



EUROPEAN CENTRAL BANK

EUROSYSTEM

## Working Paper Series

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**E pluribus plures:  
shock dependency of the USD  
pass-through to real and  
financial variables**

No 2684 / July 2022

## Abstract

This paper quantifies the pass-through of a US dollar appreciation on trade variables and domestic financial conditions in a panel of 34 countries. Pass-through coefficients are highly shock-dependent: if the appreciation is driven by a US expansionary shock, the positive effects of stronger global demand - the “real” channel-dominate the negative effects of a stronger dollar - the “exchange rate” channel. As a result, a positive US demand (supply)-drive appreciation expands global trade and stock valuations up to 2.2 (2.5) and 8% (15%) respectively, while if the appreciation is driven by a monetary policy shock the sign is opposite, leading to a contraction in the order of 2.5% (3%) depending on the country. The coefficients also exhibit a large degree of cross-country heterogeneity, we find that financial and trade exposure to the US, trade openness and USD invoicing shares explain up to 60% of the USD pass-through after demand and supply shocks. Cross-country differences, instead, are not explained by dollar invoicing if monetary policy or risk shocks determine USD movements. We explain this finding with the endogenous policy reaction of monetary authorities in emerging markets that stabilizes the exchange rate against the dollar and weakens the invoicing channel of dollar shocks.

Keywords: Exchange rate, USD, pass-through, VAR

JEL Codes: F31; F41; F44; E44; E32.

## Non-technical summary

About 40% of global trade is invoiced in US dollar (USD), despite the United State accounts for only 10% of global imports and exports (Boz et al. (2020b)). The dollar has also a unique role in the international monetary system as main reserve and funding currency, ECB (2021) and CGFS (2020). Because of its extensive use in international trade and finance, fluctuations in the value of the dollar generate sizeable foreign spillovers, much stronger than those implied by an appreciation of the euro (the second most widely used currency in global invoicing) or the yen.

The existing literature has quantifies the impact of a dollar appreciation using so-called reduced-form regressions. With this method only the *average* elasticity of the variable of interest to changes in the value of the dollar can be computed. However, the reason why the dollar appreciates, in other terms the original shock that has moved the USD, might also matter for the strength of pass-through. Consider, for example, an appreciation of the dollar induced by stronger US demand. In that case there are at least two, opposite, effects: on one hand, because of global USD invoicing, global trade should contract, as a dollar appreciation mechanically increases the price of goods invoiced in dollars, reducing demand. However, there is another important factor that need to be accounted for when estimating the *net effect* of the appreciation. More demand in the US, in fact, would increase global trade and, as a consequence, trade volumes. The *net effect* of the appreciation would then depend on the *relative elasticity* of trade volumes to the exchange rate and to US demand. A similar reasoning can be applied to the effect of an appreciation of the dollar induced by a monetary policy shock. In this case, the dollar appreciates but the shock induces a contraction in US GDP, reducing further global demand and hence trade volumes. These rich dynamics are unlikely to be captured by reduced-form models, as estimated elasticity would depend on which shock dominates the empirical sample considered.

In this paper we try to account for the different effects of the different shocks that lead to a dollar appreciation. We find that after real shock, i.e. demand and supply shocks

in the US, the pass-through is positive, suggesting that the benefits of more US demand compensate a stronger dollar. The opposite is true for financial shocks. In this case the dollar appreciates but the US economy contracts leading to a reduction in global trade. We also highlight the existence of a large cross-country heterogeneity in the responses to a dollar appreciation. These differences can be explained by structural factors. For example, after real shocks up to 60% of cross country differences is explained by financial and trade exposure to the US, trade openness and USD invoicing shares. This finding is in line with the so-called dominant currency paradigm postulating that because the US dollar is used as global invoicing currency, global trade reacts strongly to dollar movements. Invoicing shares, however, do not explain cross-country differences after financial shocks. We explain this finding with the endogenous policy reaction of monetary authorities in some countries in our sample, mostly emerging market economies (EMEs). Consider a US monetary policy shock, when US rates increase, monetary authorities in EMEs have to increase rates as well to avoid strong capital outflows and an exchange rate depreciation. If that happens, contrary to advanced economy that keep free-floating exchange rates, the domestic exchange rate remains stable against the US dollar mitigating the role of USD invoicing.

These results have deep implications for monetary policy because they show that the reactions to a dollar appreciation crucially depend on the underlying shock and, as such, also the domestic policy response should adapt.

# 1 Introduction

About 40% of global trade is invoiced in US dollar, despite the United State accounts for only 10% of global imports and exports (Boz et al. (2020b)). The dollar has also a unique role in the international monetary system as main reserve and funding currency, ECB (2021) and CGFS (2020). Because of its extensive use in international trade and finance, fluctuations in the value of the dollar generate sizeable foreign spillovers, much stronger than those implied by an appreciation of the euro (the second most widely used currency in global invoicing) or the yen.

Using custom-level data, for example, Boz et al. (2020a) estimate, that a 1% US dollar appreciation leads to a 0.6% contraction in trade volumes. This elasticity is computed by means of unconditional regressions of annual changes in trade volumes on changes in the dollar exchange rate. However, much similarly to the price pass-through literature, see Forbes et al. (2018), the source of the shock might also matter for the strength of the pass-through to trade. Consider, for example, an appreciation of the dollar induced by stronger US demand. In that case there are at least two, opposite, effects: on one hand, because of global USD invoicing, global trade should contract, as a dollar appreciations mechanically increases the price of goods invoiced in dollars, reducing demand. However, there is another important factor that need to be accounted for when estimating the *net effect* of the appreciation. More demand in the US, in fact, would increase global demand and trade volumes. The *net effect* of the appreciation would then depend on the *relative elasticity* of trade volumes to the exchange rate and to US demand. A similar reasoning can be applied to an appreciation of the dollar following a monetary policy shock. In this case, the dollar appreciates but the shock induces a contraction in US GDP, reducing further global demand and hence trade volumes. These rich dynamics are unlikely to be captured by reduced-form models, as estimated elasticity would depend on the relative importance of the different shocks in the sample considered.

In this paper we therefore estimate the *conditional* pass-through of USD appreciations. Specifically we compute the country-specific and shock-dependent pass-through of a US

dollar appreciation to trade volumes and financial variables in 34 countries. We identify four main US macro shocks: demand, supply, monetary policy and risk. The magnitude of the pass-through crucially depends on the underlying shock. When the dollar appreciates after a demand or supply shock, which has positive effects on US real activity, trade volumes increase despite a stronger US dollar. This suggests that the elasticity of trade to global demand is stronger than the elasticity to the dollar exchange rate. Conversely, if the appreciation is driven by a monetary policy or risk shock global trade tends to contract. Similar results hold when considering financial variables. Our results show also large cross-country heterogeneity in the magnitude of the pass-through. This might be the result of different country-specific exposure to global demand, US dollar funding or global financial conditions. To explain this cross-section heterogeneity, we conjecture that if one channel is indeed relevant for the transmission of a USD appreciation, then higher pass-through coefficients should correlate with country-specific observables that measure, for example, the exposure to trade or financial conditions. We test three of these possible channels considering whether higher pass-through is associated to: i) international trade linkages; ii) financial conditions; iii) trade invoicing. Overall, financial and trade exposure to the US and trade openness are a strong predictor of the heterogeneity in pass-through coefficients, explaining 30 to 60% of cross-country heterogeneity. USD invoicing shares instead are a strong predictor of demand- and supply-driven pass-through coefficients but not of the financial shocks' pass-through. This result can be explained by the policy reaction of some economies, typically small open economies or emerging markets, to US shocks. If the shock is expected to generate large capital outflows, monetary authorities might intervene to stabilize the domestic currency against the dollar and limit outflows. When that happens, the invoicing channel of dollar pass-through is muted, because monetary policy prevents a depreciation against the dollar. For this reason, invoicing shares do not explain cross-country differences after financial shocks in our sample. We verify this hypothesis using the [Boz et al. \(2020a\)](#) dominant currency model and empirical estimates from our dataset.

Operationally we rely on a two-step econometric approach. First, we identify US

shocks by means of a standard Bayesian VAR model. Similarly to [Dedola et al. \(2017\)](#), we then use the posterior distribution of these shocks to compute country-specific exchange rate pass-through coefficients using country specific VARs where US shocks enter as exogenous variables. This approach is equivalent to using country-specific local projections, with the advantage of avoiding the small sample bias of local projections identified in [Herbst and Johansson \(2020\)](#). To understand the potential drivers of US pass-through we then regress pass-through coefficients on potential determinants to test assumptions i)-iii). Because the dependent variable of this regression is generated, estimated standard errors are biased upwards, implying that our results might underestimate, if anything, the statistical significance of reduced-form regression coefficients, see [Feenstra and Hanson \(1999\)](#).

The question of how prices react to exchange rate movements is as old as international economics, [Dornbusch \(1987\)](#), with several paper highlighting the heterogeneity of exchange rate pass-through between advanced and emerging market economies, see [Campa and Goldberg \(2005\)](#), [Ca' Zorzi et al. \(2007\)](#) and [Bussière et al. \(2014\)](#). These differences might be due to trade openness, [Romer \(1993\)](#), domestic inflation and volatility, [Taylor \(2000\)](#) and [Devereux and Engel \(2001\)](#), import shares, [Casas \(2020\)](#), or monetary policy strategies, [Obstfeld \(2002\)](#). More recently the literature has begun to analyze the implications for exchange rate pass-through of the so called dominant currency paradigm, i.e. trade invoicing using neither the currency of the exporter or the importer, [Gopinath et al. \(2010\)](#). In this framework, the US dollar is largely the most important dominant-or vehicle- currency in international trade being used in over 40% of transaction despite the US accounts only for 10% of global trade, [Boz et al. \(2020b\)](#). Using micro-data [Boz et al. \(2020a\)](#) estimate that, because of the dominant role of the dollar, a 1% dollar appreciation contracts trade by 0.6%. The importance of dollar shocks appear also to have increased after the global financial crisis period, see [Erik et al. \(2020\)](#). In this regard, [Boz et al. \(2019\)](#) has argued that cross-country heterogeneity in USD pass-through can be explained by the dollar's dominance as invoicing currency.

The degree of pass-through is also dependent on the originating shock. [Forbes et al.](#)

(2018) and [Forbes et al. \(2017\)](#) are the first to document that the degree of exchange rate pass-through to prices changes depending on the underlying shock, while [Corbo and Di Casola \(2021\)](#) document the same dynamics for small open economies. [García-Cicco and García-Schmidt \(2020\)](#) provide a formal proof of these results using a theoretical macro model. In a nutshell, an appreciation of the currency used in trade invoicing tends to mechanically increase CPI, through higher import prices. However, if the exchange rate appreciates because of a shock that contracts real activity, for example a monetary policy shock, the net effect might be lower or even of opposite size, than what implied by simple arithmetic. For this reason, when the shock is accounted for, exchange rate pass-through estimates tend to differ significantly from reduced form models. Our paper fits at the crossroad of these three strands of the literature. We focus on the implications of a dollar appreciation for global trade and financial variable investigating its the cross-country heterogeneity and shock dependence. We do that by borrowing analytical tools from the spillover literature. As in [Georgiadis \(2016\)](#), [Dedola et al. \(2017\)](#) and [Iacoviello and Navarro \(2019\)](#) we use a two-step approach by first identifying US shocks and then estimating exchange rate pass-through coefficients based on such shocks; [Paul \(2020\)](#) and [Plagborg-Møller and Wolf \(2021\)](#) show analytically and numerically that this approach leads to consistent impulse response estimates.

The remaining of the paper is organized as follows: [Section 2](#) presents the data and shows how reduced-form regressions replicate the main results by [Boz et al. \(2020a\)](#); [Section 3](#) presents our methodology and main findings; specifically [Section 3.1](#) identifies US shocks, [Section 3.2](#) estimates conditional exchange rate pass-through coefficients, [Section 3.3](#) reports the domestic reaction to US shocks and [Section 3.4](#) investigates potential drivers. Finally, [Section 4](#) gives our conclusions.

## 2 Data

We construct a core database of macro variables at quarterly frequency including import and export volumes, real GDP, CPI, exchange rates, equity prices, 2- and 10-year yields

for 34 advanced and emerging market economies<sup>1</sup> and four global aggregates (world, euro area, advanced economies and emerging markets).<sup>2</sup> Import and export volumes are extracted from the CPB World Trade Monitor. Exchange rates are nominal effective exchange rates taken from the BIS while we use national sources for stock market indices. All variables are at quarterly frequency, the sample for US variables starts in 1995Q1 while trade and financial variables cover the period 2000Q1-2020Q2;<sup>3</sup> all macro variables are seasonally adjusted. [Table 2](#) and [Table A.1](#) show summary statistics for US and country-specific variables respectively. Notably data for South Africa suffer from reporting issues, therefore, despite including the country in the analysis, we consider those results with caution.<sup>4</sup> As reported in [Table A.2](#) yield data are not consistently available for all countries. This implies that when yields are included in the analysis, the estimation sample would change depending on the country considered; for this reason we decide to run a separate VAR for financial variables, to exploit a longer, and consistent, time horizon to derive the pass-through of a dollar appreciation to real trade.

The core database of macro-financial time series is complemented by data on the possible determinants of the drivers of the dollar pass-through to real financial variables: the 10-year yield spread against the US, foreign currency reserves and the US dollar invoicing shares from [Boz et al. \(2020b\)](#).

## 2.1 Reduced form estimates

As preliminary investigation, we replicate the reduced-form USD exchange rate pass-through by [Casas et al. \(2017\)](#) and [Boz et al. \(2020a\)](#) using aggregate data. We estimate

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<sup>1</sup>We include: Canada, China, France, Germany, Italy, Japan, the UK, the US, Austria, Belgium, Denmark, Finland, Greece, Ireland, Netherlands, Norway, Sweden, Switzerland, Portugal, Spain, Argentina, Australia, Brazil, Chile, Colombia, Israel, Mexico, New Zealand, Peru, South Africa, Turkey, Bulgaria, Czech Republic, Hungary, India, Indonesia, South Korea, Malaysia, Philippines, Poland, Russia, Thailand, Vietnam.

<sup>2</sup>Aggregates are constructed as the real-GDP weighted average of single countries.

<sup>3</sup>Therefore, the first-stage var covers the period 1995-2020 while the second-stage VAR the period 2000-2020.

<sup>4</sup>All VARs in our setup are independent, hence there is no cross-country contamination; we also exclude South Africa from the panel regressions reported later.

the following regression, separately for each country:

$$\Delta x_t = \alpha + \beta \Delta e_t + \sum_{i=1}^N X_{t-i} \Gamma + \varepsilon_t \quad (2.1)$$

where  $\Delta x_t$  is the one-year change in the variable of interest (i.e. import and export volumes),  $\Delta e_t$  the one-year change in the USD nominal effective exchange rate and  $X_{t-i}$  a set of control variables to capture the economic cycle.<sup>5</sup>

Figure 1 and Figure 2 report the estimated coefficients from Equation (2.1). Notably, the pass-through for a 1% US dollar appreciation to world export volume is 0.5%, which is similar to the 0.6% estimate by Boz et al. (2020a) based on a panel regression and custom-level data. In our sample, on average, the USD pass-through is stronger in emerging markets compared to advance economies, with the notable exception of Mexico which shares stronger linkages with the US. Our results suggest a large degree of cross country heterogeneity that might be explained by country-specific characteristics. If the exchange rate pass-through is also shock dependent, the sensitivity or exposure of each country to US shocks might also explain those differences. In the next section we investigate the shock-dependency of USD pass-through coefficients as implied by the analytical results of García-Cicco and García-Schmidt (2020).

### 3 Methodology

To investigate the *conditional* pass-through of a USD appreciation, we use a two-step approach. First we identify four key US shocks: demand, supply, monetary policy and risk through a standard Bayesian VAR model. We then use the identified shocks to compute the impulse responses of the US dollar and of the variable of interest. This approach is similar in spirit to other empirical models where shocks are identified in a first-stage and then used to compute spillover effects, for example Georgiadis (2016), Dedola et al. (2017), Iacoviello and Navarro (2019) and Ioannou et al. (2020). The conditional pass-through at horizon  $T$  is the ratio between the accumulated response of

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<sup>5</sup>Similarly to Boz et al. (2020a) we include 4 lags of global real GDP growth to control for the global business cycle.

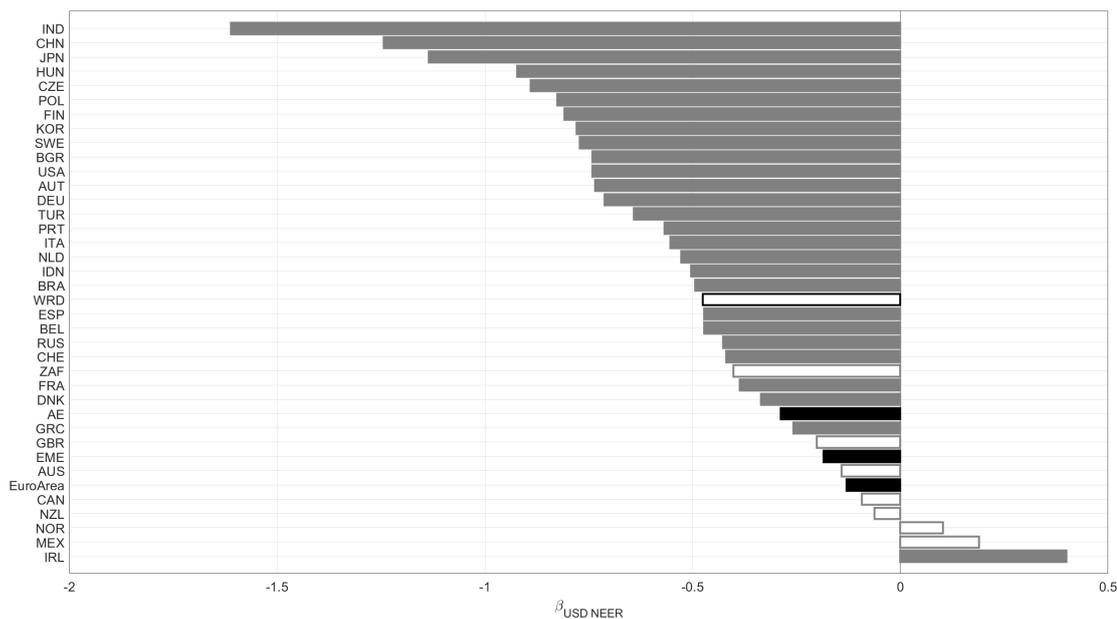


Figure 1: Country-specific estimates of the pass-through to export volumes from equation Equation (2.1).

**Notes:** pass-through coefficients are estimated separately for each country. Empty bars denote coefficients that are not significant at the 68% confidence interval. Black bars represent regional aggregates.

