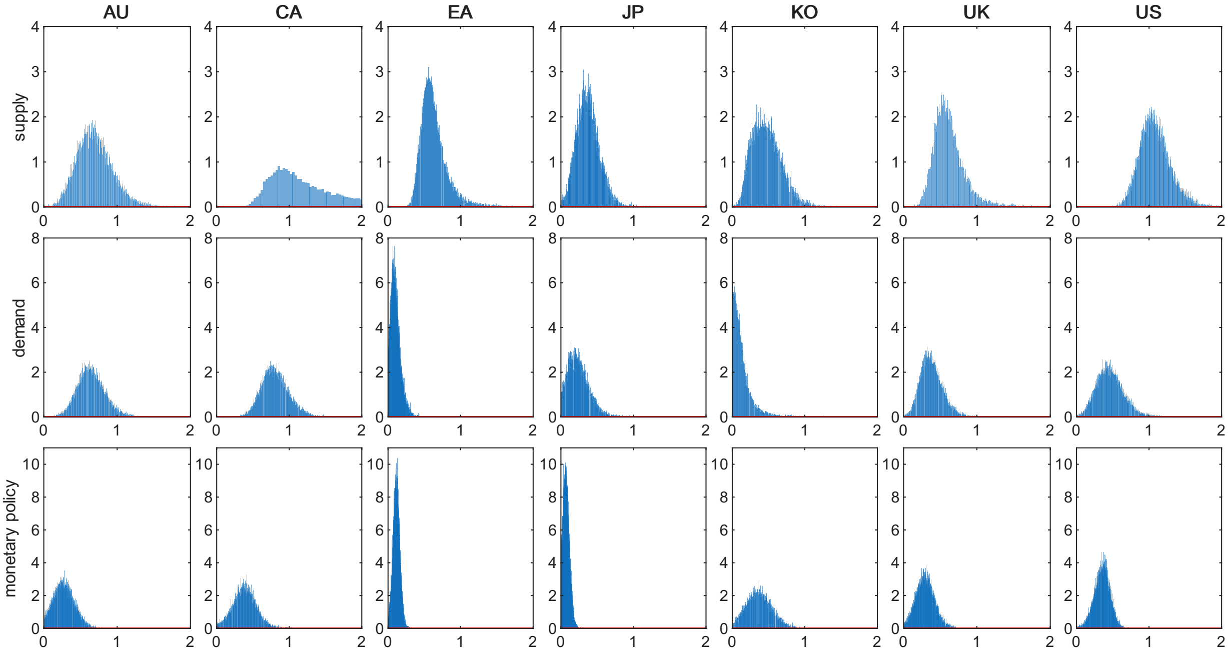


NOTES: The histograms show the posterior distribution of structural contemporaneous coefficients (blue bars; monetary policy equation, and coefficients on foreign variables) and the prior distribution (red line).

D.3 Impulse-response functions in the baseline model

The solid lines in all the following figures show median impulse responses of country-specific variables (in columns, variable name in title) to country-specific demand, supply, monetary policy and exchange rate shocks (in rows) over 20 quarters. The shaded areas (dotted lines) show the 68% (95%) posterior credibility sets. Red dashed lines show median prior impulse response functions. The shocks have size of one unit. Figures D.8 to D.11 show the impulse responses to domestic shocks; Figures D.12 to D.14 those to global shocks; Figures D.15 and D.16 responses to demand and MP shocks from other countries.

Figure D.7: Posterior distributions of loadings



NOTES: The histograms show the posterior distribution of global shock loadings together with the uninformative prior distribution (red line).