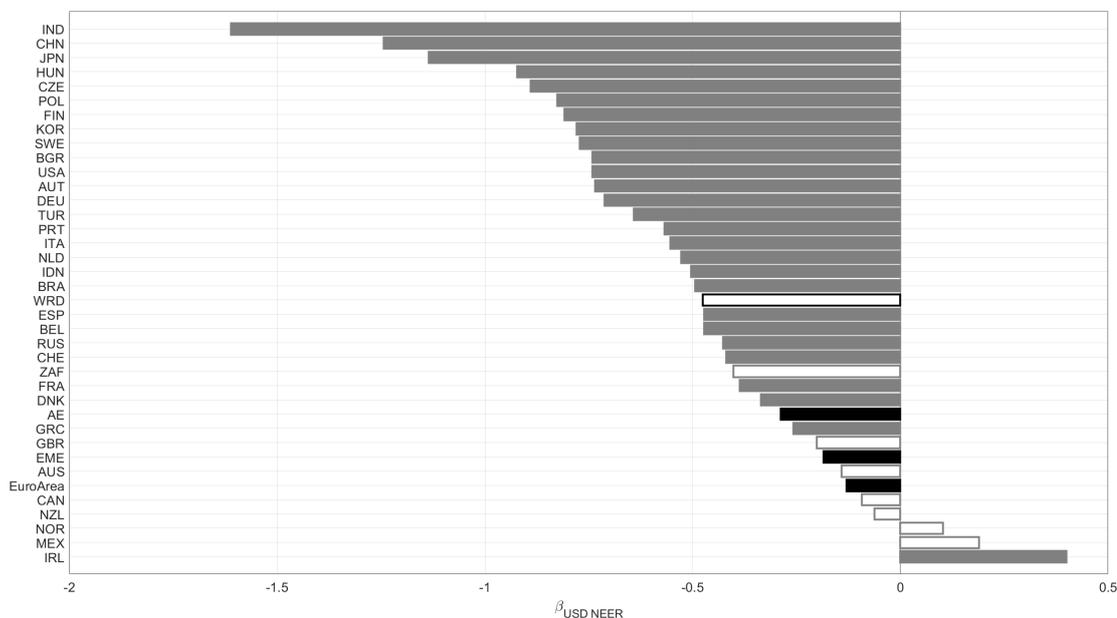


Figure 2: Country-specific estimates of the pass-through to import volumes from equation Equation (2.1).

**Notes:** pass-through coefficients are estimated separately for each country. Empty bars denote coefficients that are not significant at the 68% confidence interval. Black bars represent regional aggregates.

the variable of interest and of the US dollar. This is a standard metric used, between others, by [Forbes et al. \(2018\)](#) and [García-Cicco and García-Schmidt \(2020\)](#). It is also known as the “dynamic multiplier” and is formally defined as:

$$\Phi_{y,z}(K) = \left[ \frac{\sum_{k=0}^K \frac{\partial y_{t+k}}{\partial \epsilon_t^x}}{\sum_{k=0}^K \frac{\partial z_{t+k}}{\partial \epsilon_t^x}} \right] \quad (3.1)$$

where  $\Phi_{y,z}(K)$  is the pass-through of variable  $z$  to variable  $y$ , at horizon  $K$  conditional on the shock  $\epsilon^x$ . Dynamic multipliers are also convenient in practice because they do not require any standard definition for the underlying shocks. The elasticity, in fact, is independent on whether shocks have positive or negative impact on  $z$  because  $y$  should also switch sign accordingly. Practically, there are different empirical methods that could be used to derive the impulse responses needed to evaluate [Equation \(3.1\)](#). If identified time series of shocks are available, the simplest approach is to estimate a VAR-X for each country where the USD NEER is include as endogenous variable and the shocks as exogenous. Notably, there is no need to impose any identification on the residuals of this second-stage VAR, as the only relevant responses are those to the exogenous variables in the system (i.e. first-stage structural shocks). The second-stage VAR, in other terms, is simply used as a statistical device to compute the dynamic response of the variables considered. This is preferable to including directly more country-specific variables in the first-stage VAR for several reasons. First, Monte-Carlo analysis suggests that spillover estimates from two-country BVAR might suffer from significant biases, see [Georgiadis \(2015\)](#). Second, the reaction to the same US shock might differ significantly between countries. Consider, for example, the euro area and an emerging market: the same US shock might trigger capital inflows in the first and outflows in the latter. As a result, the estimated model’s parameters (and with the underlying structural shocks) will likely be completely different resulting in more difficult comparison of pass-through coefficients across countries. In our framework, instead, all countries react to the exact same US shock and difference across them arise only from country-specific reactions (which are captured by the estimated coefficients in the second-stage VAR). Finally, including more

variables in the first-stage VAR would also require to impose more identifying restrictions, including to US shocks.<sup>6</sup> Our framework, instead, is more data-driven as we do not impose assumptions on the reaction of country-specific variables to shocks originating in the US. An alternative approach would be to use local projection methods. Local projections have become increasingly popular in the economic literature to conduct spillover analysis as they are flexible and require very few identification assumptions. However, recent evidences, see [Herbst and Johannsen \(2020\)](#), suggest that local projections are biased in empirical small samples, with the bias leading to an over-estimation of the actual response. Considering the time span of our data, which corresponds to about 80 observations, Monte Carlo results show that the bias could be sizeable and, hence, the two-stage approach appears to be preferable. We estimate one second-stage VAR for each country and evaluate [Equation \(3.1\)](#) for 1- to 4-quarter ahead pass-through.

Because the four US shocks are estimated variables, standard errors from the second stage could potentially be biased.<sup>7</sup> For this reason, we computed confidence intervals using a bootstrapping procedure based on 1000 draws from the posterior distribution of shocks in [Equation \(3.2\)](#).<sup>8</sup>

### 3.1 Identifying US shocks

US shocks are identified by means of a Bayesian VAR with 4 macro US variables: (log) real GDP, (log) CPI, the 10-year yield and the (log) US dollar nominal effective exchange rate. Variables enter the model in first differences. The reduced-form representation is:

$$Y_t = A_0 + \sum_{i=1}^N A_i Y_{t-1} + B\mathcal{E}_t \quad (3.2)$$

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<sup>6</sup>[Wolf \(2020\)](#) indeed shows that the response to shocks might be driven by specific assumptions on the sign restrictions; therefore it is advisable to avoid ad-hoc choices for the impact matrix that are not common in the literature.

<sup>7</sup>In other terms, this is a generated regressors problem, see [Murphy and Topel \(2002\)](#) and [Hardin \(2002\)](#).

<sup>8</sup>The algorithm involves four steps: 1. draw N times the vector of shocks from the posterior of [Equation \(3.2\)](#); 2. for each draw estimate the second stage model and collect the impulse response functions; 3. on each of the N sets of impulse responses compute the dynamic multipliers; 4. compute the percentiles of the distribution of dynamic multipliers for each shock. In this we adapt the procedure of [Swanson \(2020\)](#).

where  $N = 4$ ,  $A_i$  are coefficient matrices on lagged endogenous variables and  $\mathcal{E}_t$  the reduced-form residuals. Shocks are identified by sign restrictions: a negative demand shock contracts real activity and CPI, reduces 10-year yields and leads to a depreciation of the dollar; a positive monetary policy shock entails negative real GDP and CPI growth while appreciates the USD and increases interest rates; a negative risk shock also reduces real GDP but triggers safe haven flows to the US leading to an appreciation of the US currency and a reduction of yields; a supply shock increases prices and yields while contracts real activity. This identification scheme is not new in the macro literature and follows, between others, [Farrant and Peersman \(2006\)](#), [Forbes et al. \(2017\)](#) and [Hristov et al. \(2020\)](#). All restrictions are also reported in [Table 1](#) and shocks are defined as contractionary.

Table 1: Sign restriction table

	US Demand shock	US Monetary policy shock	Risk shock	US supply shock
Real GDP	-	-	-	-
10-year yield	-	+	-	+
USD NEER	-	+	+	
CPI	-	-	-	+

**Notes:** “+” indicates a positive response of the variable to the shock on impact; “-” a negative response and empty cells indicate unrestricted responses.

Impulse responses for a 1 standard deviation shock are reported in [Figure 3](#). Results are in line with standard macro literature results. Notably a negative demand shock entails a persistent depreciation, up to two years, and a somewhat more short-lived contraction of real GDP growth, inflation and interest rates. A monetary policy shock appreciates the dollar and increases yields while reducing prices and output. A risk shock is equally contractionary but leads to an appreciation of the exchange rate and a reduction in long-term yields due to safe haven flows to the US. Movements in the dollar and the 10-year yield are relatively persistent with the model converging back to the equilibrium after about two years. Because output contracts, also prices decline. Finally a supply shock leads to an increase in prices but a contraction of output. Interest rates rise as well while the exchange rate depreciates, although the reaction of the US dollar is characterized by high uncertainty. It is also important to notice that a dollar appreciation driven

by demand or supply shocks is expansionary for the US economy leading to positive real spillover to the rest of the world. The opposite, instead, is true for monetary policy and risk shocks. Turning to the historical decomposition, reported in [Figure 4](#) for the USD nominal effective exchange rate and [Appendix B.1](#) for the other variables, on average the four shocks explain 86% of the volatility of the USD NEER with the largest contributors being risk and monetary policy (28 and 27% respectively) followed by demand (19%) and supply (12%). To put these numbers into prospective, the model identifies at the peak of the global financial crisis negative demand, monetary policy, risk and supply shocks equal to 1.3, 4.5, 1.4 and 4.2 standard deviations respectively. In Q2 2020, the same figures are 3.9, 2.8, 3.0 and 2.2. In other words, the model reads the global financial crisis as mainly driven by tighten domestic financial conditions in the US and a fall in aggregate supply while the COVID-19 pandemic appears to be mostly driven by changes in aggregate demand and only to a lesser extent by supply. The time series for identified shocks are plotted in [Figure B.1](#). Estimated structural shocks are uncorrelated, see [Table 3](#), which allows to include them contemporaneously in a regression framework. [Table 2](#) reports summary statistics for US variables and the estimated structural shocks of the US model.

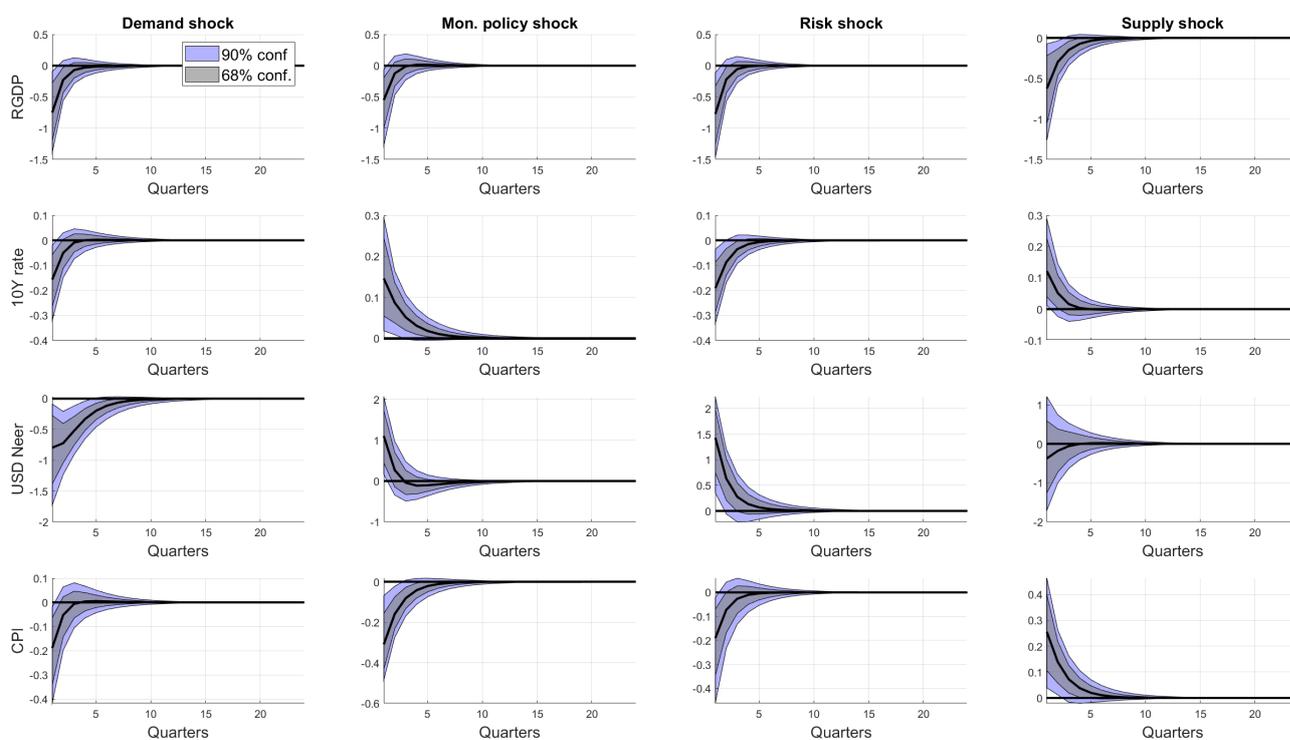


Figure 3: Impulse responses (in percent) of the VAR described by [Equation \(3.2\)](#). US shocks are defined as contractionary.

Table 2: Description of US variables and structural shocks

	QoQ RGDP	QoQ 10-year	QoQ USD	QoQ CPI
Mean	0.55	-0.05	0.29	-0.01
Std	1.36	0.35	2.45	0.52
	Demand	Mon. policy	Risk	Supply
Mean	0.00	0.00	0.00	0.00
Std	1.18	1.14	1.15	1.19

**Notes:** US variables are expressed in percent quarter on quarter changes. Structural shocks are the median identified shocks.

Table 3: Correlation across structural shocks

	Demand shock	Mon. policy shock	Supply shock	Risk shock
Demand shock	1.000	0.007 (0.782)	-0.132 (0.217)	-0.0165 (0.736)
Mon. policy shock		1.000	-0.007 (0.508)	-0.017 (0.738)
Supply shock			1.000	-0.046 (0.641)
Risk shock				1.000

**Notes:** correlation between median structural shocks. P-values for the null-hypothesis of  $\neq 0$  correlation are reported in parenthesis below correlation coefficients.

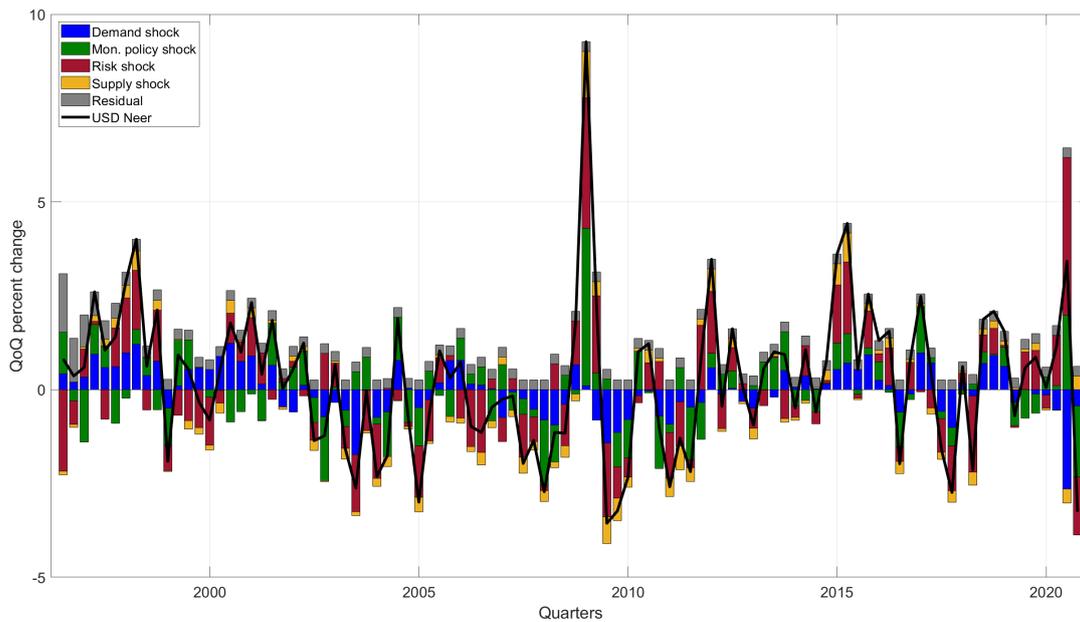


Figure 4: Historical decomposition of the US dollar nominal effective exchange rate.

## 3.2 Conditional exchange rate pass-through

We compute the *conditional* exchange rate pass-through estimating a set of country specific VARs where the identified shocks from Equation (3.2) enter as exogenous variables. More formally we estimate:<sup>9</sup>

$$Y_t = A_0 + \sum_{i=1}^N A_i Y_{t-1} + C S_t + B \mathcal{E}_t \quad (3.3)$$

where  $Y$  is a vector of endogenous variables and  $S_t$  a matrix containing the four *identified* structural shocks from Equation (3.2).<sup>10</sup> For each country a *real* model, whereby  $Y = [\text{Export volumes}', \text{Import volumes}', \text{USD NEER}', \text{Domestic NEER}', \text{RGDP}']$ <sup>11</sup>, and a *financial* model, whereby  $Y = [\text{Stock index}', \text{10y}', \text{USD NEER}', \text{Domestic NEER}', \text{RGDP}']$  are estimated; all variables are expressed in log-differences except 10-year yields (10y) which enter as simple first differences.<sup>12</sup> The exchange rate pass-through is computed as the ratio between the response of the variable of interest relative to the response of the USD NEER (for the same shock) as in Forbes et al. (2018). Confidence intervals are bootstrapped using using 1000 draws from the posterior estimate of Equation (3.2). One-year pass-through coefficients are reported in Figures (8) to (11). Country-specific IRFs are reported in the Appendix B.3. Second-stage impulse responses show that the four US shocks, which are defined as contractionary, always entail negative spillovers to trade volumes in the sample of 38 economies, with the exception of some small European countries (Austria, Greece and Norway and Sweden) and few emerging market economies (South Africa, Turkey, India) for which real trade expands following a contractionary

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<sup>9</sup>Notice that in this case there is no need for identifying assumptions on reduce-form residuals of the VAR as the only impulse responses of interest are those to the (already) identified US shocks. Standard estimation methods allow to consistently estimate the parameters of  $A_0$ ,  $C$  and  $A_i$  of this second-stage VAR.

<sup>10</sup>Notice that the four shocks in  $S$  do not account for all the volatility of the USD nominal effective exchange rate in Equation (3.3) because i) the set of endogenous variables and the VAR estimated parameters in Equation (3.3) are different from those in Equation (3.2) and ii) there is a residual component in the first-stage VAR that the four shocks do not explain.

<sup>11</sup>With the exclusion of Russia and China for which real GDP growth data are collinear with real exports and imports and thus excluded from the VAR and the US for which the nominal effective exchange rate is included only once.