Figure D.8: Impulse responses of output gaps to domestic shocks

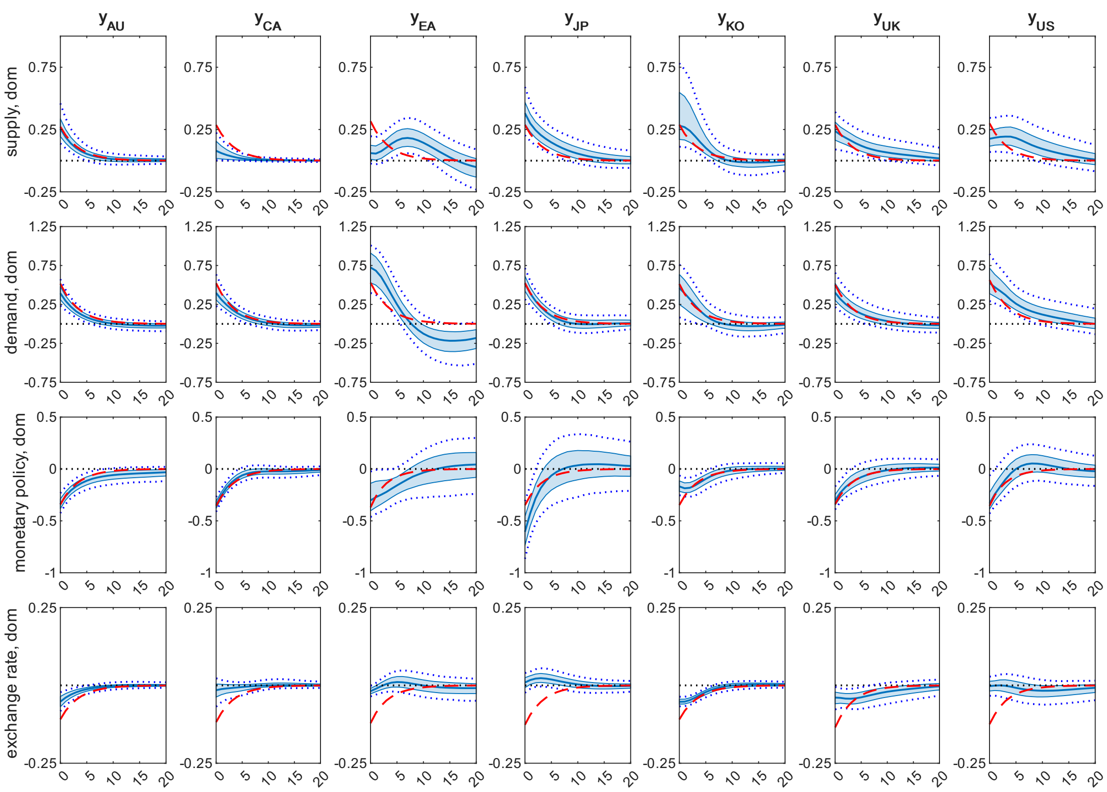


Figure D.9: Impulse responses of inflation to domestic shocks

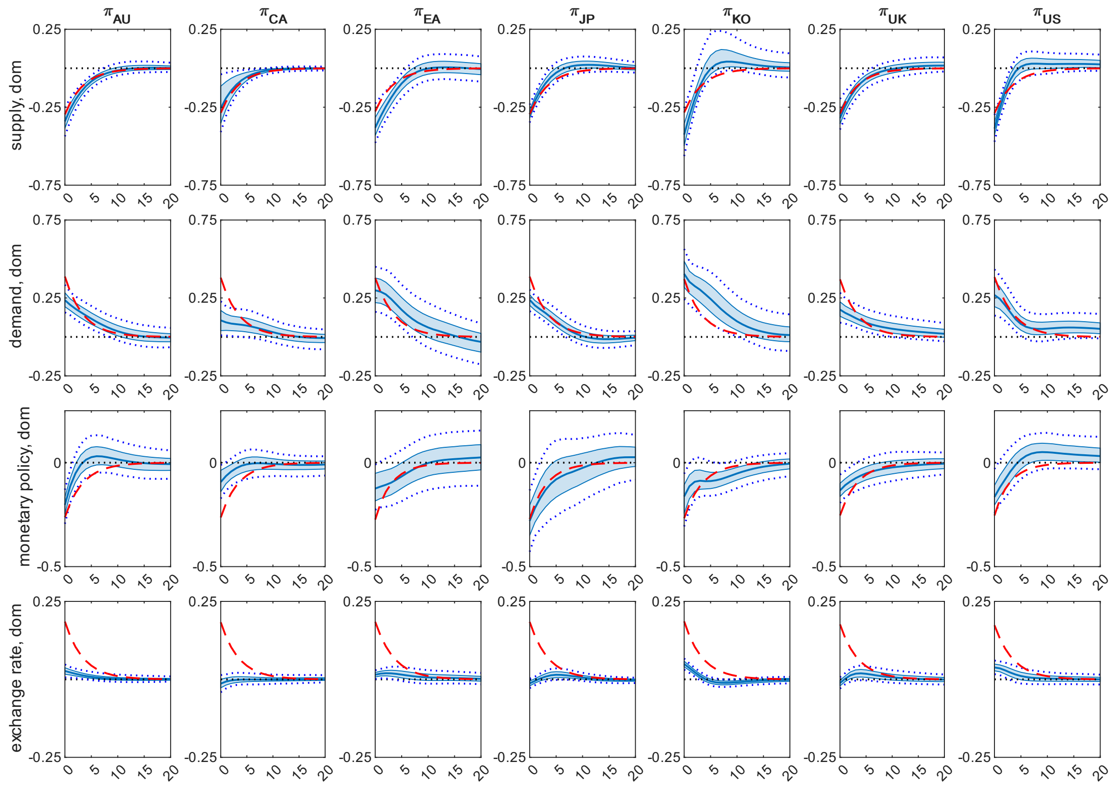


Figure D.10: Impulse responses of interest rates to domestic shocks

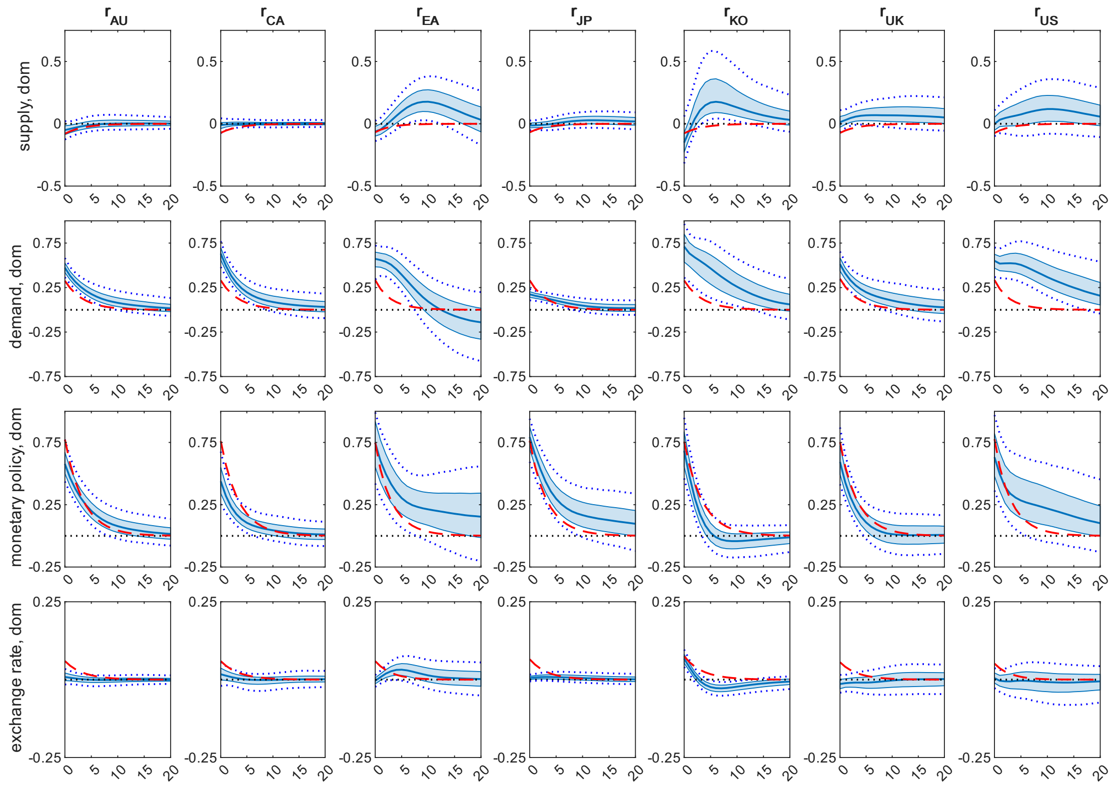


Figure D.11: Impulse responses of exchange rate growth to domestic shocks

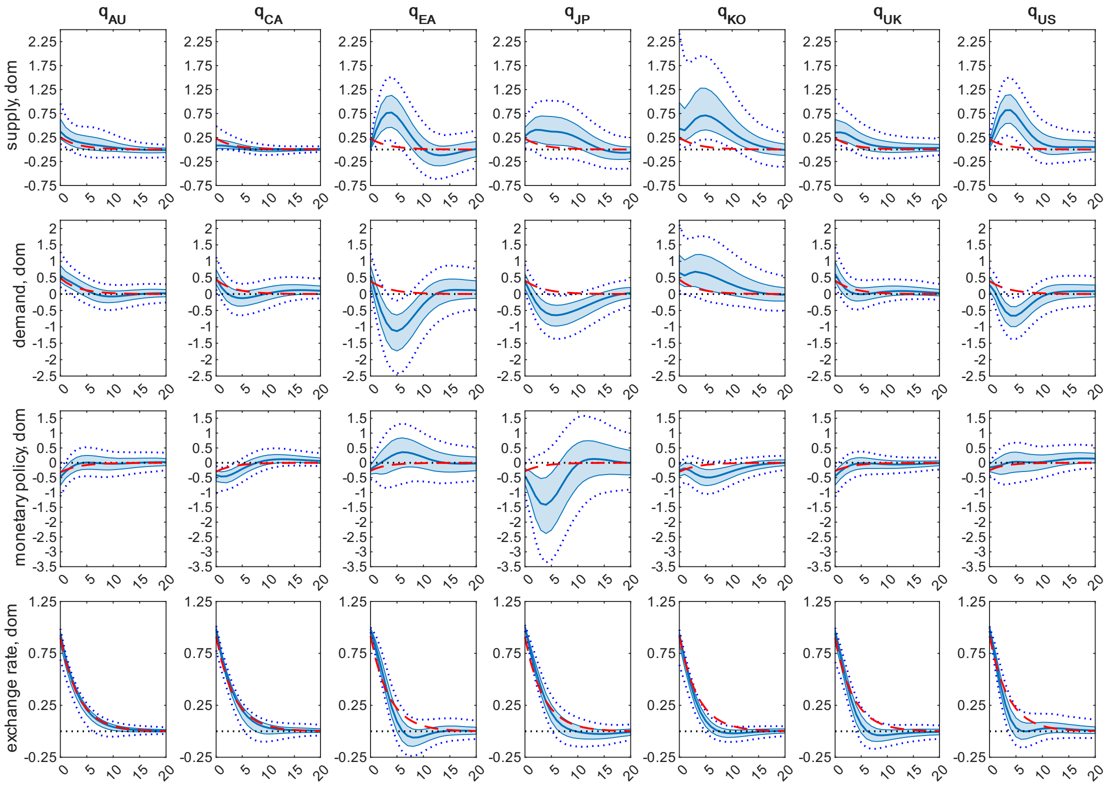