<sup>12</sup>Yield time series are not available for all country over the same time period. For this reason it is preferable to estimate two VARs to have an homogeneous sample for export and import volumes.

supply shock in the US, most likely because of trade diversion. Notably, estimates for South Africa are to be taken with extreme caution because of the large volatility in the underlying real import and export series, see [Table A.1](#), most likely reflecting reporting errors. Supply and demand shocks generally lead to an appreciation of domestic exchange rates in nominal effective terms because the US dollar weakens. Risk and monetary policy shocks, on the contrary, depreciate domestic currencies only in some countries, while in others the domestic nominal exchange rate appreciates. Difference can be due to domestic policies or to higher domestic yields. Because all US shocks are defined as contractionary, spillovers to real GDP and equity prices are also negative. Finally, international long-term yields tend to move in synchrony with the US, in line with the evidence of the global financial cycle literature, see [Miranda-Agrippino and Rey \(2020\)](#) and [Habib and Venditti \(2019\)](#).<sup>13</sup>

To analyze the US dollar pass-through we compute the dynamic multipliers of real exports and imports, equity prices and 10-year yields for each country. Results are scaled to show the pass-through, in percentage points, of a 1% dollar appreciation. Consider first the one-year pass-through to trade variables, [Figure 8](#) and [Figure 9](#). Shock-specific estimates are significantly different from the unconditional coefficients from [Equation \(2.1\)](#), reported as dots in the chart, in line with the literature on conditional inflation pass-through. There is a substantial heterogeneity across countries with the difference between *conditional* and *unconditional* estimates being more marked for emerging markets than for advanced economies. A demand (supply) driven appreciation of the dollar increases real exports by a maximum of about 2.3% (2.5%). Almost all countries experience an expansion of real exports following a demand-driven appreciation with the exception of Poland, Japan, Norway and India, for which the estimated pass-through is not statistically different from zero, and Indonesia which records a contraction of exports by about 1.2%. An appreciation driven by a supply shock, instead, has no statistically significant impact on exports from the World aggregate, Advanced Economies, Norway, Greece, Spain, Sweden,

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<sup>13</sup>Notably, for some countries, estimated impulse responses for the financial model are significantly less smooth, because of the more limited sample size available. Because of large movements in domestic yields the financial model for Turkey is non-stationary and results are not reported.

Poland, Austria, South Africa, Indonesia, Korea and Japan while real exports contract in Turkey and India by between 1.0 and 1.2%. Not all these coefficients are, however, statistically significant. The responses of real imports follow a similar pattern being positive, up to 2.5% for demand and supply-driven appreciations, with a larger share of countries however recording non-significant responses and 9 of them (Poland, Greece, Indonesia, Japan, India, Turkey, and the AE, EME and world aggregates) turning to negative territory up to -4% (India and Indonesia). There are two forces that drive the response of real trade to a dollar appreciation. On one hand there is a direct “exchange rate” channel by which a stronger USD makes trade in goods more expensive. This is not only due to the use of the dollar as invoicing currency in trade, but also to the impact of a stronger dollar on the cost of trade finance, see [Boissay et al. \(2020\)](#) and [Gopinath and Stein \(2021\)](#). On the other hand, if the appreciation of the dollar is driven by an expansionary shock, as in the case of demand and supply shocks, the positive spillovers from the US to the world economy may compensate those costs leading to an expansion of trade volumes; we refer to this as the “real” channel. Our results suggest that the latter channel dominates in most economies so that, when the dollar appreciates following an expansionary real US shock, trade volumes increase despite the stronger dollar. Turning to financial shocks (monetary policy and risk), excluding New Zealand, Ireland, Turkey, Mexico and Norway<sup>14</sup>, an appreciation of the USD contracts global exports by 0.1 to 2.1%. Results are similar, despite somewhat larger in magnitude (up to -2.7%) and all negative when considering import volumes. Also in this case, conditional pass-through coefficients are largely different from unconditional estimates. However, both monetary policy and risk shocks appreciate the dollar while leading to a contraction of real activity. In other terms the “real” and the “exchange rate” channel work in the same direction and reinforce each other leading to a stronger contraction in trade relative to what suggested by reduced form estimates. Simple regression results, in fact, average across different underlying shocks, reflecting their historical patterns. Looking at other horizons, the pass-through appears to be stronger on impact, with coefficient going above 5% for real shocks and

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<sup>14</sup>Not all these coefficients, however, are statistically significant.

below -3% for financial shocks. These larger impacts die out over time as reported in [Figure B.14](#) and [Figure B.15](#).

Turning to financial variables, at one-year horizon the effects of a dollar appreciation are more homogeneous across countries. A stronger US dollar leads to a limited pass-through to long-term yields in the order, on average, of 10 to 30 basis points, see [Figure 10](#), with Greece being an outlier most likely because of the inclusion of the European sovereign debt crisis in the sample. The pass-through is positive for demand shocks, in line with a dominance of the “real” channel, while it is negative for risk and supply shocks, suggesting that in this cases the “exchange rate” channel dominates. After a monetary policy shock, finally, long term yields tend to increase. This evidence is likely mostly driven by the global reach of US monetary policy, see [Miranda-Agrippino and Rey \(2020\)](#), [Obstfeld \(2020\)](#) and [Ca’Zorzi et al. \(2021\)](#).

Demand- and supply-driven dollar appreciations have positive spillovers to equity prices, from 15 to 0.5%, with larger and more uncertain exchange rate pass-through estimated for countries with more limited data coverage, see [Figure 11](#). Monetary policy and risk shocks, instead, entail in general a negative pass-through to equity prices between -0.2 and -5% with larger point estimates associated to countries with more limited data coverage, for example Turkey. Also in this case, the “real” and “exchange rate” channel push in the opposite directions. When the global economy booms firms have higher expected profits and a lower cost of credit; as a result, equity prices rise despite the stronger dollar. Indeed credit, typically in EMEs, might be denominated in dollars, therefore a dollar appreciation should tighten firms’ credit conditions. However, as discussed above, the net effect depends on relative elasticities, in this case on whether firms expected profits are more impacted by higher global demand or more expensive dollar credit. Our results suggest that the former channel is dominant. Similarly to trade volumes, instead, appreciations driven by monetary policy or risk shocks entail a contraction of global activity which reinforces the direct “exchange rate” effects of a stronger USD. [Figure B.16](#) and [Figure B.17](#) report pass-through coefficients at shorter horizon and show how the effects of a dollar appreciation tend to be stronger in the short-term.

Pass-through coefficients generally show a large degree of cross-country heterogeneity. This likely reflects country-specific characteristics and economic conditions that affect the degree of conditional pass-through. For example, countries that share more trade links with the US, such as China, Mexico and Canada, tend to show the largest pass-through coefficients, in line with a strong “real” channel of transmission. The degree of USD invoicing might also be relevant, because it should strengthen the “exchange rate” channel. Finally, also the financing of trade credit might impact the pass-through of shocks. Countries that rely more on global banks and fund largely in dollars should be more exposed to the negative effects of a USD appreciation.

### 3.3 Domestic exchange rates and US shocks

Impulse responses for all countries and variables are reported in [Appendix B.3](#). As shown in the Appendix, the reaction of *domestic* exchange rates to the four US shock may vary significantly across countries. Consider, for example, two opposite cases: Germany and China. [Figure 5](#) reports the accumulated responses of German real export and imports, nominal effective exchange rate and the USD nominal effective exchange rate to the US shocks considered. A contractionary US demand shock depreciates the dollar, as implied by the sign restrictions discussed in [Section 3.1](#). Because the dollar weakens, the euro appreciates. Turning to trade variable, lower US demand and a stronger euro reduce export volumes. Imports also decrease, because general equilibrium forces dominate the substitution effect of relatively cheaper imported goods through a stronger exchange rate. Similar dynamics take place following a US supply shock. A monetary policy or risk shock, instead, appreciates the dollar and weakens the euro. Because the shock is contractionary, real import and exports fall. For Germany a contractionary monetary policy has similar effects, but with reverse sign, to an expansionary demand shock.

Turn now to the response of China, [Figure 6](#). The impact of real shocks (demand and supply) is similar to Germany. After a monetary policy shock, instead, impulse responses are markedly different. A US monetary policy shock implies a dollar appreciation but in this case the Chinese currency appreciates as well. There are several potential ex-

planations for this empirical finding. For instance, when the FED tightens monetary authorities in emerging markets might tighten as well to avoid sizeable capital outflows, in line with what documented by the literature on the “fear-of-floating” in EMEs, see [Obstfeld et al. \(2005\)](#), [Mimir and Sunel \(2015\)](#), [Han and Wei \(2018\)](#) and [Georgiadis and Zhu \(2021\)](#). Alternatively, interest rates spillovers might be positive at the short-end of the yield curve. In both cases, there should be a partial exchange rate appreciation that, in bilateral terms, counters the appreciation of the dollar induced by the original US monetary policy shock. Because both currencies appreciate, the bilateral exchange rates between the two economies remains relatively stable. This has important implications for trade. If Chinese trade is invoiced in USD and the exchange rate against the dollar remains relatively stable, fluctuations in export and import prices (and volumes as a result) should also be more limited. If this is indeed the case, in countries that endogenously react to US monetary policy changes invoicing shares should not influence the size of spillovers because the “exchange rate” channel is muted. The impulse responses for a risk shock follow the same pattern implying as well that the “exchange rate” channel might be muted.

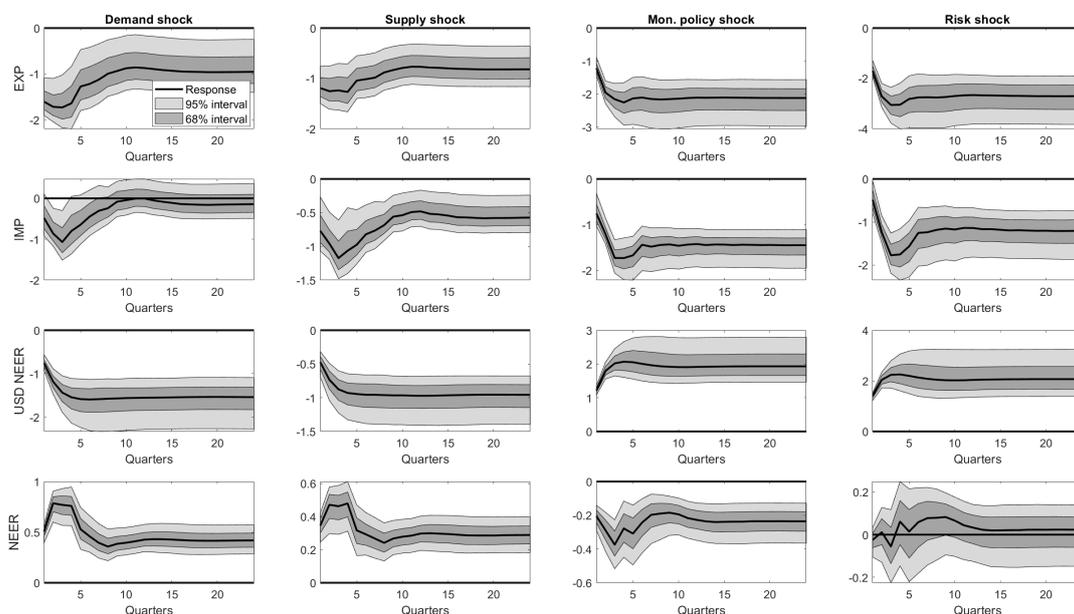


Figure 5: Accumulated IRFs for Germany.

**Notes:** response to 1 standard deviation shock from [Equation \(3.3\)](#). Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#). Real GDP is not reported

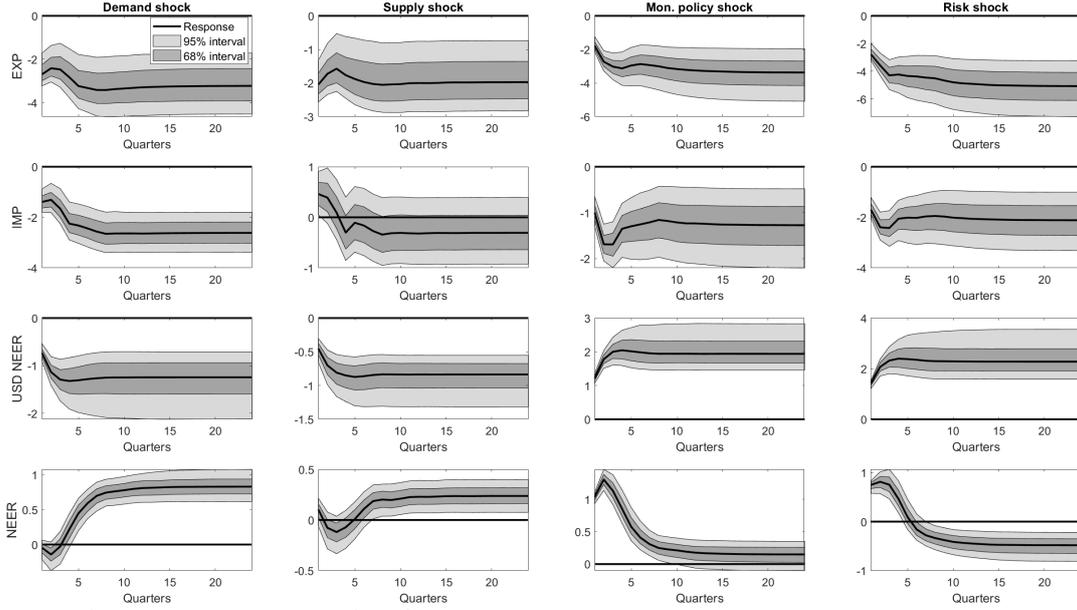


Figure 6: Accumulated IRFs for China.

**Notes:** response to 1 standard deviation shock from Equation (3.3). Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of Equation (3.2). Real GDP is not reported.

### 3.3.1 Evidences from a structural model

The aforementioned dynamics can be illustrated in a structural model where the implications of alternative invoicing patterns can be formally accounted for.

Consider the economy discussed in Boz et al. (2020a) featuring three currency areas: the US, a large open economy and the rest of the world (RoW).<sup>15</sup> International trade can be invoiced in the domestic currency (LCP), in the currency of the producer (PCP) or in a dominant currency, the dollar (DCP). In particular, the price of exports from country  $j$  to country  $i$  is determined by the equilibrium condition:

$$E_t \sum_{s=t}^{\infty} \delta_p^{s-t} \Lambda_{j,t,s} Y_{ji,s|t}^k [\sigma_{ji,s}^k(\omega) - 1] \left[ \mathcal{E}_{kj,s} \bar{P}_{ji,t}^k(\omega) - \frac{\sigma_{ji,s}^k(\omega)}{\sigma_{ji,s}^k(\omega) - 1} MC_{j,s} \right] = 0 \quad (3.4)$$

where  $\delta_p$  is the Calvo-pricing parameter,  $\Lambda_{j,t,s}$  is the stochastic intertemporal discount factor,  $Y_{ji,s|t}^k$  are exports from  $j$  to  $i$ ,  $\sigma_{ji,s}^k(\omega)$  is the elasticity of demand,  $\bar{P}_{ji,t}^k$  the optimal price and  $MC_{j,s}$  the marginal cost of production.  $\mathcal{E}_{kj,s}$  is the exchange rate used to settle trade between  $j$  and  $i$ , where  $k$  is the currency of choice. With LCP  $k = i$ ; with PCP

<sup>15</sup>The underlying theoretical model is described in Boz et al. (2020a).

$k = j$  and finally under DCP  $k = US$ . Invoicing choices have non-trivial implications in this model. If, for example, trade is invoiced in dollars, any movement in the dollar changes export prices from  $j$  to  $i$  (and as a consequence volumes) even if the bilateral exchange rate between  $j$  and  $i$  remains constant. Because import prices enter CPI through import shares, a dollar appreciation also rises inflation in both countries, triggering an endogenous monetary policy reaction. As discussed in [Boz et al. \(2020a\)](#) these are some of the reasons why US monetary policy shocks have such large foreign spillovers. We replicate these results in the upper panel of [Figure 7](#) where we plot the response of total export and exchange rates for the open economy under a free-floating exchange rate regime. A US contractionary monetary policy shock depreciates the domestic currency against the dollar but leaves unchanged the bilateral exchange rate with other countries (the RoW in this model, that is equally affected by the US shock). However, because exports are invoiced in dollars they become proportionally more expensive; consequently export volumes contract leading to a fall in total output. These effects are stronger the higher is the USD invoicing share of exports.

Next we simulate, in the lower panel of [Figure 7](#), the same shock for a country that does not tolerate a currency depreciation against the dollar, for example an EME. In other terms, whenever the US tightens its policy rate, the monetary authority in the country is forced to tighten as well. This policy reaction is indeed able to stabilize the exchange rate against the US, that remains constant. However, it also entails a stronger contraction in real activity and an appreciation against other currencies (RoW). The reaction of real variables depends significantly less from the degree of USD currency invoicing; the difference between no dollar invoicing and full invoicing is reduced by about two-third. This happens because the domestic currency of the EME remains stable against the dollar and, therefore, the relevant exchange rate in [Equation \(3.4\)](#) does not move, reducing the importance of dollar invoicing in trade. The empirical findings of our second-stage VAR can be explained by these dynamics. The nominal exchange rate of some countries, for example China, appreciates following a US monetary policy shock. This happens because Chinese authorities want to avoid large capital outflows and act to contrast the effects

of a US policy tightenings. In practice, however, policy actions can be only partially effective in offsetting dollar shocks, therefore in some countries the domestic exchange rate might still react, albeit to a smaller extent or with some delay.<sup>16</sup> This hypothesis can be tested using our empirical pass-through coefficients. If many countries in the panel react to US policy tightenings, one would expect that USD invoicing share do not explain cross-country differences in pass-through to trade, in line with the experiment discussed above. If countries, instead, do not endogenously react to demand shocks USD invoicing shares should correlate with the magnitude of pass-through coefficients.

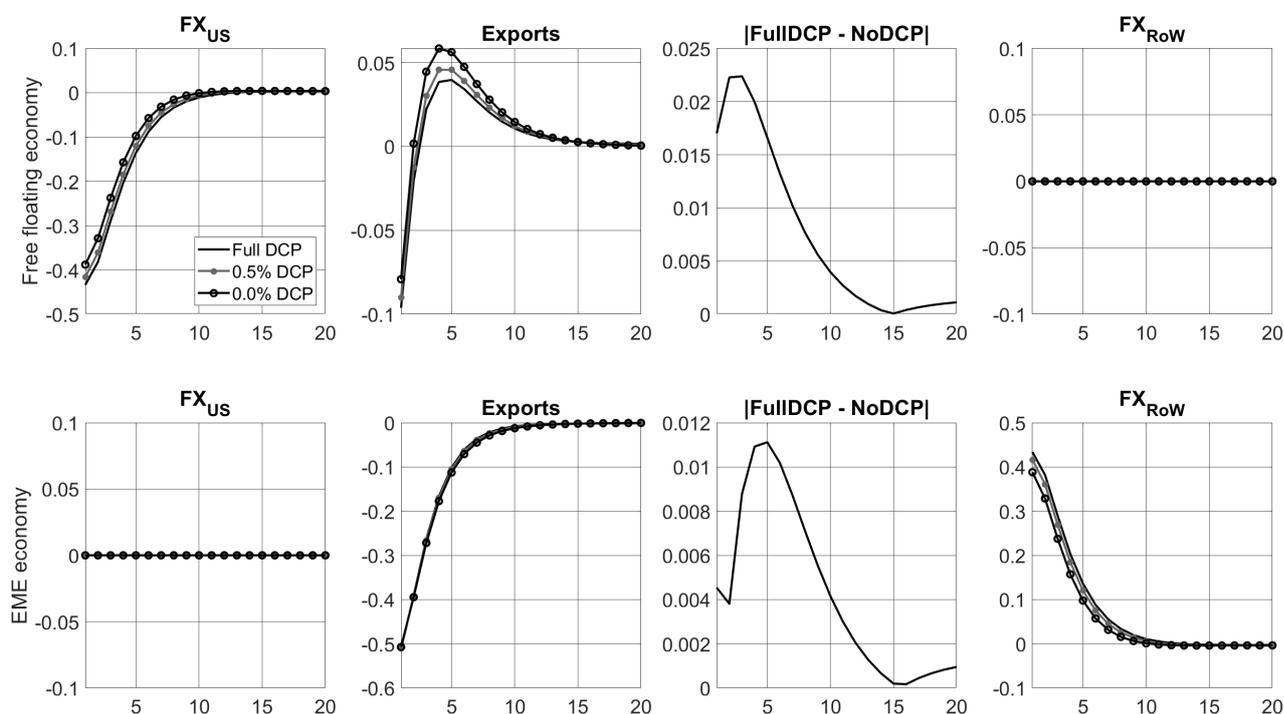


Figure 7: Response to a US monetary policy shock.