Figure D.12: Impulse responses to global supply shocks, all variables

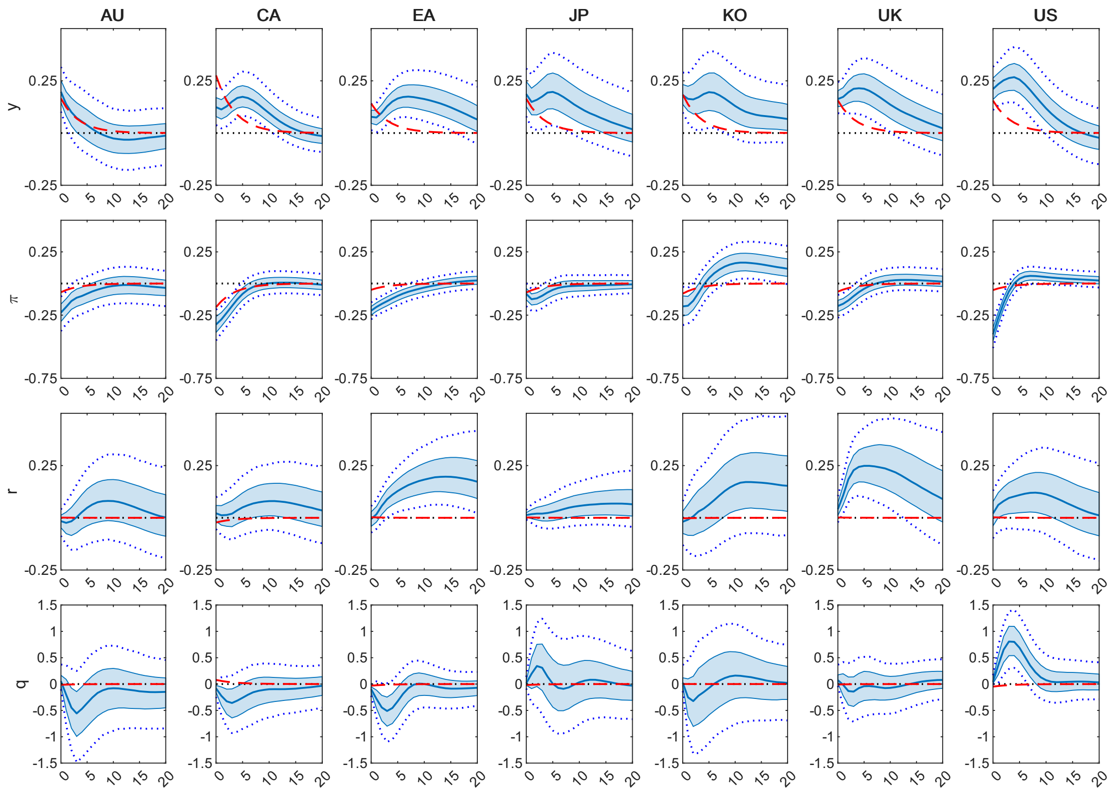


Figure D.13: Impulse responses to global demand shocks, all variables

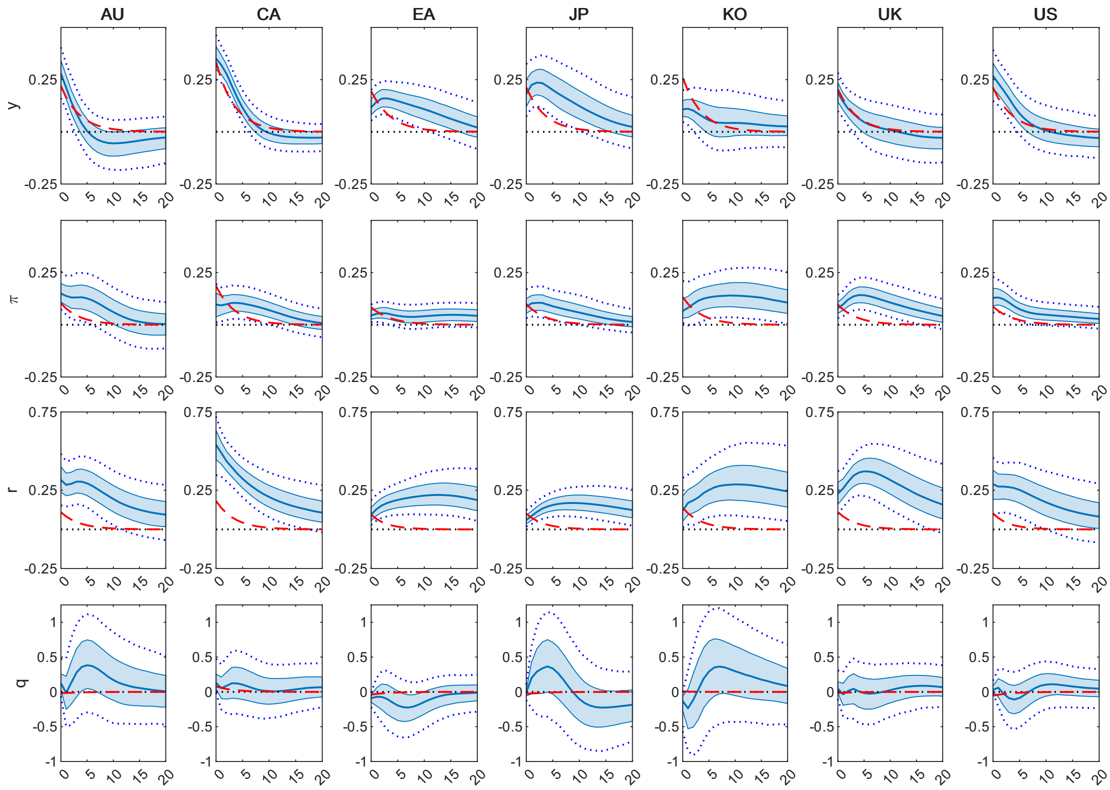


Figure D.14: Impulse responses to global monetary policy shocks, all variables

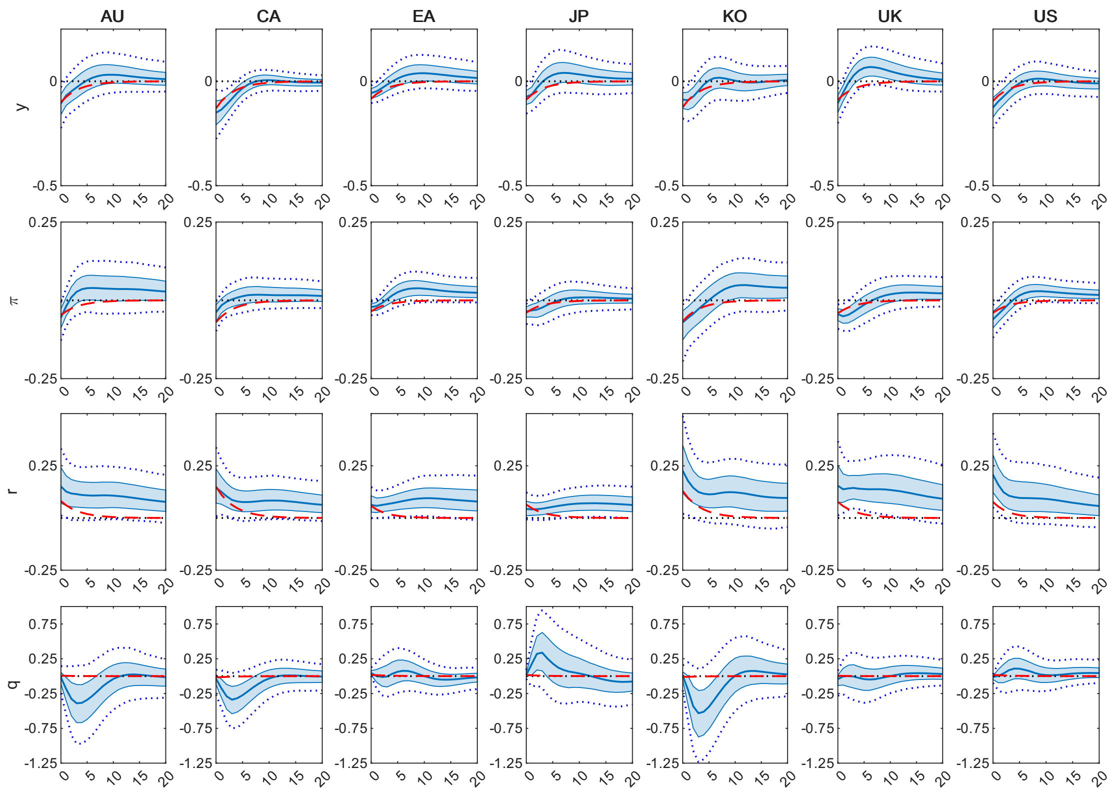


Figure D.15: Impulse responses to country-specific demand shocks

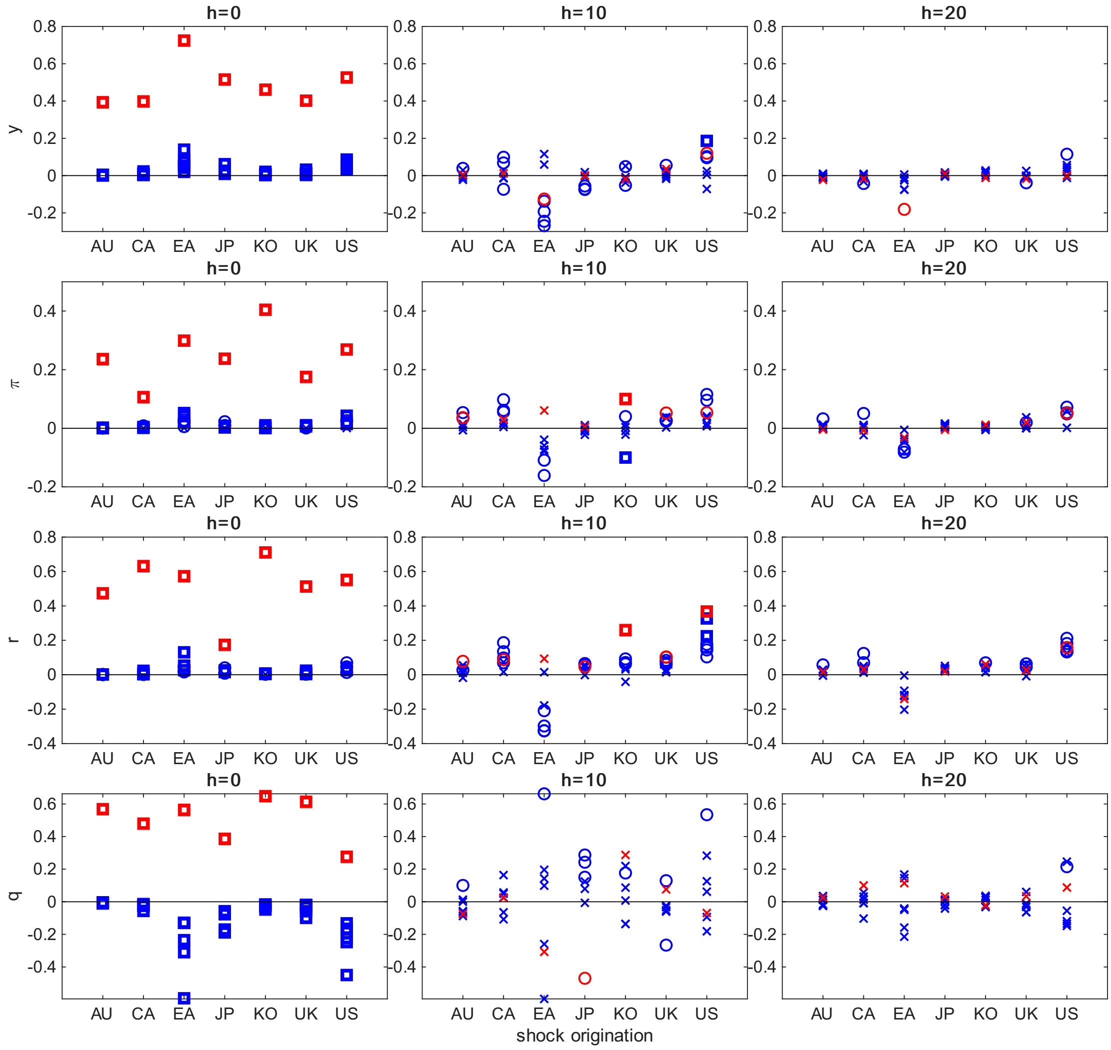


Figure D.16: Impulse responses to country-specific monetary policy shocks

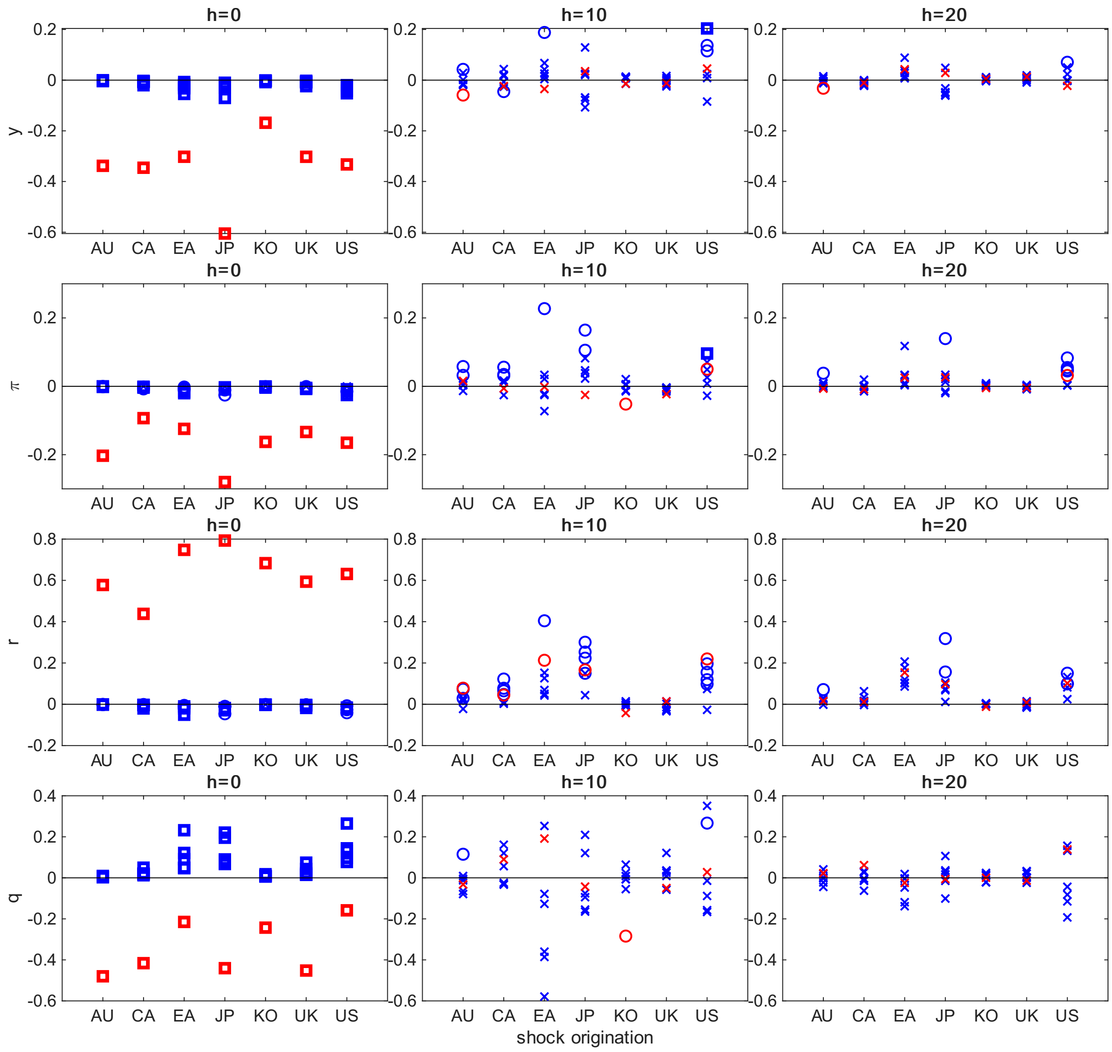
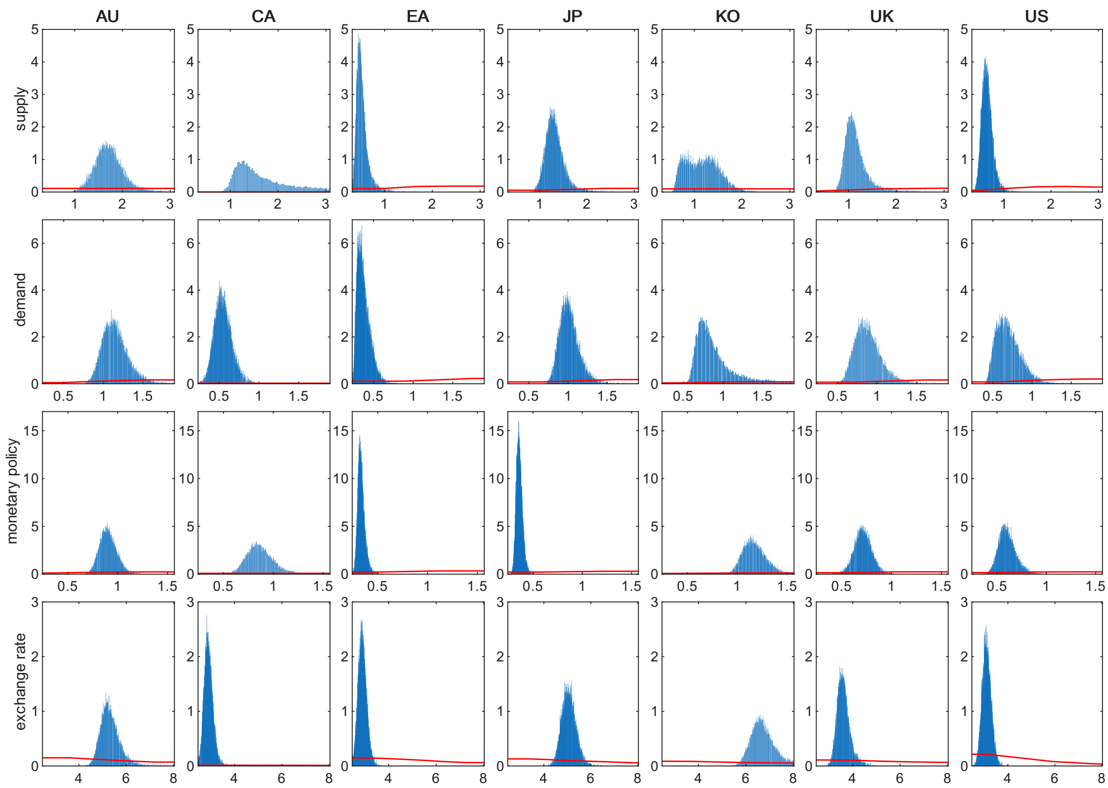


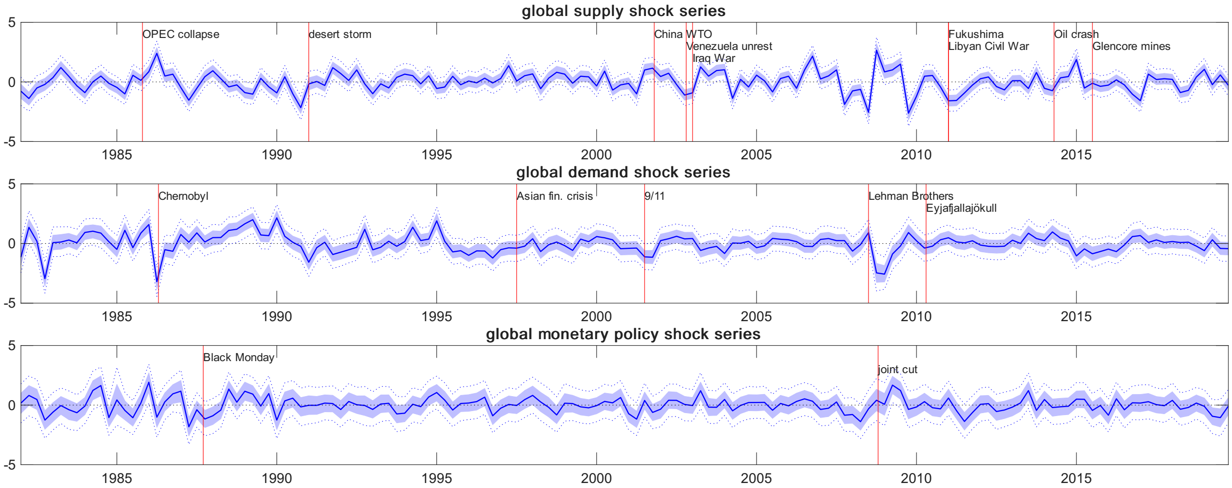
Figure D.17: Standard deviation of structural shocks



NOTES: The histograms show the posterior distribution of structural shock standard deviations, together with the uninformative prior distribution (red line). Global shocks have unit variance.

D.4 Global shocks

Figure D.18: Estimated time series of global shocks



NOTES: The solid lines in the figure show median global shock series. The shaded areas (dotted lines) show the respective 68% (95%) posterior credibility sets. Oil supply events are drawn from Antolín-Díaz and Rubio-Ramírez (2018); Känzig (2021) and reference therein.