**Notes:** response to 1 standard deviation US monetary policy tightening based on [Boz et al. \(2020a\)](#). The upper panel reports the response of the open economy with flexible exchange rate. The lower panel reports the response of an economy that seeks to maintain constant the exchange rate against the dollar. We call this economy an emerging market for the sake of exposition.

### 3.3.2 Yield response to US shocks

We test whether the aforementioned hypothesis holds in our sample by deriving the response of the domestic 2-year rate, a standard proxy for the monetary policy target stance.

<sup>16</sup>For a comparison of the spillovers of US and euro area shocks see [Ca'Zorzi et al. \(2021\)](#); [Iacoviello and Navarro \(2019\)](#) instead provide estimates for US monetary policy spillovers to a large group of countries.

We do that by projecting US shocks on yields on a VAR similar to [Equation \(3.3\)](#).<sup>17</sup>

In most countries of the sample, the response of the 2-year yield to US monetary policy should be negative, because of portfolio rebalancing with the US and the domestic economy. On the contrary, there might be countries in which 2-year yields increase possibly because of monetary policy or different capital flow dynamics. In that case, higher domestic yields would put pressure on the exchange rate, limiting the depreciation of the domestic currency against the dollar. Responses of 2-year yields are reported in [Figure B.18](#) of the Appendix. They decline indeed in most economies after a US tightening shock. However, their reaction is muted for China and Mexico and even positive in some large EMEs (Turkey, Brazil, Indonesia) and some small advanced open-economies (Ireland, Portugal and New Zealand). These empirical results might reflect different underlying economic mechanisms. In EMEs, for example, they might be triggered by the reaction of domestic monetary authorities to US monetary policy. To avoid strong capital outflows they might tighten policy rates thus limiting interest rate differentials against the United States, see [Obstfeld \(2002\)](#). In small open advanced economies, instead, they might be linked to different capital flows patterns. What is relevant for our analysis is that in both cases there are implications for the exchange rate pass-through. If domestic policy rates moves, in fact, the exchange rate should depreciate by less or even appreciate therefore fluctuations in the value of the currency against the US dollar should be smaller. That, in turn, would reduce the impact of the “exchange rate” channel and potentially explain cross-country differences.

## 3.4 Determinants of exchange rate pass-through

### 3.4.1 Possible channels

Excluding policy reactions, there might be several potential determinants for the different degree of exchange rate pass-through across countries. For example, countries

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<sup>17</sup>Because these shocks are generated, we sample 1000 draws from the posterior of [Equation \(3.3\)](#) and compute confidence intervals on the distribution of simulated IRFs. When including yields the sample reduces significantly, especially for emerging market economies. For China, for example, observations start in Q1 2006.

with stronger trade linkages with the US, or higher degree of integration in the global value chain, might be more exposed to US demand shocks; this could explain why pass-through coefficients are particularly high for China or Mexico. Financial linkages with the US might also matter, as financial conditions of countries that borrow more in US dollar should be relatively more sensitive to increases in US yields or dollar appreciations. Finally, the currency of trade invoicing should also be relevant as countries with a higher share of exports invoiced in US dollar should benefit less from a demand driven US dollar appreciation as domestic exports become relatively more expensive. Considering this, we focus on three potential determinants for the degree of pass-through: international trade linkages, financial linkages, and invoicing currency patterns. We postulate that if one of these channels is indeed relevant, pass-through coefficients should correlate with some macro-variables that capture it.

**International trade linkages.** Direct trade connections to the US should matter: countries with closer trade linkages with the US would be more affected by any shock to US demand. Moreover, countries more integrated in the global value chain might also be more exposed to shocks from the US, because of the higher exposure to fluctuations in the global economy. Trade composition should also be relevant. Countries with a higher share of energy products in total exports may be less sensitive to demand-driven exchange rate movements, considering the lower price sensitivity of oil consumption, but also the dominance of the US dollar in the invoicing of energy products. Taken together, the “real” channel of a dollar appreciation should be stronger for those countries that rely more on foreign demand for non-energy products. We test these hypotheses by controlling for the share of exports to the US over domestic GDP, the degree of global value chain participation, and the share of energy in total exports.

**Financial linkages.** Financial linkages could change the degree of pass-through, in particular to financial asset prices. Countries with higher net foreign USD dollar positions are more exposed to US dollar movements. For example, in response to US dollar appreciations, the debt service burden of countries with net US dollar liabilities

increases, tightening financial conditions. Moreover, international lending in dollars declines, because the balance sheets of borrowers in economies which mostly borrow in dollars weakens; this, in turn, discourages global banks to provide the borrowers with US dollar-denominated credit (see [Bruno and Shin \(2015\)](#)). Similarly, countries with higher interest rates are generally riskier and hence more exposed to a tightening of US financial conditions driven by US monetary policy or risk shocks.

**Trade invoicing.** Also trade invoicing might be an important determinant of USD pass-through. If trade is largely invoiced in dollars, any fluctuation in the dollar exchange rate would affect relative prices, hence demand for export and imports. Moreover, dollar movements would also disproportionately impact domestic inflation, with possible effects on financial markets. [Gopinath et al. \(2010\)](#) shows how USD invoicing affects these channels in an open-economy theoretical model while [Boz et al. \(2019\)](#) tests empirically if the dollar’s dominance as invoicing currency can explain the cross-country heterogeneity in exchange rate pass-through. The dynamics might be, however, offset by the reaction of domestic yields in some countries, as discussed in [Section 3.3](#). We test these channels controlling for invoicing shares in USD using the database constructed by [Boz et al. \(2020b\)](#).

### 3.4.2 Cross-country evidence

We regress the estimated pass-through coefficients from [Equation \(3.2\)](#) on the aforementioned macroeconomic determinants. Because coefficients are estimated on the full sample, we use the average of explanatory variables between 2000-2020. Specifically we estimate:

$$\Phi_i(K) = \alpha + X_i^{macro} \beta^{macro} + X_i^{financial} \beta^{financial} + X_i^{trade} \beta^{trade} + X_i^{invoicing} \beta^{invoicing} + \epsilon_i \quad (3.5)$$

where  $\Phi_i(K)$  is the pass-through coefficient at horizon  $K$  for country  $i$  of the US dollar on a specific endogenous variable. These coefficients are regressed on trade linkages  $X_i^{trade}$  (exports to the US over GDP, the VAX ratio, and fuel exports over total exports), financial

exposure  $X_i^{financial}$  (10-year bond yield spread against the US, and net USD-denominated foreign liabilities), US dollar invoicing  $X_i^{invoicing}$ , and macro controls  $X_i^{macro}$  (real GDP and CPI growth).

We use exports to the US over GDP as a measure of bilateral trade linkages with the US. The share of domestic value added in an economy's gross exports, the VAX ratio (see [Johnson and Noguera \(2012\)](#)), is used as a measure of global value chain participation (GVCP). Likewise, the share of fuel exports in total exports captures an economies' exposure to commodities. We then assess to what extent differences in economies' bilateral trade linkages with the US, GVCP and commodity exposure can account for differences in the estimates of their exchange rate pass-through to trade volumes and financial conditions. Regarding financial exposure, we consider two measures that may have a meaningful impact on pass-through to export volumes and financial markets: 10-year bond yield spread against the US, and net USD-denominated foreign liabilities. Finally, we use the share of exports (imports) in total exports (imports) invoiced in US dollar to assess the role of invoicing for cross-country heterogeneity in pass-through to trade volumes and financial markets.

In this regression framework the dependent variable is generated, hence standard errors are potentially biased. [Feenstra and Hanson \(1999\)](#) indeed shows that in models with a generated regressands standard errors from the second stage are inflated by the variance of the first stage; as a result, the estimated standard errors of [Equation \(3.5\)](#) are an upper bound to the true, unbiased, errors. In other terms, the confidence intervals around our estimates of  $\beta^*$  are larger than in the true data generating process. This implies that there is a bias against the significance of our point estimates, i.e. the bias works against our assumptions. Notice that the limited sample size in [Equation \(3.5\)](#) also increases standard error estimates.<sup>18</sup>

Results are reported in [Table 5](#). US dollar invoicing mitigates the real effects of demand and supply shocks that appreciate the US dollar. Consider for example the

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<sup>18</sup>The countries included in the regression are: Australia, Austria, Belgium, Bulgaria, Brazil, Canada, Switzerland, Czech Republic, Germany, Denmark, Spain, Finland, France, Greece, Hungary, Indonesia, Ireland, Italy, Japan, Korea, the Netherlands, Norway, New Zealand, Poland, Portugal, Russia, Sweden and Turkey.

impact on export volumes of a US demand shock, which is expansionary for the US economy and appreciates the dollar. Coefficients reported in [Table 5](#) suggest that dynamic multipliers are lower, after a demand shock, for countries which have a higher share of exports invoiced in US dollar. The positive demand effects, which boost global exports, are partly offset by the US dollar appreciation because exports invoiced in US dollar become more expensive. For monetary policy and risk shocks, invoicing does not seem to matter for the pass through of the US dollar exchange rate to export and import volumes. This result may reflect that US monetary policy and risk shocks tend to trigger capital outflows from emerging market economies, as has been observed, *inter alia*, during the Global Financial Crisis or the 2013 Taper tantrum period. If monetary authorities in countries subject to capital outflows react by tightening monetary policy to limit the depreciation of the domestic currency, the overall exchange rate movement may be limited; and invoicing hence appears meaningless for spillovers. As shown in [Section 3.3](#), when domestic yields respond to US shocks exchange rate fluctuations against the USD are sterilized and USD invoicing shares do not imply a significant variation in the reaction of export volumes. We have shown that these dynamics are relevant for several economies in our sample, mostly EMEs, therefore it is not surprising that pass-through coefficients for financial shocks are not explained by dollar invoicing shares.<sup>19</sup>

Closer trade linkages with the US are found to amplify the exchange rate pass-through to export volumes for demand, supply and risk shocks. Countries more connected by trade with the US benefit more from US shocks that appreciate the US dollar. This result speaks to the notion that the elasticity of trade to global demand indeed matters in determining the pass-through of a dollar appreciation. For shocks that appreciate the dollar but increase foreign demand, the negative effects of the dollar appreciation are more limited, because real demand compensates higher dollar prices or tighter global financial conditions. Besides trade invoicing and trade openness, the composition of trade also matters for pass-through to real exports. Countries with a higher share of energy goods in total exports are less affected by the negative global demand impact of monetary policy

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<sup>19</sup>These dynamics can be also explained by the so-called “fear-of-floating” in EMEs as discussed by [Calvo and Reinhart \(2002\)](#).

tightenings and adverse risk shocks that appreciate the US dollar. This likely reflects the lower sensitivity of energy products to global demand relative to non-energy goods. The role of global value chain participation, finally, cannot explain differences in pass-through to trade volumes beyond the effect captured by trade openness and trade composition. This channel, however, is generally muted for real imports.

Regarding financial linkages, net US dollar liabilities amplify the negative real effects of monetary policy driven dollar appreciations. Countries with a larger net US dollar liability positions see a stronger decline in export volumes. In line with the international risk taking channel of US monetary policy, US tightening shock impinges on global bank lending conditions and may hence amplify the negative demand effects in emerging market economies where the bulk of credit is in dollars.

Turning to the quantitative significance of these results, overall, our suggested variables explain 40 to 60% of cross country differences in exchange rate pass-through. However, as mentioned, these results are affected by some degree of uncertainty, in particular for financial variables.

## 4 Conclusion

This paper provides estimates of the shock-dependency and cross-country heterogeneity of the pass-through of the US dollar to trade and financial variables. We show that pass-through is highly shock dependent, suggesting that reduced-form regression estimates are driven by the relative importance of shocks in the estimation sample. Comparing panel to country-specific results also highlights a large degree of cross country heterogeneity. These cross-country dimension can be rationalized by looking at country characteristics. We find that the position in the business cycle, exposure to US demand and GVC participation, monetary and financial conditions are important determinants of pass-through coefficients. The size and sign of such determinants varies significantly across shocks and variables. That depends on specific transmission channels. For example, the exposure to US demand makes the pass-through of a demand shock driven dollar appreciation

Table 4: Determinants of 1-year exchange rate pass-through – real trade

	Exports				Imports			
	Demand	Mon. policy	Risk	Supply	Demand	Mon. policy	Risk	Supply
Exp. USD invoicing	-0.021*** (0.00)	-0.003 (0.47)	-0.002 (0.74)	-0.022*** (0.01)				
Exp. to US/GDP	0.195*** (0.00)	0.047 (0.33)	0.104* (0.08)	0.301*** (0.00)	-0.260 (0.60)	-0.085 (0.64)	0.011 (0.96)	-0.436 (0.50)
Net USD liab.	-0.004 (0.47)	-0.007* (0.07)	-0.005 (0.33)	0.002 (0.76)	-0.017 (0.15)	-0.010** (0.03)	-0.007 (0.31)	-0.018 (0.22)
Exported fuel share	0.001 (0.92)	0.013** (0.03)	0.016** (0.03)	0.011 (0.21)				
VAX	1.103 (0.53)	-0.228 (0.84)	-0.887 (0.51)	-0.783 (0.82)	-0.255 (0.95)	0.090 (0.96)	-0.281 (0.90)	-2.621 (0.61)
Spread vs. US	0.019 (0.85)	0.043 (0.57)	-0.021 (0.84)	0.097 (0.47)	-0.383** (0.03)	0.048 (0.44)	-0.057 (0.58)	-0.424* (0.06)
Imp. USD invoicing					-0.042** (0.03)	-0.009 (0.16)	-0.004 (0.65)	-0.051* (0.07)
Imported fuel share					0.064 (0.24)	0.042* (0.10)	0.024 (0.47)	0.107 (0.17)
R-squared	0.54	0.57	0.42	0.44	0.66	0.45	0.21	0.56
Observations	28	28	28	28	27	27	27	27

Notes: The Table reports coefficient estimates of Equation (3.5) with robust standard errors in parenthesis.

The US are excluded from the sample. Controls not reported are  $\Delta GDP$  and  $\Delta CPI$ . \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ , +  $p < 0.15$ .

Table 5: Determinants of 1-year exchange rate pass-through – financial conditions

	Equity prices				10-year yields			
	Demand	Mon. policy	Risk	Supply	Demand	Mon. policy	Risk	Supply
Exp. USD invoicing	0.056* (0.06)	-0.019* (0.09)	-0.007 (0.63)	0.063** (0.05)	0.012 (0.52)	-0.002 (0.55)	-0.001 (0.49)	-0.021 (0.43)
Exp. to US/GDP	-0.700** (0.02)	0.274** (0.04)	0.151 (0.42)	-0.771 (0.27)	-0.063 (0.68)	0.019 (0.48)	0.008 (0.62)	0.073 (0.71)
Net USD liab.	-0.020 (0.29)	-0.000 (0.98)	-0.017 (0.23)	-0.058 (0.21)	-0.000 (0.99)	0.001 (0.49)	0.001 (0.41)	-0.002 (0.87)
Exported fuel share	0.004 (0.86)	-0.031*** (0.00)	-0.039*** (0.01)	-0.002 (0.96)	-0.007 (0.66)	0.003 (0.23)	0.003 (0.20)	0.012 (0.55)
VAX	-16.995* (0.06)	3.919 (0.29)	-1.187 (0.79)	-26.695** (0.03)	2.312 (0.49)	-0.830 (0.16)	-0.291 (0.56)	1.843 (0.68)
Spread vs. US	-0.708 (0.18)	-0.009 (0.97)	-0.010 (0.96)	-0.576 (0.39)	0.645 (0.18)	-0.161** (0.02)	-0.080 (0.16)	-0.405 (0.56)
R-squared	0.46	0.36	0.59	0.43	0.43	0.63	0.47	0.32
Observations	27	27	27	27	27	27	27	27

Notes: The Table reports coefficient estimates of Equation (3.5) with robust standard errors in parenthesis.

The US are excluded from the sample. Controls not reported are  $\Delta GDP$  and  $\Delta CPI$ . \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.10$ , +  $p < 0.15$ .







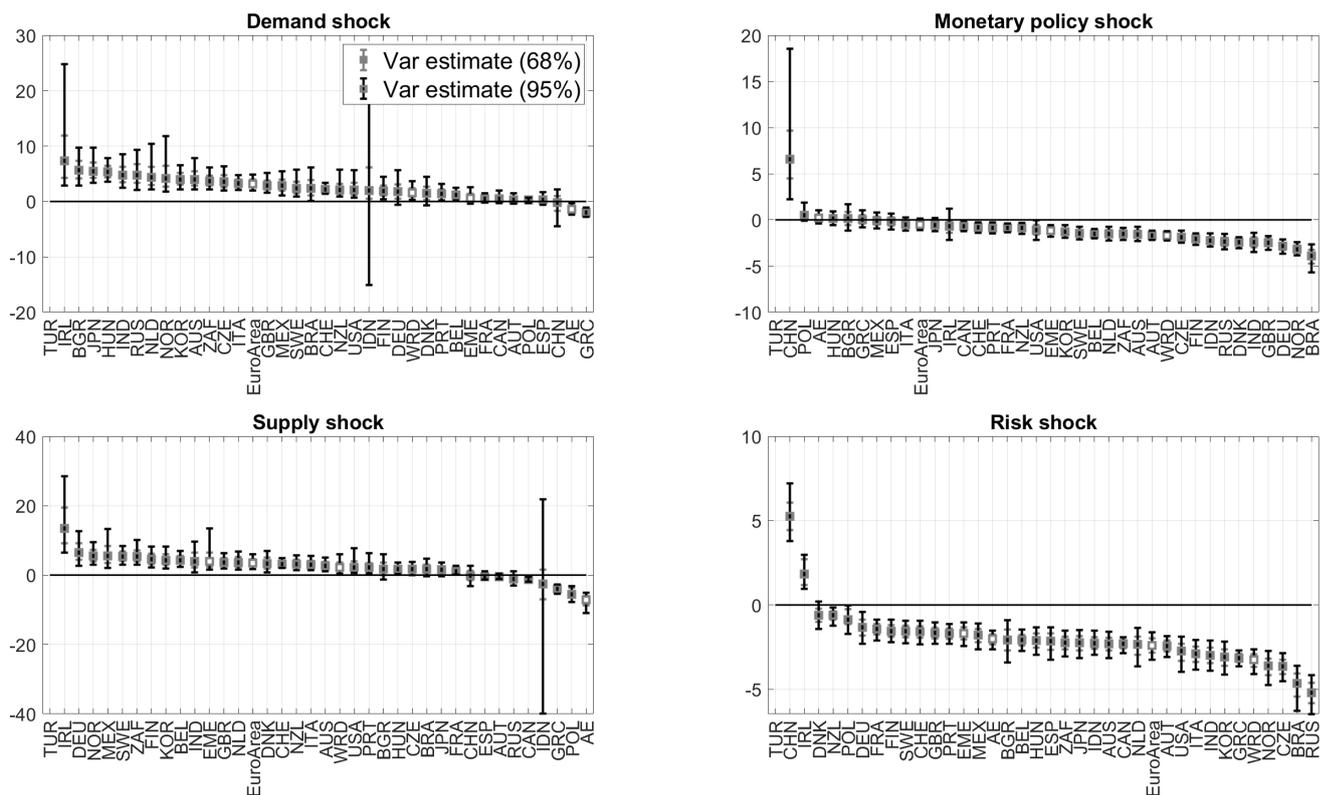


Figure 11: Country-specific estimates of the pass-through to equity prices from the VAR in Equation (3.3) after 4 quarters.

**Notes:** pass-through coefficients are estimated separately for each country and describe the elasticity of equity indices (in percent points) to a 1% USD appreciation. Lines report 68% and 90% confidence intervals over the estimates obtained bootstrapping 1000 draws from the posterior distribution of identified US shocks.

more positive, while the contribution is negative when considering a supply shock driven appreciation. This result is rationalized by the different effect of each shock. After a demand shock, higher demand in the US uniquely benefits foreign countries, increasing trade. That is not the same for an expansionary supply shock. After a supply shock, domestic producing prices fall, giving US producers a competitive advantage over importers. As a result, consumers move away from imports to domestic goods, generating negative spillovers for foreign demand. For this reason the impact on US pass-through is negative. The centrality in the trade network matters also differently depending on the shock and the country group. For example, between EMEs exports of more central economies benefit more from a demand-driven dollar appreciation, while AEs do not experience the same effect. These results might be explained by the different position of the economies on the global value chain. USD invoicing shares also explain cross-country differences in pass-through but only if the dollar appreciation is determined by a real shock. After monetary policy and risk shocks, instead, USD invoicing shares do not correlate with larger pass-through coefficients. The result is rationalized considering the endogenous reaction of yields in the domestic economies. In several countries in the sample, short-term yields increase after US monetary policy shocks, reflecting, for example, the possible reaction of domestic monetary policy authorities in EMEs. When that happens, the exchange rate against the US dollar remains more stable; as a result the dollar invoicing channel of pass-through is significantly muted because the dollar appreciates by a smaller amount in bilateral terms.

Overall, our results suggest that pass-through coefficients are crucially dependent on the underlying shocks. When the originating shock is taken into account, coefficients could drastically change, bearing completely different implications for the appropriate policy reaction to a dollar shock.

## References

- F. Boissay, N. Patel, and H. S. Shin. Trade credit, trade finance, and the Covid-19 Crisis. BIS Bulletins 24, Bank for International Settlements, June 2020.
- E. Boz, G. Gopinath, and M. Plagborg-Møller. Dollar Invoicing and the Heterogeneity of Exchange Rate Pass-Through. *AEA Papers and Proceedings*, 109:527–532, 2019.
- E. Boz, C. Casas, F. J. Díez, G. Gopinath, P.-O. Gourinchas, and M. Plagborg-Møller. Dominant currency paradigm. *American Economic Review*, 110(3):677–719, 2020a.
- E. Boz, C. Casas, G. Georgiadis, G. Gopinath, H. Le Mezo, A. Mehl, and T. Nguyen. Patterns in invoicing currency in global trade. Working Paper Series 2456, European Central Bank, 2020b.
- V. Bruno and H. S. Shin. Capital flows and the risk-taking channel of monetary policy. *Journal of Monetary Economics*, 71(C):119–132, 2015.
- M. Bussière, S. Delle Chiaie, and T. A. Peltonen. Exchange rate pass-through in the global economy: The role of emerging market economies. *IMF Economic Review*, 62(1):146–178, 2014.
- G. A. Calvo and C. M. Reinhart. Fear of floating. *The Quarterly journal of economics*, 117(2):379–408, 2002.
- J. M. Campa and L. S. Goldberg. Exchange Rate Pass-Through into Import Prices. *The Review of Economics and Statistics*, 87(4):679–690, 2005.
- C. Casas. Industry heterogeneity and exchange rate pass-through. *Journal of International Money and Finance*, 106(C), 2020.
- C. Casas, F. J. Diez, G. Gopinath, and P.-O. Gourinchas. Dominant currency paradigm: A new model for small open economies. *IMF Working Papers*, 264, 2017.
- M. Ca’Zorzi, L. Dedola, G. Georgiadis, M. Jarocinski, L. Stracca, and G. Strasser. Making waves: Monetary policy and its asymmetric spillovers in a globalised world. *CEPR Discussion Papers*, (16134), May 2021.
- M. Ca’ Zorzi, E. Hahn, and M. Sánchez. Exchange Rate Pass-Through in Emerging Markets. *The IUP Journal of Monetary Economics*, 0(4):84–102, 2007.
- CGFS. US dollar funding: an international perspective. Technical report, Bank for International Settlements, June 2020.
- V. Corbo and P. Di Casola. Drivers of consumer prices and exchange rates in small open economies. *Journal of International Money and Finance*, 2021.
- L. Dedola, G. Rivolta, and L. Stracca. If the Fed sneezes, who catches a cold? *Journal of International Economics*, 108(S1):23–41, 2017.
- M. B. Devereux and C. Engel. Endogenous Currency of Price Setting in a Dynamic Open Economy Model. NBER Working Papers 8559, National Bureau of Economic Research, Inc, Oct. 2001.

- R. Dornbusch. Exchange Rates and Prices. *American Economic Review*, 77(1):93–106, 1987.
- ECB. The International Role of the Euro, June 2021. Technical report, European Central Bank, June 2021.
- B. Erik, M. J. Lombardi, D. Mihaljek, and H. S. Shin. The Dollar, Bank Leverage, and Real Economic Activity: An Evolving Relationship. *AEA Papers and Proceedings*, 110: 529–534, 2020.
- K. Farrant and G. Peersman. Is the exchange rate a shock absorber or a source of shocks? new empirical evidence. *Journal of Money, Credit and Banking*, 38(4):939–961, 2006.
- R. Feenstra and G. Hanson. The impact of outsourcing and high-technology capital on wages: Estimates for the united states, 1979–1990. *The Quarterly Journal of Economics*, 114(3):907–940, 1999.
- K. Forbes, I. Hjortsoe, and T. Nenova. Shocks versus structure: explaining differences in exchange rate pass-through across countries and time. *Bank of England discussion papers*, 50, 2017.
- K. Forbes, I. Hjortsoe, and T. Nenova. The shocks matter: Improving our estimates of exchange rate pass-through. *Journal of International Economics*, 114(C):255–275, 2018.
- J. García-Cicco and M. García-Schmidt. Revisiting the exchange rate pass through: A general equilibrium perspective. *Journal of International Economics*, 127, 2020.
- G. Georgiadis. To bi, or not to bi? differences in spillover estimates from bilateral and multilateral multi-country models. *ECB Working Paper Series*, 1868, 2015.
- G. Georgiadis. Determinants of global spillovers from US monetary policy. *Journal of International Money and Finance*, 67(C):41–61, 2016.
- G. Georgiadis and F. Zhu. Foreign-currency exposures and the financial channel of exchange rates: Eroding monetary policy autonomy in small open economies? *Journal of International Money and Finance*, 110(C), 2021.
- G. Gopinath and J. C. Stein. Banking, Trade, and the Making of a Dominant Currency. *The Quarterly Journal of Economics*, 136(2):783–830, 2021.
- G. Gopinath, O. Itskhoki, and R. Rigobon. Currency Choice and Exchange Rate Pass-Through. *American Economic Review*, 100(1):304–336, 2010.
- M. M. Habib and F. Venditti. The global capital flows cycle: structural drivers and transmission channels. *ECB Working Paper Series*, (2280), 2019.
- X. Han and S.-J. Wei. International transmissions of monetary shocks: Between a trilemma and a dilemma. *Journal of International Economics*, 110(C):205–219, 2018.
- J. W. Hardin. The robust variance estimator for two-stage models. *The Stata Journal*, 2(3):253–266, 2002.

- E. Herbst and B. K. Johannsen. Bias in local projections. *Finance and Economics Discussion Series, Board of Governors of the Federal Reserve System (U.S.)*, 10, 2020.
- N. Hristov, O. Hülseswig, and T. Wollmershäuser. Capital flows in the euro area and TARGET2 balances. *Journal of Banking & Finance*, 113(C), 2020.
- M. Iacoviello and G. Navarro. Foreign effects of higher U.S. interest rates. *Journal of International Money and Finance*, 95(C):232–250, 2019.
- D. Ioannou, L. Stracca, and M. S. Pagliari. The international dimension of an incomplete EMU. *ECB Working Paper Series*, 2459, 2020.
- R. C. Johnson and G. Noguera. Accounting for intermediates: Production sharing and trade in value added. *Journal of International Economics*, 86(2):224–236, 2012.
- Y. Mimir and E. Sunel. External shocks, banks and optimal monetary policy in an open economy. *BIS Working Papers*, (528), 2015.
- S. Miranda-Agrippino and H. Rey. U.S. Monetary Policy and the Global Financial Cycle. *Review of Economic Studies*, 87(6):2754–2776, 2020.
- K. M. Murphy and R. H. Topel. Estimation and inference in two-step econometric models. *Journal of Business & Economic Statistics*, 20(1):88–97, 2002.
- M. Obstfeld. Inflation-Targeting, Exchange-Rate Pass-Through, and Volatility. *American Economic Review*, 92(2):102–107, 2002.
- M. Obstfeld. Global Dimensions of U.S. Monetary Policy. *International Journal of Central Banking*, 16(1):73–132, February 2020.
- M. Obstfeld, J. C. Shambaugh, and A. M. Taylor. The Trilemma in History: Tradeoffs Among Exchange Rates, Monetary Policies, and Capital Mobility. *The Review of Economics and Statistics*, 87(3):423–438, 2005.
- P. Paul. The time-varying effect of monetary policy on asset prices. *Review of Economics and Statistics*, 102(4):690–704, 2020.
- M. Plagborg-Møller and C. K. Wolf. Local projections and VARs estimate the same impulse responses. *Econometrica*, 89(2):955–980, 2021.
- D. Romer. Openness and Inflation: Theory and Evidence. *The Quarterly Journal of Economics*, 108(4):869–903, 1993.
- E. T. Swanson. Measuring the effects of federal reserve forward guidance and asset purchases on financial markets. *Journal of Monetary Economics*, 2020.
- J. B. Taylor. Low inflation, pass-through, and the pricing power of firms. *European Economic Review*, 44(7):1389–1408, 2000.
- C. K. Wolf. SVAR (Mis)identification and the Real Effects of Monetary Policy Shocks. *American Economic Journal: Macroeconomics*, 12(4):1–32, 2020.

# Appendix

## A Tables

### A.1 Descriptive statistics

Table A.1: Summary statistics for country-specific variables

	Export volume growth		Import volume growth		Equity market growth	
	Mean	Std	Mean	Std	Mean	Std
CHN	2.26	4.89	2.23	4.81	3.77	16.16
FRA	0.03	2.64	-0.03	2.41	0.15	7.25
DEU	0.61	2.78	0.51	2.47	0.99	8.34
ITA	0.18	2.81	0.10	2.56	-0.53	8.34
JPN	0.80	5.00	0.53	2.88	0.55	8.89
GBR	0.00	5.86	0.07	4.31	0.25	5.55
USA	0.71	2.75	0.65	2.73	1.29	5.46
AUT	0.69	2.79	0.41	2.75	1.73	10.30
BEL	0.51	2.27	0.46	2.40	0.62	7.68
DNK	0.44	2.20	0.43	3.15	2.12	7.97
FIN	0.21	5.30	0.44	3.85	-0.13	9.66
GRC	1.21	5.91	0.26	6.30	-1.23	13.13
IRL	1.07	4.63	0.45	4.99	0.76	9.12
NLD	0.97	2.30	0.70	2.57	0.16	8.02
NOR	0.14	3.53	0.73	5.37	2.54	9.39
SWE	0.31	2.96	0.39	3.38	1.10	8.00
CHE	0.97	2.65	0.82	2.72	1.39	6.54
PRT	0.79	3.37	0.31	3.36	-0.87	8.46
ESP	0.72	2.63	0.36	3.18	0.08	7.90
AUS	0.71	2.91	1.22	4.01	1.09	5.82
BRA	1.77	11.85	0.79	6.62	2.84	10.96
MEX	0.94	3.25	0.79	3.58	2.51	8.11
NZL	0.71	3.60	1.17	3.05	2.42	5.05
ZAF	0.55	4.45	-262.15	1104.86	2.27	7.89
TUR	1.95	4.67	1.34	6.07	3.14	12.46
BGR	1.79	5.00	1.73	5.26	3.24	16.61
CZE	1.71	3.74	1.49	3.55	1.09	9.11
HUN	1.55	3.51	1.35	3.53	2.29	9.72
IND	1.94	6.71	2.13	7.66	2.99	10.52
IDN	0.64	5.42	2.02	9.38	3.39	10.93
KOR	2.03	3.77	1.15	3.71	1.44	9.15
POL	2.09	3.02	1.41	3.24	1.99	9.29
RUS	0.86	2.90	1.97	5.75	3.77	15.60
WRD	0.44	1.89	1.46	5.05	0.64	7.80
AE	0.17	1.34	0.16	0.99	0.98	8.25
EME	0.27	0.74	1.30	4.83	1.52	9.75
EuroArea	0.08	0.53	0.05	0.47	-0.19	7.40

**Notes:** mean and standard deviations for growth rates of country specific variables. FCIs are omitted as they are computed as standardized indices.

Table A.2: Main data sources

	Export volumes			Import volumes			Nominal effective exchange rate			Equity index			10-year yield		
	Start	End	Source	Start	End	Source	Start	End	Source	Start	End	Source	Start	End	Source
CAN	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
CHN	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2012Q1	2020Q1	NS
FRA	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
DEU	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
ITA	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
JPN	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
GBR	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
USA	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
AUT	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
BEL	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
DNK	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
FIN	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
GRC	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
IRL	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2012Q1	2020Q1	NS
NLD	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
NOR	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
SWE	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
CHE	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
PRT	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
ESP	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
AUS	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
BRA	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2008Q1	2020Q1	NS
MEX	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2003Q1	2020Q1	NS
NZL	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
ZAF	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
TUR	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2012Q4	2020Q1	NS
BGR	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2003Q1	2020Q1	NS
CZE	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
HUN	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
IND	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
IDN	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2010Q4	2020Q1	NS
KOR	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q3	2020Q1	NS
POL	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2012Q1	2020Q1	NS
RUS	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2003Q1	2020Q1	NS
WRD	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
AE	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
EME	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS
EuroArea	2000Q1	2020Q1	CPB	2000Q1	2020Q1	CPB	2000Q1	2020Q1	BIS	2000Q1	2020Q1	NS	2000Q1	2020Q1	NS

Notes: CPB, Netherlands Bureau for Economic Policy Analysis World Trade Monitor; BIS, Bank for International Settlements; NS, National Sources.

## B Figures

### B.1 Historical decomposition

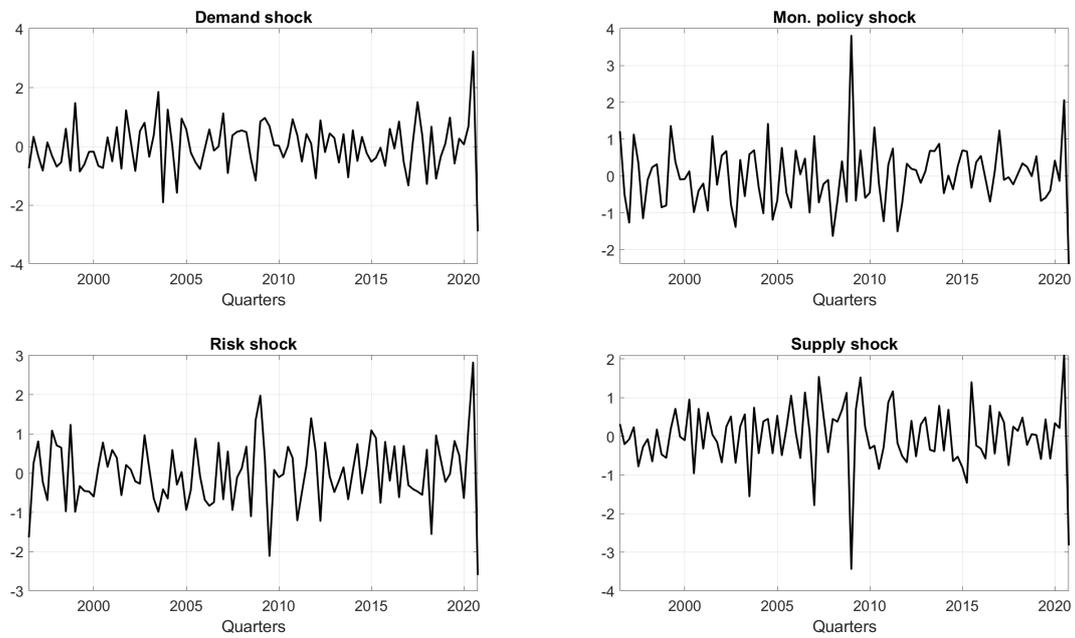
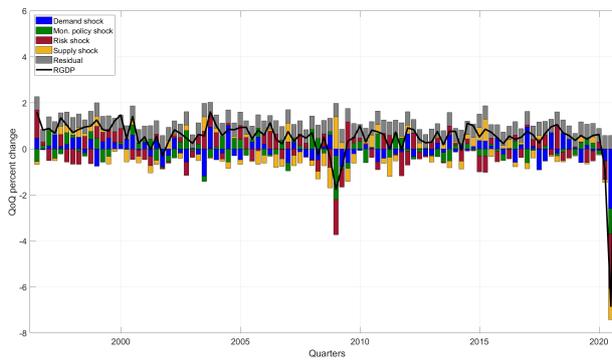
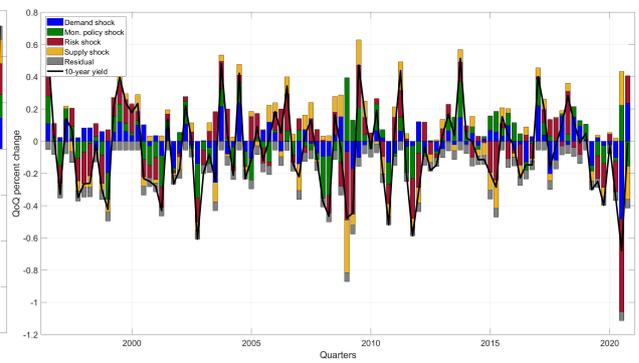


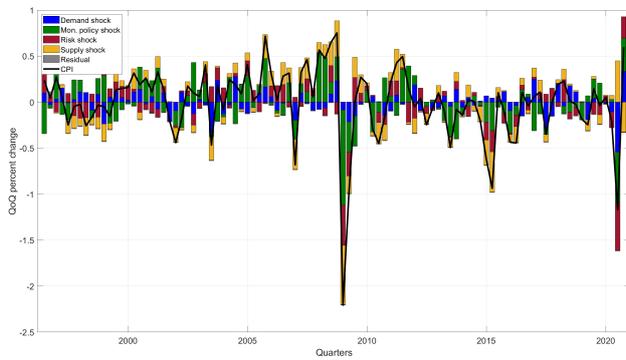
Figure B.1: Median structural shocks from [Equation \(3.2\)](#).