E Further robustness analysis

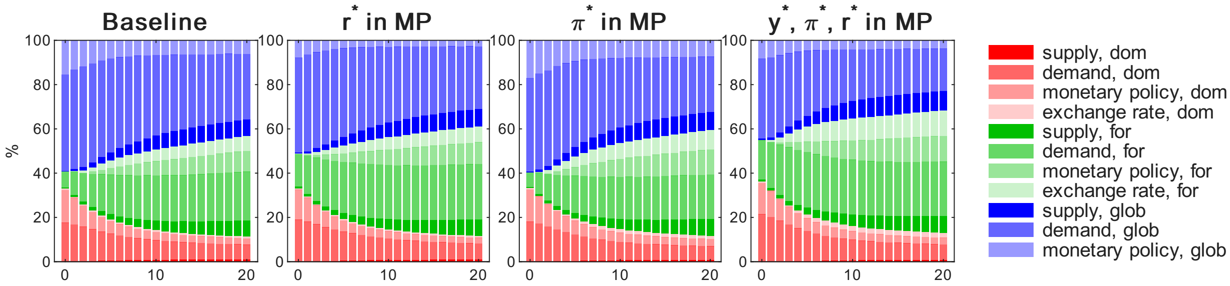
This section shows results for several robustness checks changing the model set-up and adjusting the structural contemporaneous relations. We show the forecast error correlation decomposition between global and country-specific interest rates for the alternative specifications in comparison to our main results (baseline). Further results are available on request.

E.1 Alternative specifications of structural equations

Relaxing the restrictions that monetary policy endogenously reacts only to contemporaneous changes in foreign interest rates, output and inflation does not significantly change our results, see Appendix Figure E.1. We extend the monetary policy rules to contain coefficients on foreign interest rates (labeled r^* *in MP*), foreign inflation (labeled π^* *in MP*) and foreign output gaps, inflation and interest rates (labeled y^*, π^*, r^* *in MP*). The main difference to the baseline results is an increase in the importance of foreign shocks to up to 20% (JP, UK) at short horizons in the first (solid lines) and third (dotted lines) variant, at the expense of domestic shocks. This is because the coefficients on foreign interest rates in monetary policy rule are both economically and statistically significantly positive. All other additional coefficients in the monetary policy rules are identified to be zero.

Four specifications adjust the structural contemporaneous relations of supply and exchange rate equations in the baseline model, shown in Appendix Figure E.2: The first

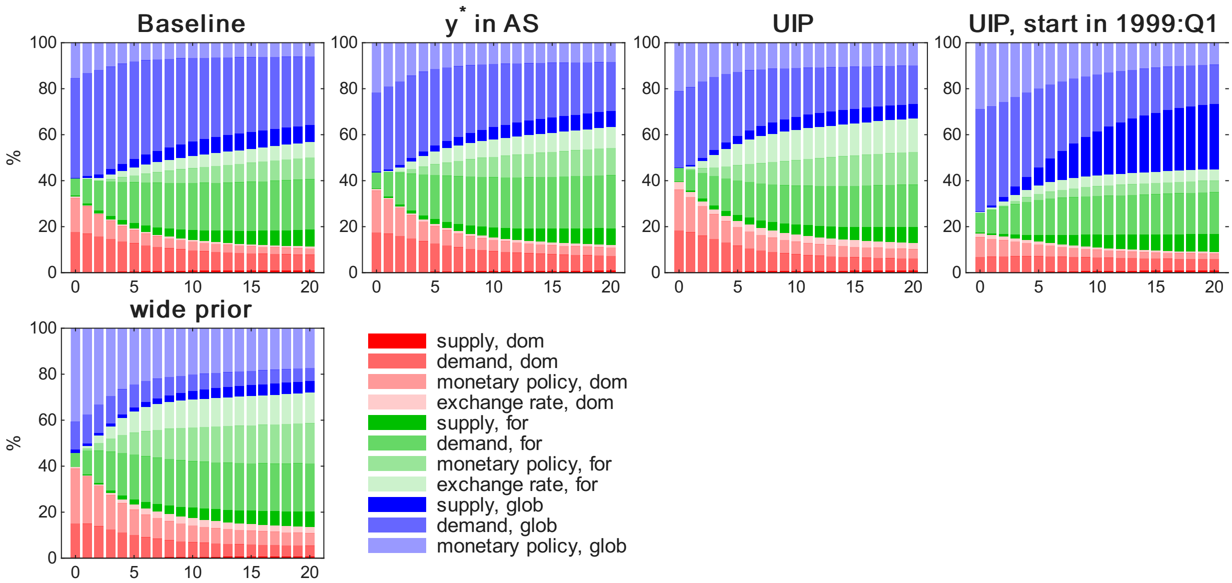
Figure E.1: Forecast error correlation decomposition between global and country-specific interest rates for alternative monetary policy rule specifications



NOTES: Figure shows the forecast error correlation decomposition between global and country-specific interest rates for the baseline model (bars) together with three alternative monetary policy rule specifications (lines).

adds foreign output gaps to the supply equation, restricting the coefficient to be positive (labeled "y^* in AS"). The second adjusts the exchange rate equation such that interest rate differentials enter (labeled "UIP"). Our third specification ("UIP, start in 1999Q1") also adds interest rate differentials, but restricts the sample to 1999:Q1 to 2019:Q4. Our fourth specification uses priors with a variance of 1 (instead of 0.4) for the coefficients $\alpha^{c,\pi}, \theta^{c,y}$ (labeled "wide prior").

Figure E.2: Forecast error correlation decomposition between global and country-specific interest rates for alternative AS and ER equation specifications

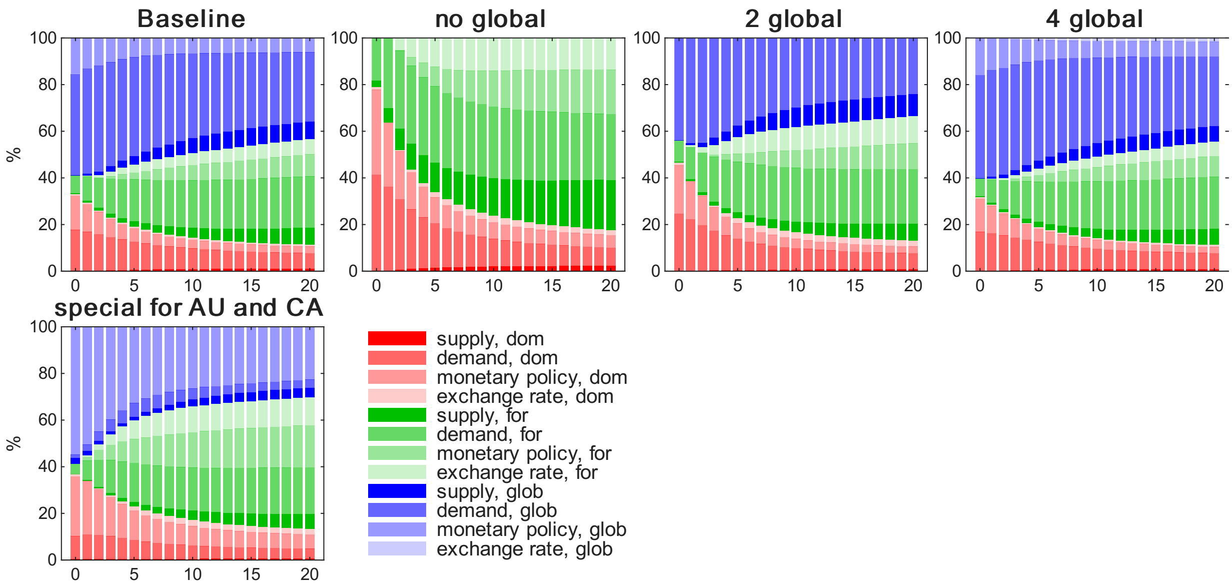


NOTES: Figure shows the forecast error correlation decomposition between global and country-specific interest rates for the baseline model (bars) together with a model including foreign output gaps in the supply equation (solid lines), a model with an interest rate differential in the exchange rate equation (dashed lines), the same model starting in 1999:Q1 (dotted lines), and a model with wide priors (dash-dotted lines).