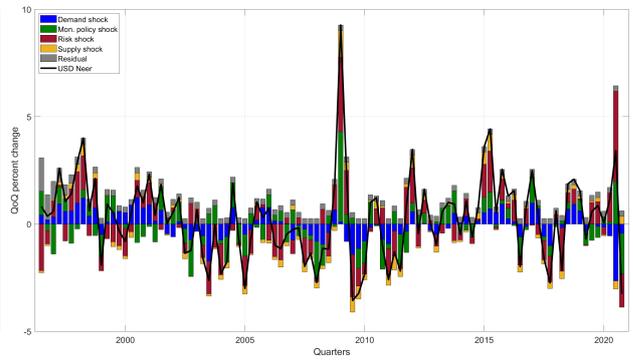
(a) Real GDP



(b) 10-year yields



(c) CPI



(d) USD Neer

Figure B.2: Historical decomposition of US variables.

## B.2 Pass-through at different horizons

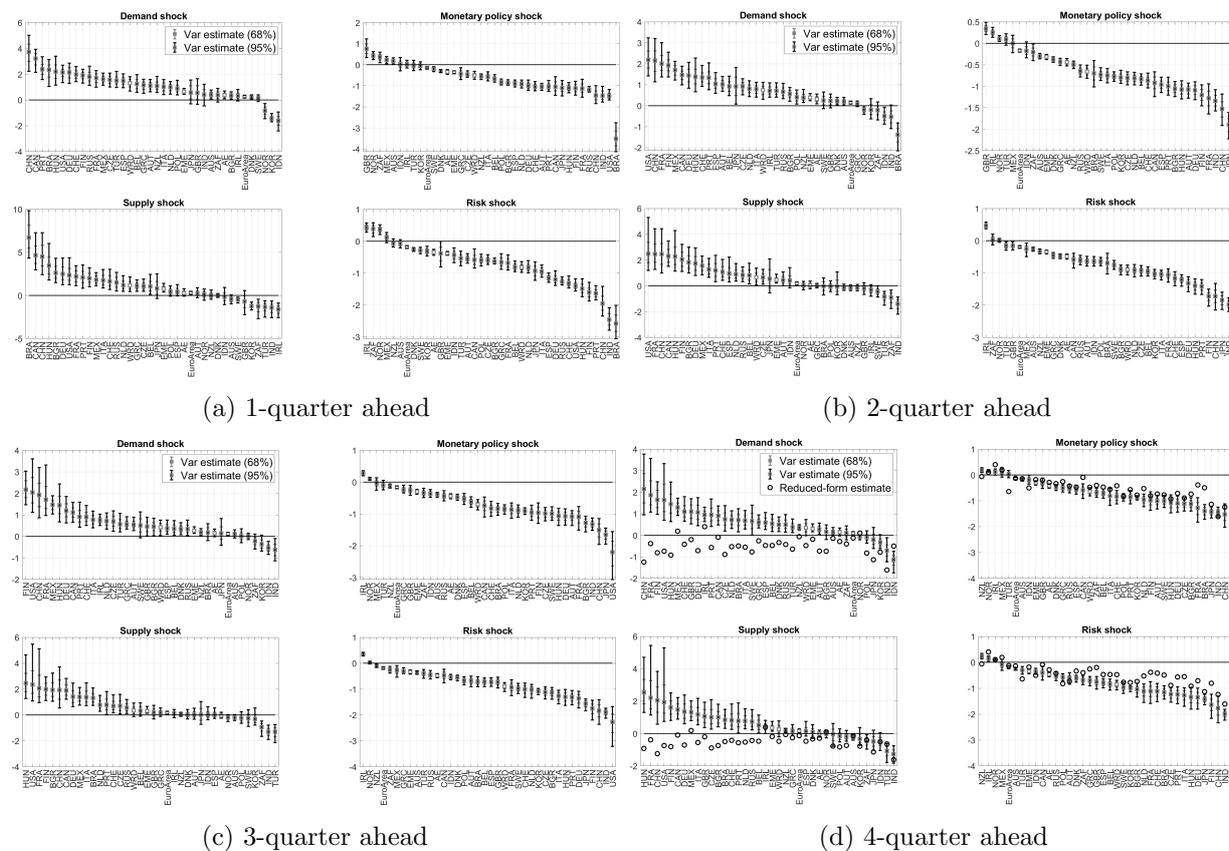


Figure B.3: Country-specific estimates of the pass-through to export volumes from the VAR in Equation (3.3) at different horizons.

**Notes:** pass-through coefficients are estimated separately for each country and describe the elasticity of exports (in percent points) to a 1% USD appreciation. Lines report 68% and 90% confidence intervals over the estimates obtained bootstrapping 1000 draws from the posterior distribution of identified US shocks. Black dots are the reduced-form pass-through estimates from Equation (2.1).

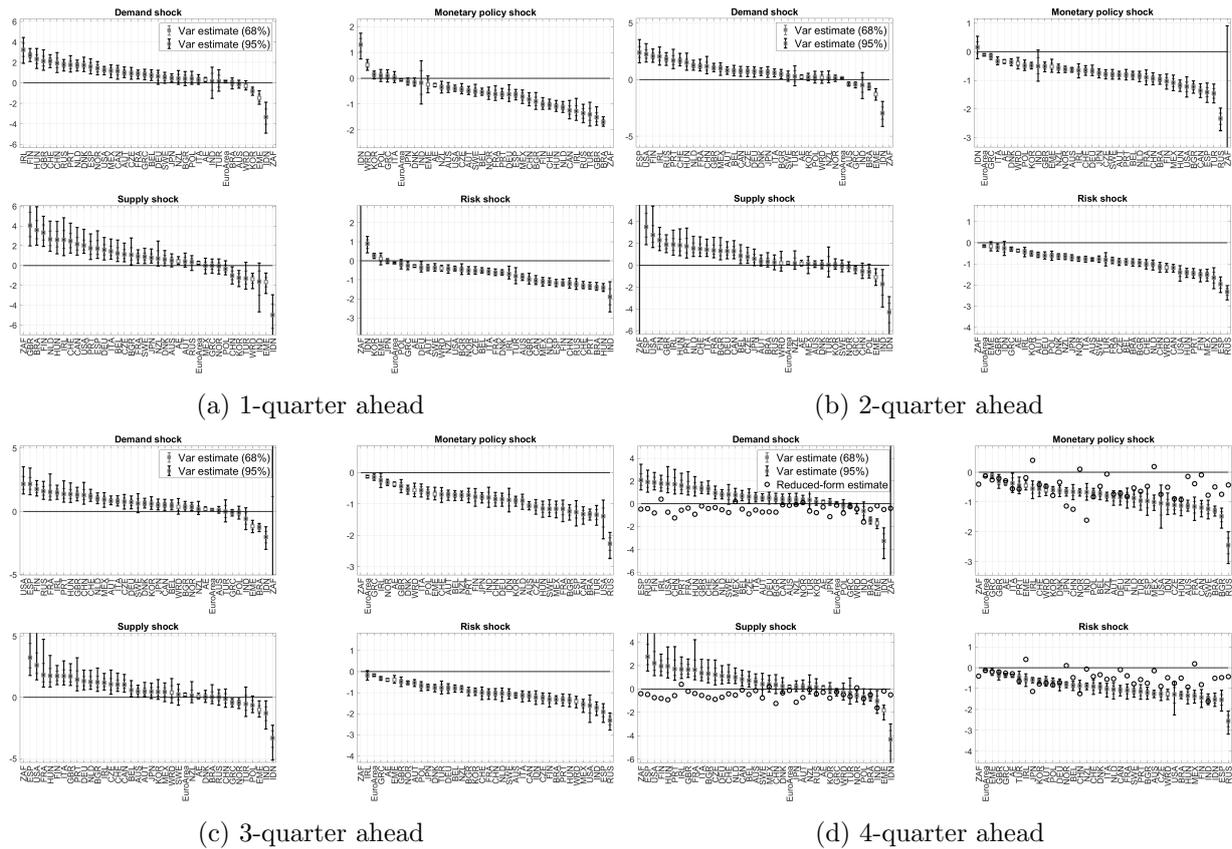


Figure B.4: Country-specific estimates of the pass-through to import volumes from the VAR in Equation (3.3) at different horizons.

**Notes:** pass-through coefficients are estimated separately for each country and describe the elasticity of imports (in percent points) to a 1% USD appreciation. Lines report 68% and 90% confidence intervals over the estimates obtained bootstrapping 1000 draws from the posterior distribution of identified US shocks. Black dots are the reduced-form pass-through estimates from Equation (2.1).

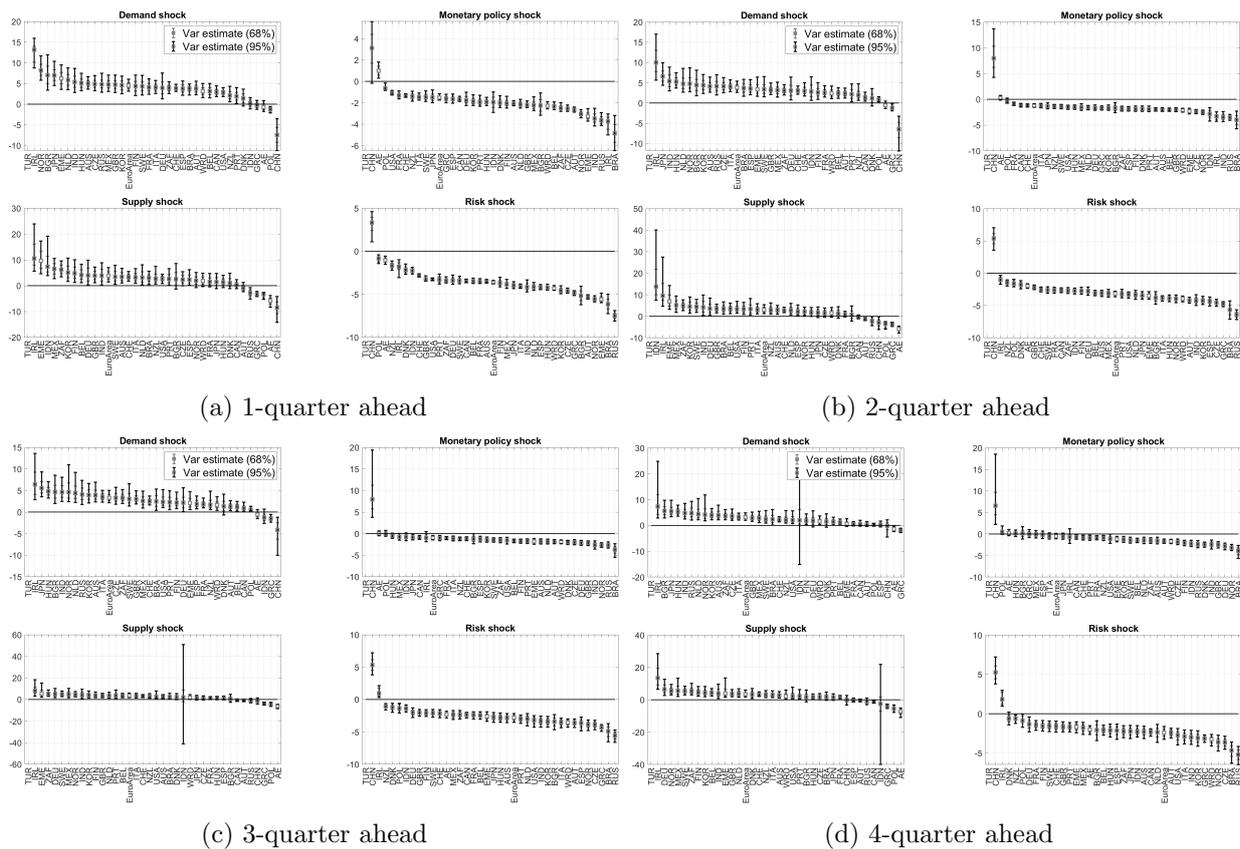


Figure B.5: Country-specific estimates of the pass-through to equity indices from the VAR in Equation (3.3) at different horizons.

**Notes:** pass-through coefficients are estimated separately for each country and describe the elasticity of equity indices (in percent points) to a 1% USD appreciation. Lines report 68% and 90% confidence intervals over the estimates obtained bootstrapping 1000 draws from the posterior distribution of identified US shocks.

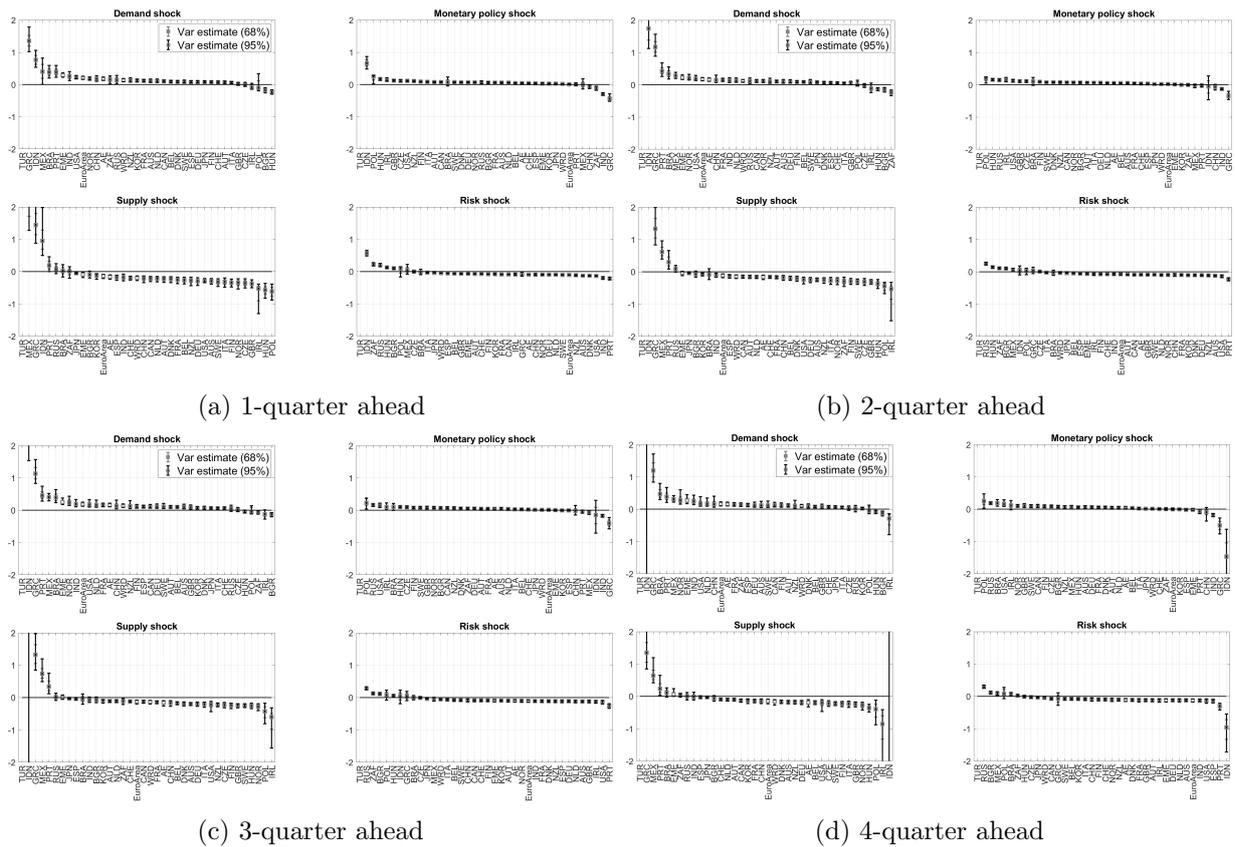


Figure B.6: Country-specific estimates of the pass-through to 10-year yields from the VAR in Equation (3.3) at different horizons.

**Notes:** pass-through coefficients are estimated separately for each country and describe the elasticity of 10-year yields (in percent) to a 1% USD appreciation. Lines report 68% and 90% confidence intervals over the estimates obtained bootstrapping 1000 draws from the posterior distribution of identified US shocks.

### B.3 IRFs of trade variables

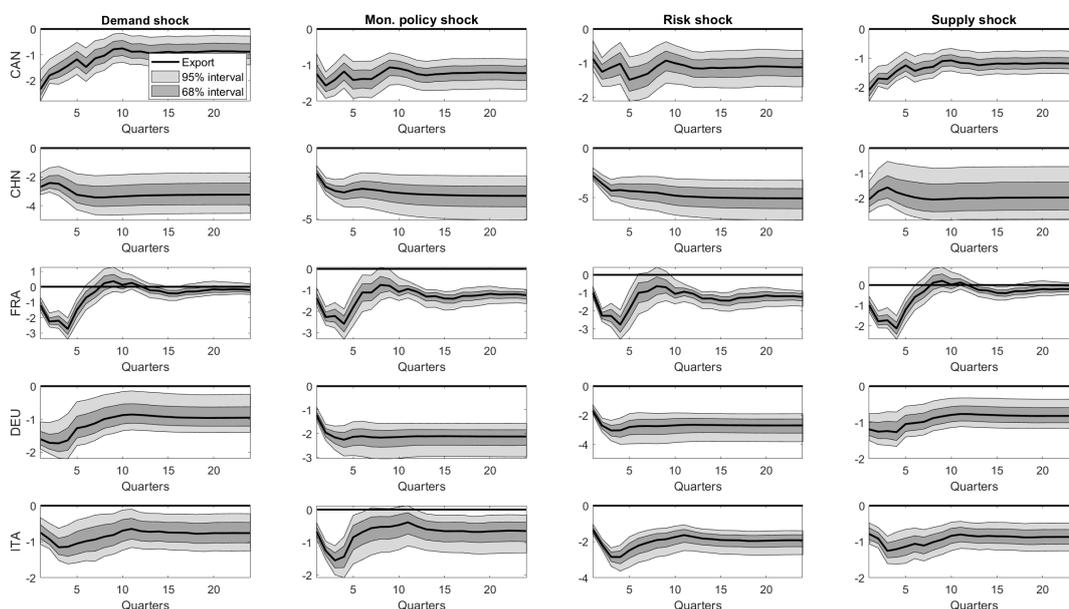
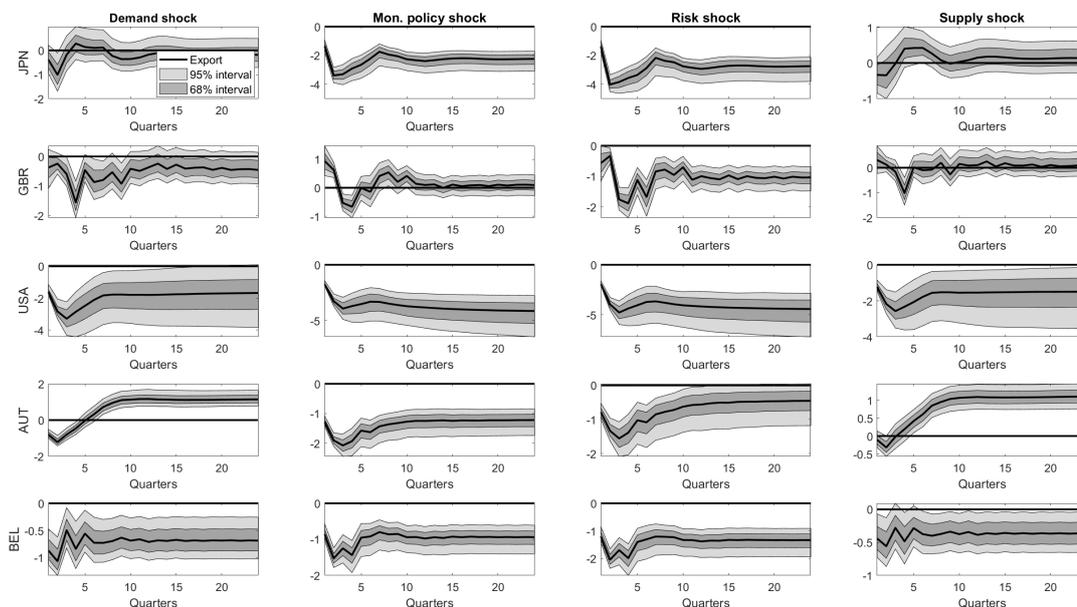


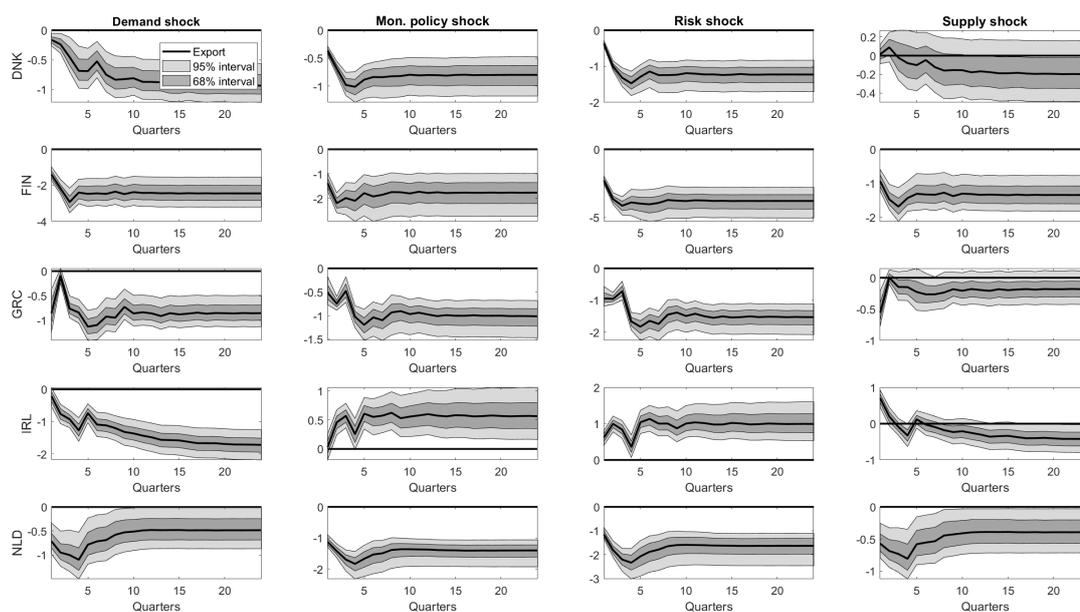
Figure B.7: Accumulated impulse responses (in percent) of export volumes.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).

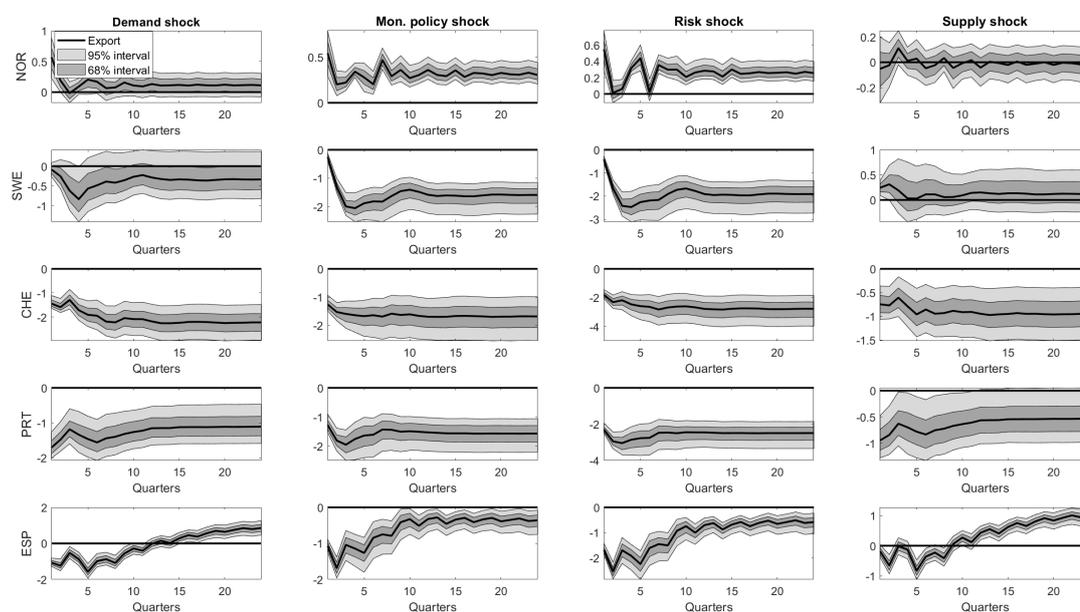


Continuation of [Figure B.7](#) – impulse responses (in percent) of export volumes.

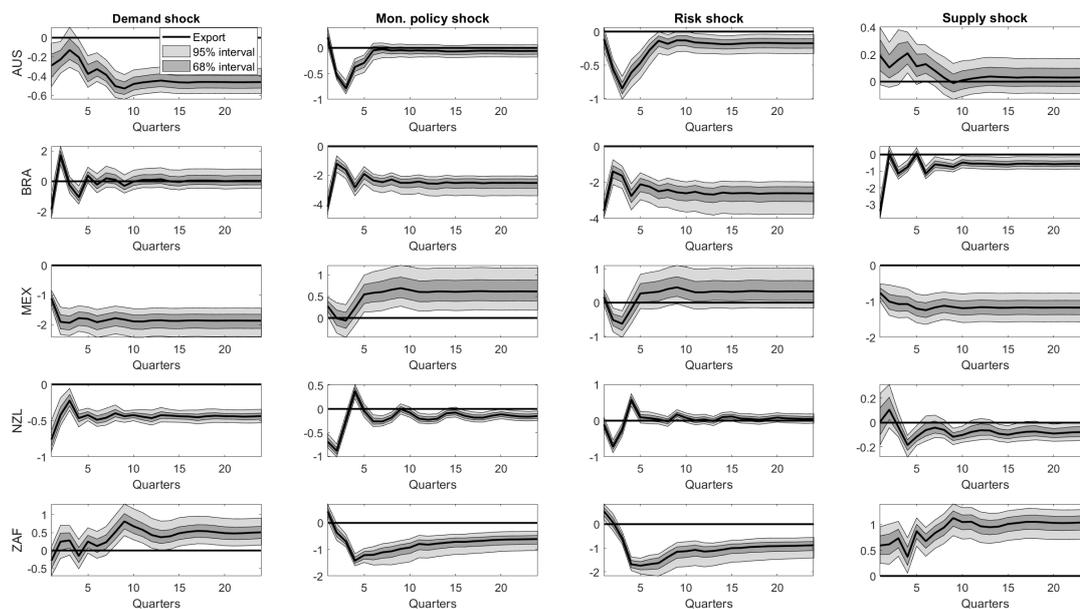
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.7](#) – impulse responses (in percent) of export volumes.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).

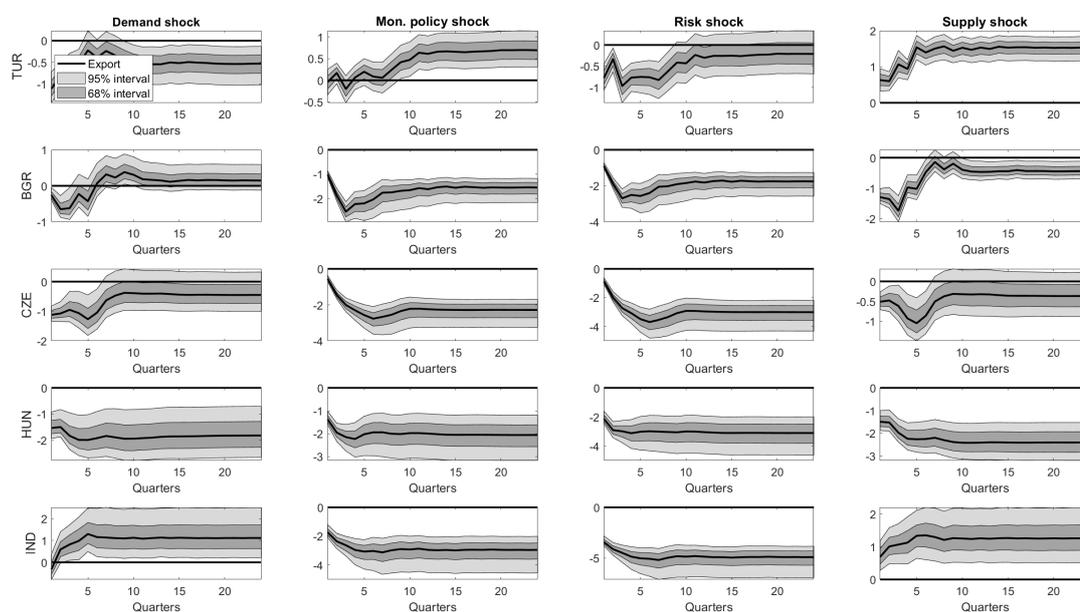


Continuation of [Figure B.7](#) – impulse responses (in percent) of export volumes.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



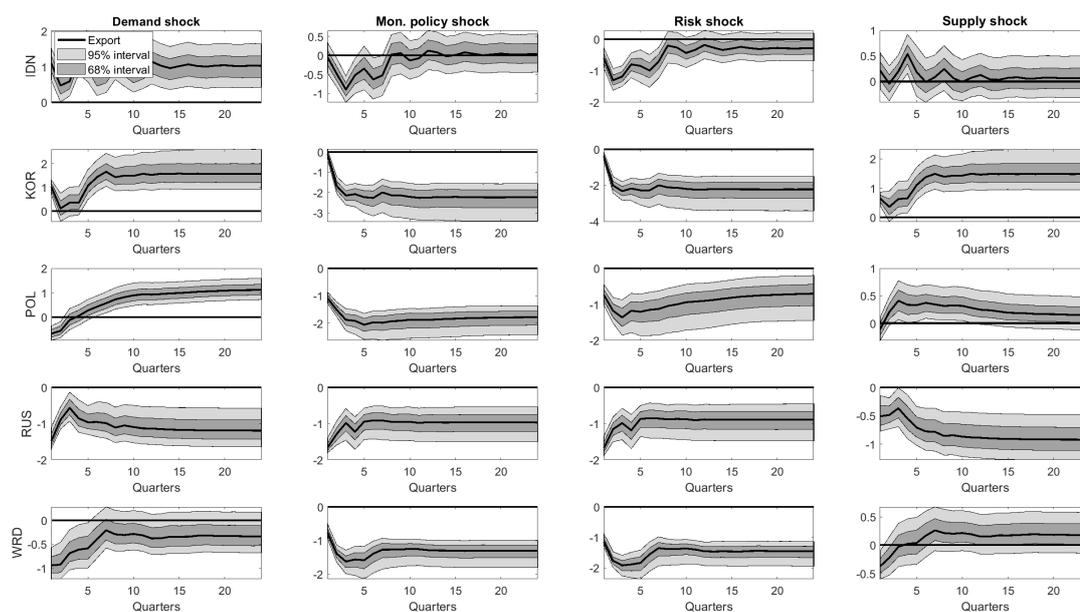
Continuation of [Figure B.7](#) – impulse responses (in percent) of export volumes.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



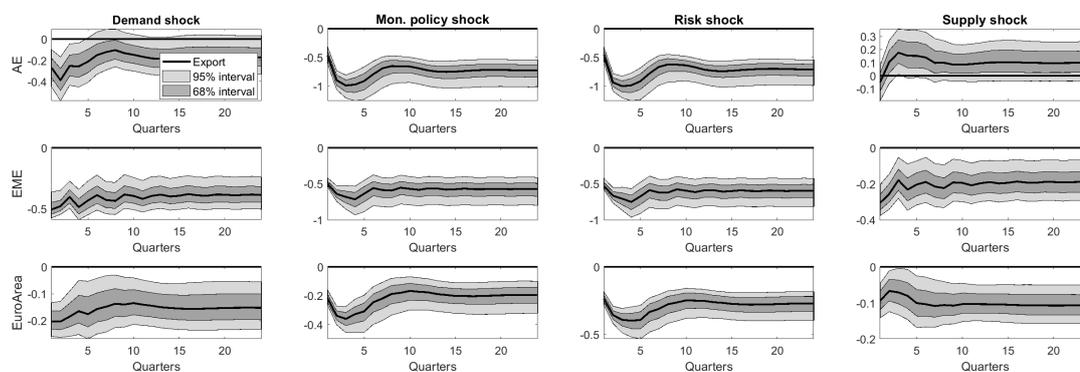
Continuation of [Figure B.7](#) – impulse responses (in percent) of export volumes.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.7](#) – impulse responses (in percent) of export volumes.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.7](#) – impulse responses (in percent) of export volumes.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).

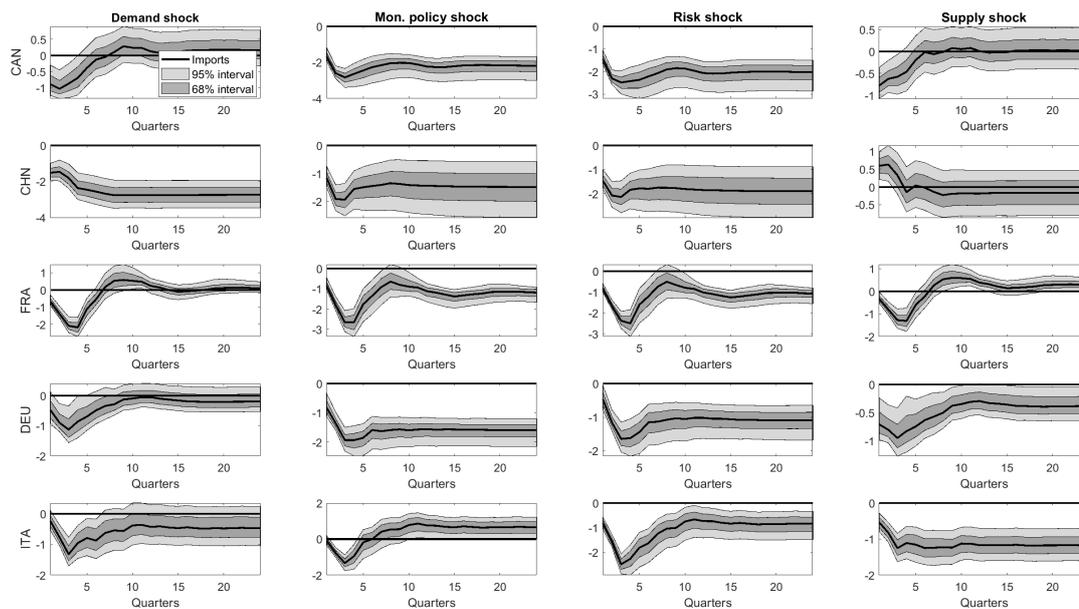
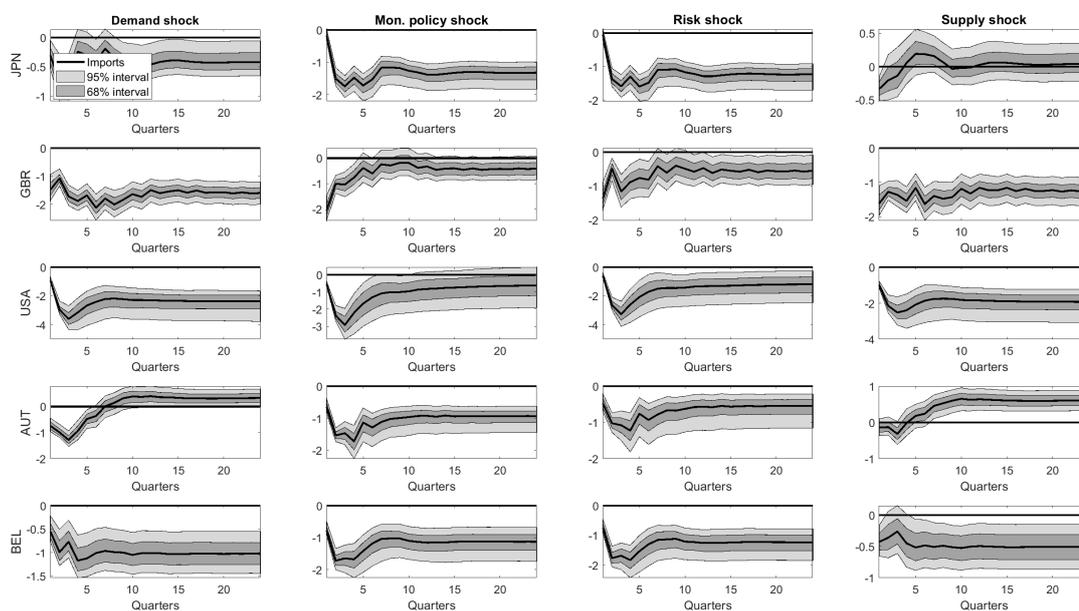


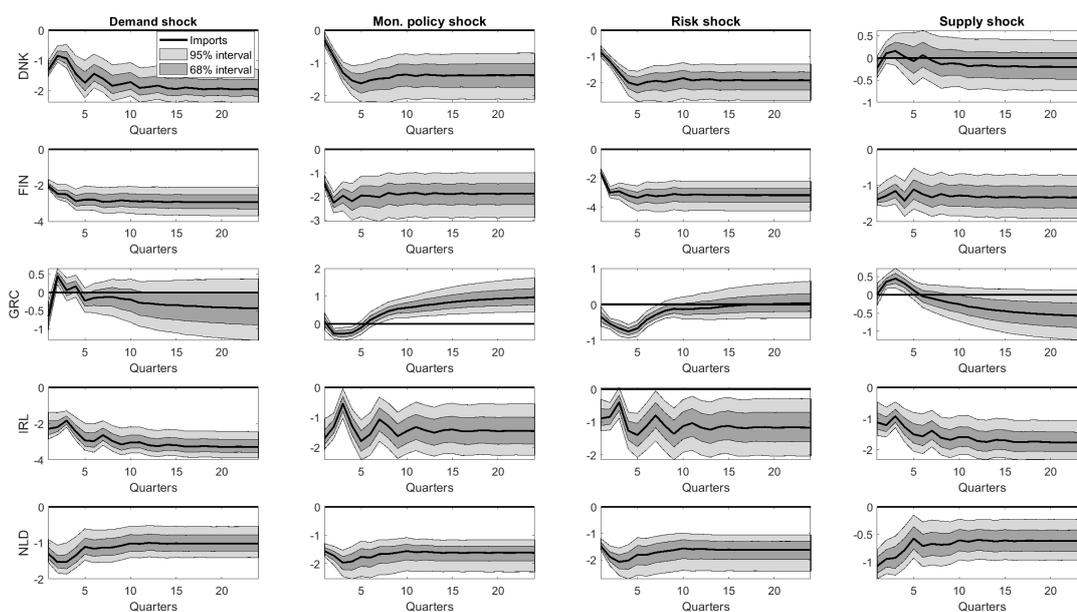
Figure B.8: Accumulated impulse responses (in percent) of import volumes.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