E.2 Alternative global shock specifications

Four specifications change the set-up of the global shocks, shown in Appendix Figure E.3: a model without global shocks, a model with two global shocks (demand and supply shocks), a model with four global shocks (additionally a global exchange rate shock), and a model where for Australia and Canada global supply and demand shocks enter the exchange rate equation.

Figure E.3: Forecast error correlation decomposition between global and country-specific interest rates for alternative global shock specifications



NOTES: Figure shows the forecast error correlation decomposition between global and country-specific interest rates for the baseline model (bars) together with a model without global shocks (solid lines), a model with two global shocks (dashed lines), a model with four global shocks (dotted lines), and a model where for Australia and Canada global supply and demand shocks enter the exchange rate equation (dash-dotted lines).

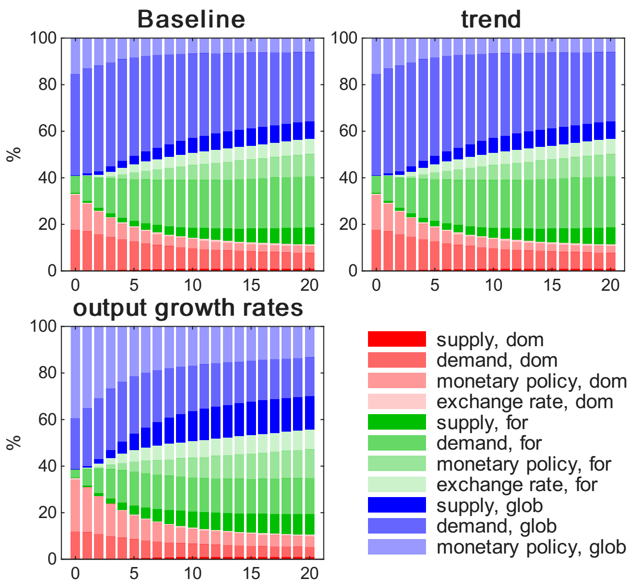
E.3 Alternative model set-ups and samples

Four specifications change the model-set up, shown in Appendix Figure E.4: a model with a deterministic trend, a model with 8 lags, a model with no size-dependent shrinkage (no GDP weight included in the Minnesota prior), and a model with log differences of real GDP instead of output gap. Three additional specifications use shorter samples, shown in Appendix Figure E.5: a model with data starting in 1999:Q1, a model with data ending in 2007:Q2, and a model with data ending in 2007:Q2 that additionally excludes Japan.

E.4 Accounting for financial transmission channels

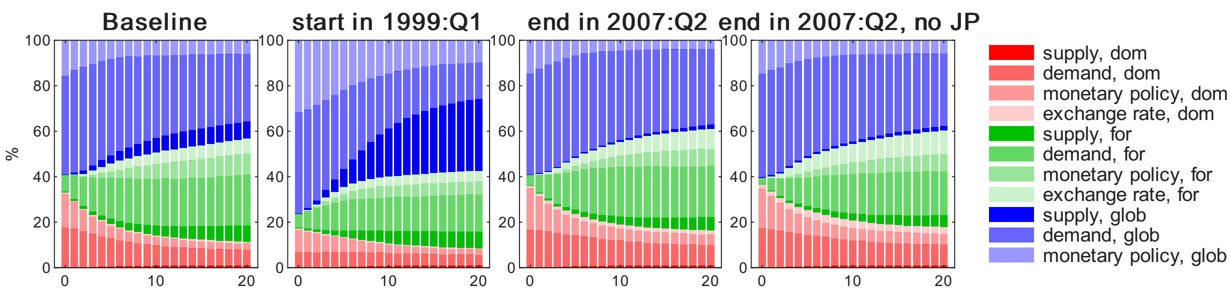
Monetary policy shocks might be transmitted internationally via financial channels, such as the wealth and credit channel (for a description of different financial channels see, for

Figure E.4: Forecast error correlation decomposition between global and country-specific interest rates for alternative model set-ups



NOTES: Figure shows the forecast error correlation decomposition between global and country-specific interest rates for the baseline model (bars) together with a model with a deterministic trend (solid lines), with 8 lags (dashed lines), no size-dependent shrinkage (dotted lines), and with output growth rates (dash-dotted lines).

Figure E.5: Forecast error correlation decomposition between global and country-specific interest rates with alternative samples



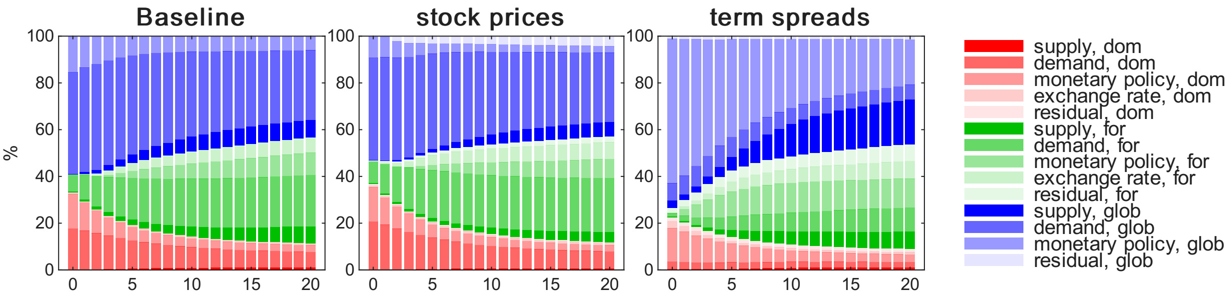
NOTES: Figure shows the forecast error correlation decomposition between global and country-specific interest rates for the baseline model (bars) together with a model with data starting in 1999:Q1 (solid lines), with data ending in 2007:Q2 (dashed lines), and additionally excluding Japan (dotted lines).

example, Bauer and Neely, 2014; Neely, 2015; Fratzscher et al., 2018). The central banks' actions can alter asset prices by stimulating or dampening the demand for assets. Changes in asset prices impact the wealth of households and companies leading to adjusted spending (wealth channel). The monetary authority actions can affect the availability of credit in the market which in turn alters spending and investments (credit channel).

We augment our model by growth in stock prices (wealth channel) or term spreads (credit channel), measured as 5-year yields minus shadow interest rates. We include the additional channel variable (domestic and foreign) contemporaneously in all baseline equations and allow all variables to contribute contemporaneously to the development of the channel variable, with the exception of foreign exchange rates and foreign channel variables. We set Student t priors with mode zero and scale one on the additional contemporaneous parameters. We add prior beliefs that contractionary monetary policy increases domestic interest rates, lowers domestic output gaps and inflation, and decreases competitiveness, by setting asymmetric t distributions with $\mu = 0$, $\sigma = 1$, $v = 3$, and $\lambda = 20$ on the impact effects of monetary policy shocks. We restrict the impact response of the stock prices or term spreads to a domestic monetary policy shock to be negative.

Adding stock prices does not alter the main results substantially, while including term spreads strengthens the importance of global shocks for all countries except Canada, see Appendix Figure E.6.

Figure E.6: Forecast error correlation decomposition between global and country-specific interest rates with additional variables

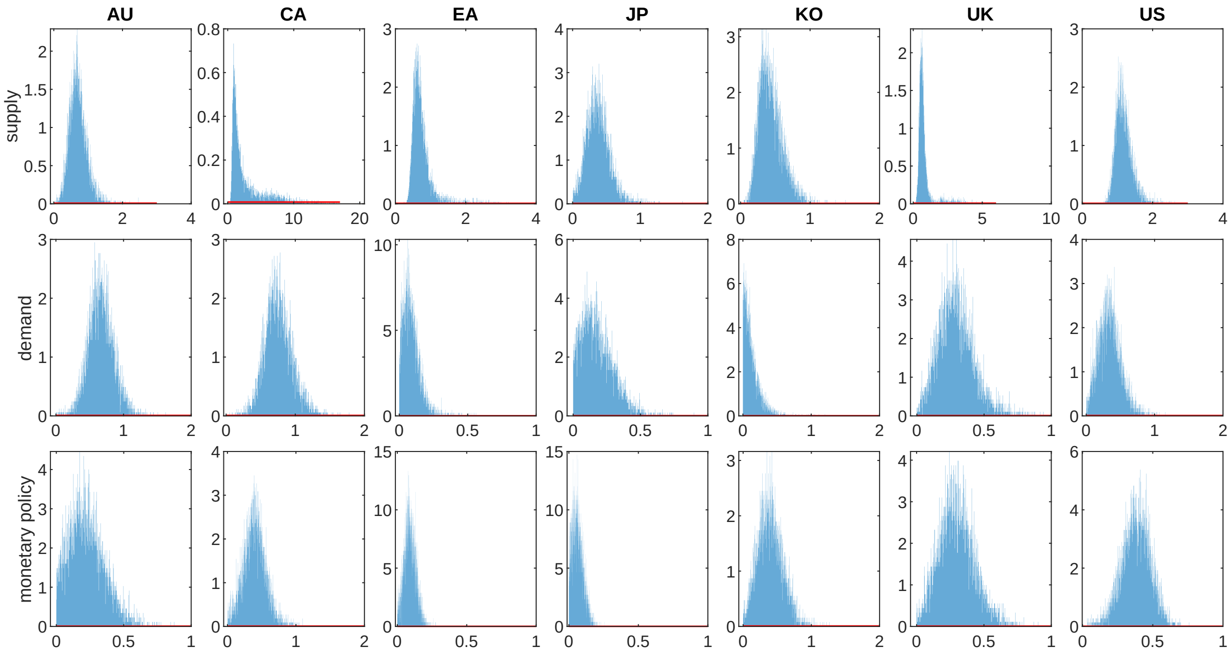


NOTES: Figure shows the forecast error correlation decomposition between global and country-specific interest rates for the baseline model (bars) together with a model including stock prices (solid lines) and a model including term spreads (dotted lines).

E.5 Including the global financial cycle

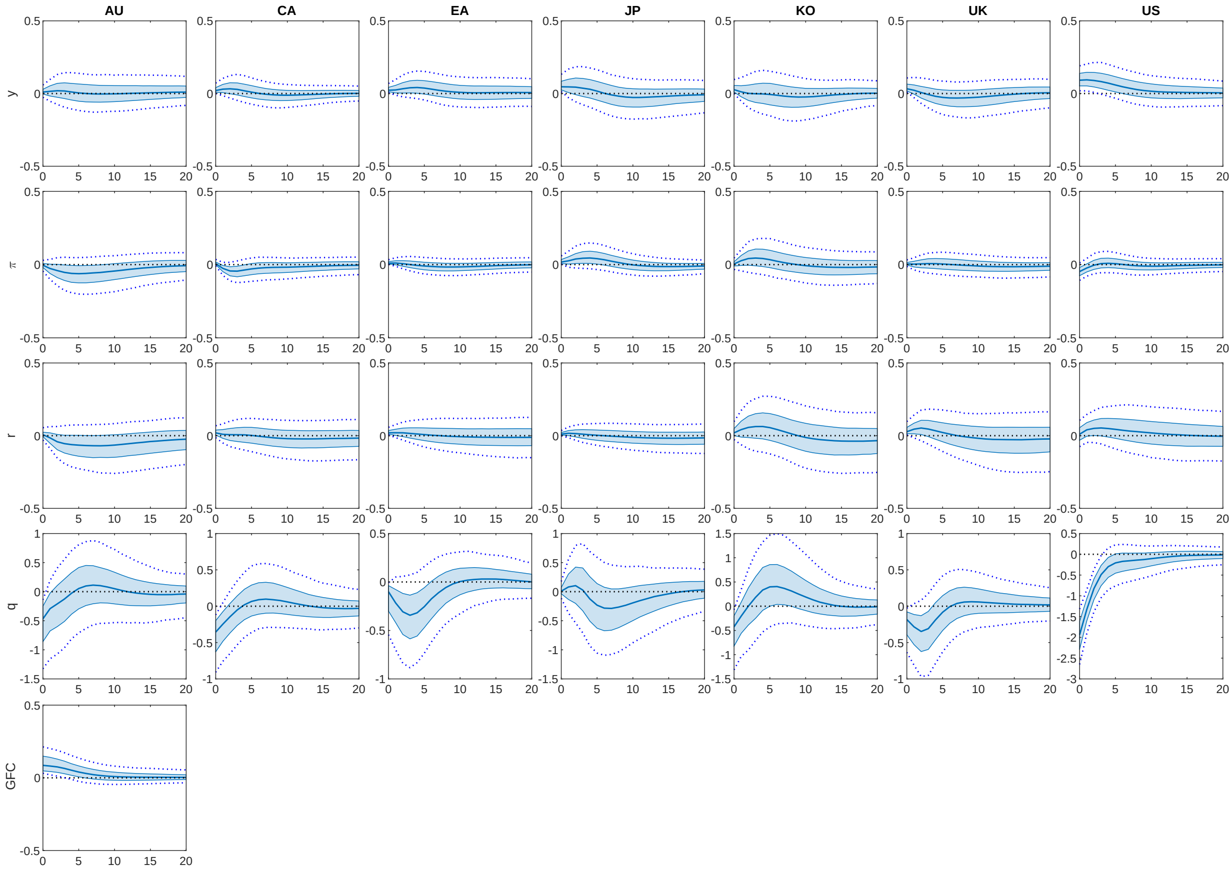
In the specification including the global financial cycle (GFC), the GFC factor enters contemporaneously into all baseline equations, while all variables contemporaneously affect the GFC factor in the new equation. Priors on the additional contemporaneous parameters are wide (Student t priors with mode zero and scale one). We provide additional evidence on the loadings of global shocks in Appendix Figure E.7 and on impulse responses to the residual shock to the GFC.

Figure E.7: Posterior distributions of loadings, model including GFC



NOTES: The histograms show the posterior distribution of global shock loadings from the model including GFC, together with the prior distribution (red line).

Figure E.8: Impulse responses of all variables to the residual shock to the GFC



NOTES: The solid lines in the figure show median impulse responses of all variables (in rows) from all countries (in columns) to a residual shock to the global financial cycle over 20 quarters. The shaded areas (dotted lines) show the 68% (95%) posterior credibility sets. The shocks have size of one unit (i.e., one percentage point).

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