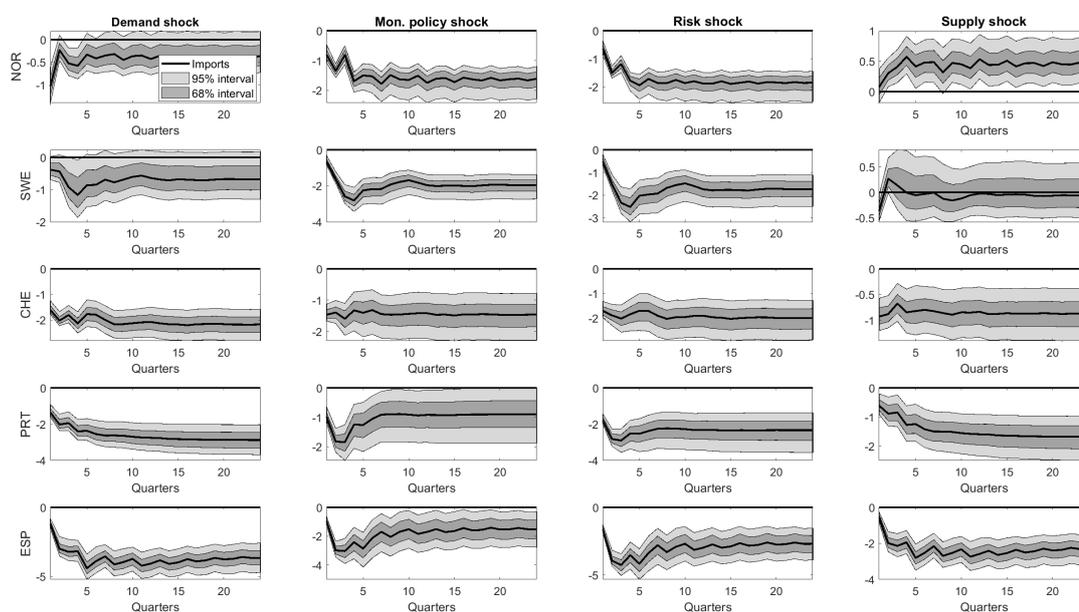
Continuation of [Figure B.8](#) – impulse responses (in percent) of import volumes.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



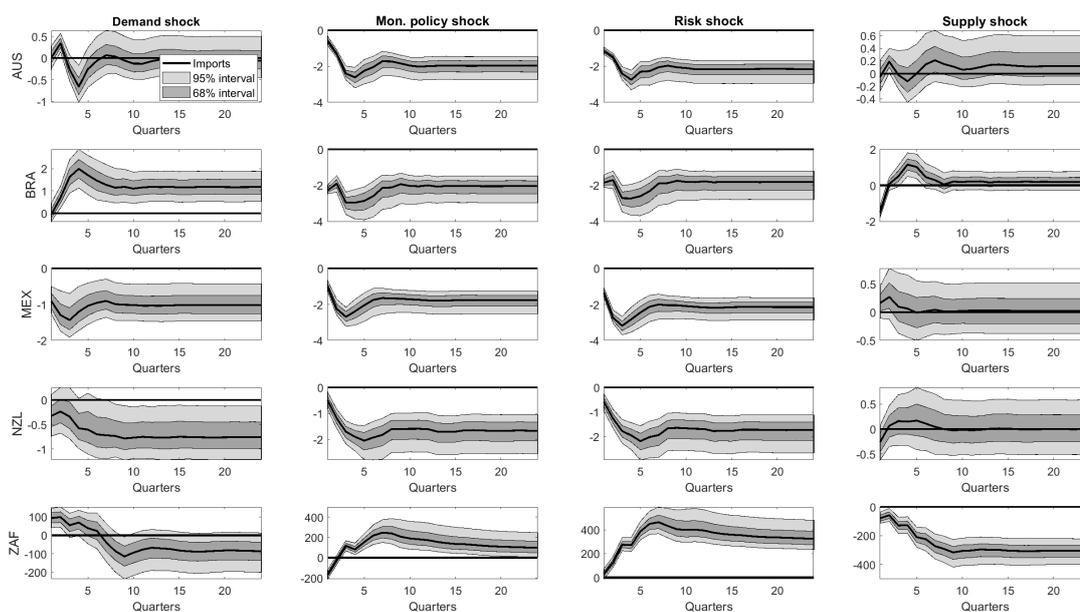
Continuation of [Figure B.8](#) – impulse responses (in percent) of import volumes.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



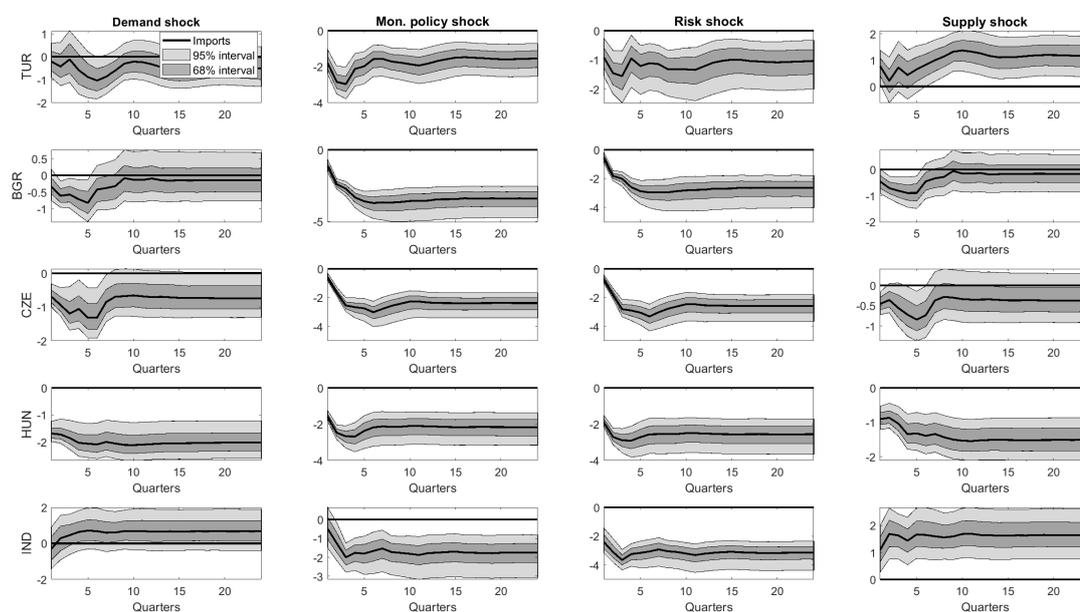
Continuation of [Figure B.8](#) – impulse responses (in percent) of import volumes.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



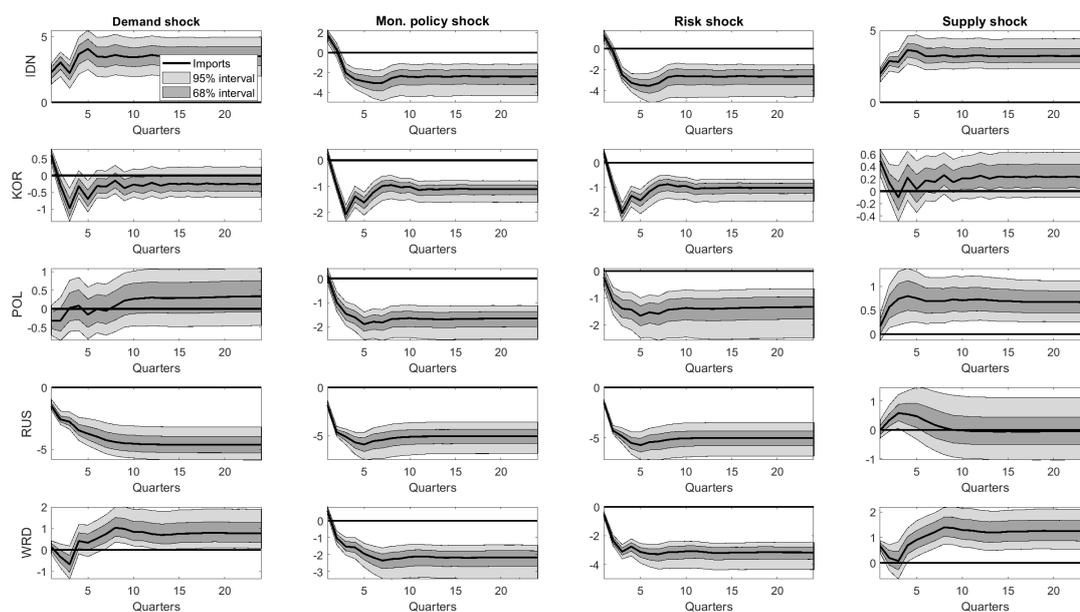
Continuation of [Figure B.8](#) – impulse responses (in percent) of import volumes.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



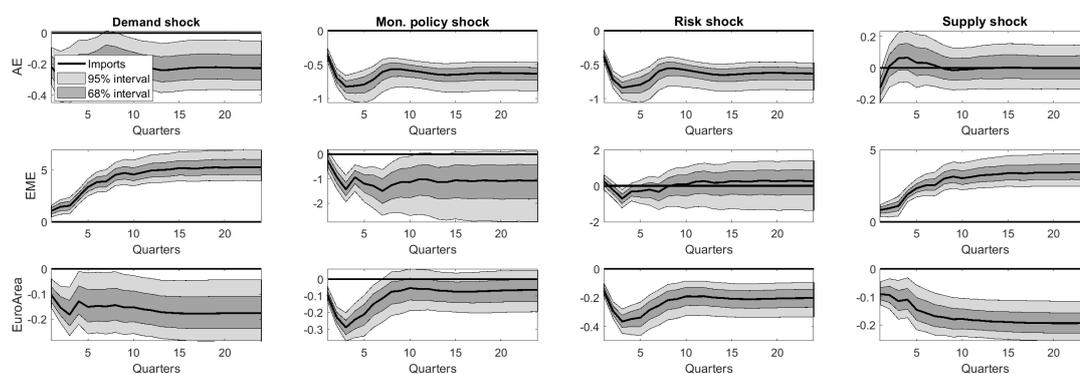
Continuation of [Figure B.8](#) – impulse responses (in percent) of import volumes.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.8](#) – impulse responses (in percent) of import volumes.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.8](#) – impulse responses (in percent) of import volumes.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).

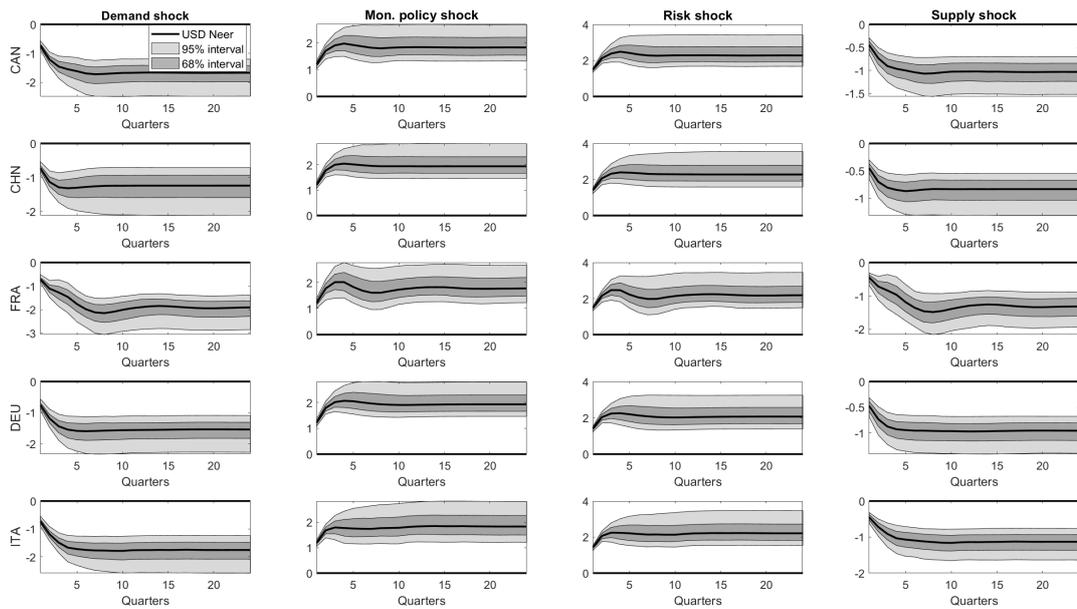
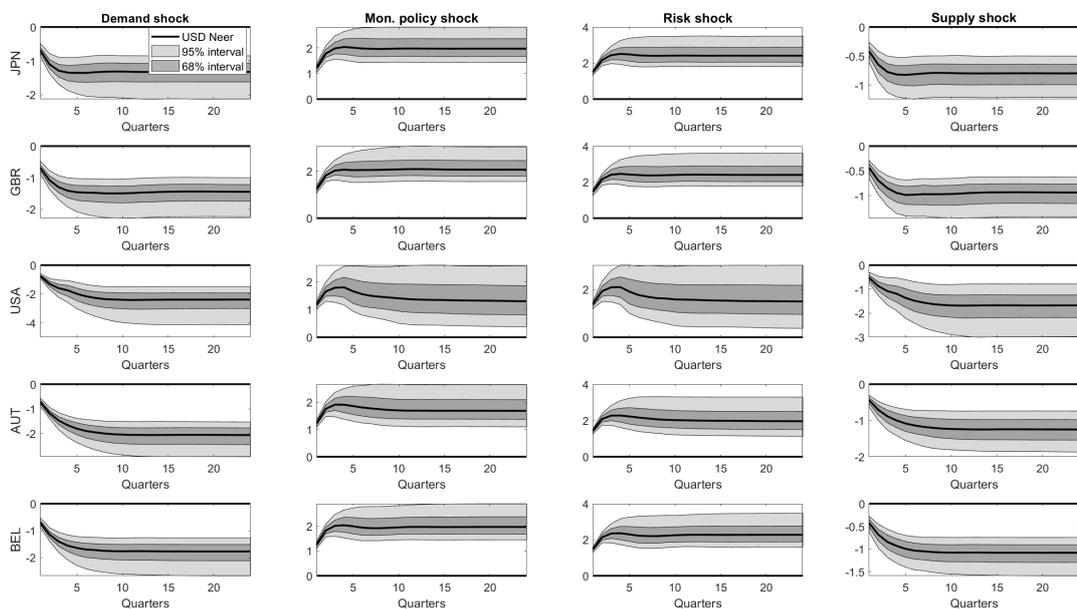


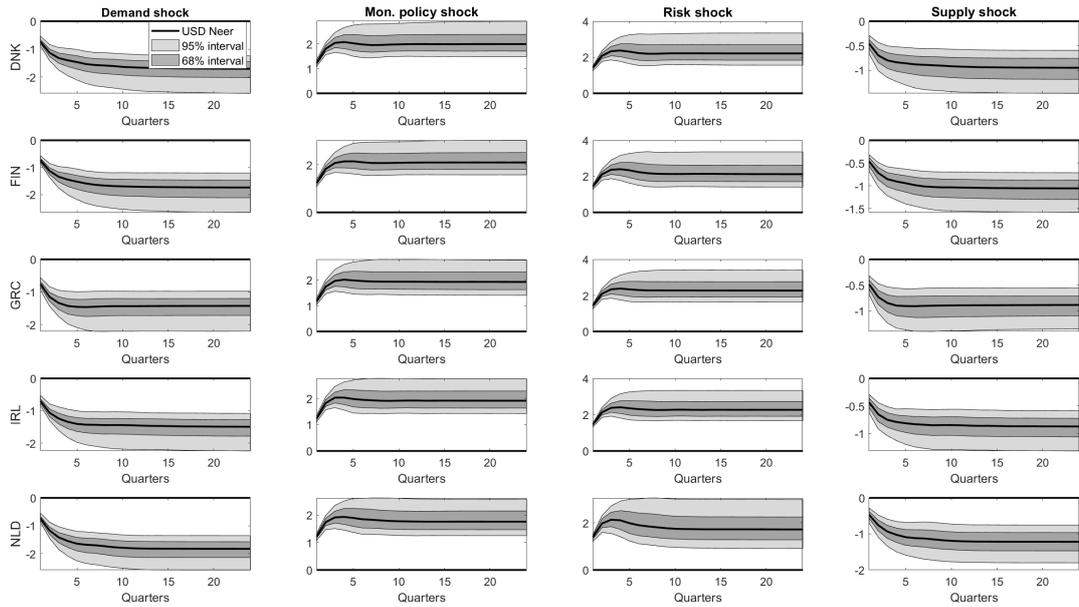
Figure B.9: Accumulated impulse responses (in percent) of the USD Neer.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



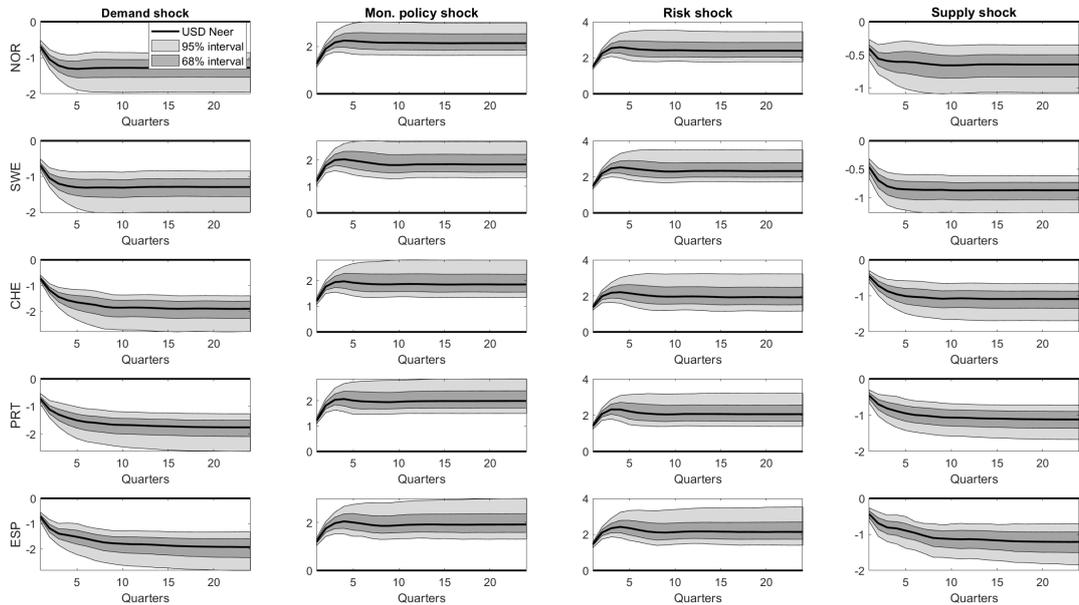
Continuation of [Figure B.9](#) – impulse responses (in percent) of the USD Neer.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



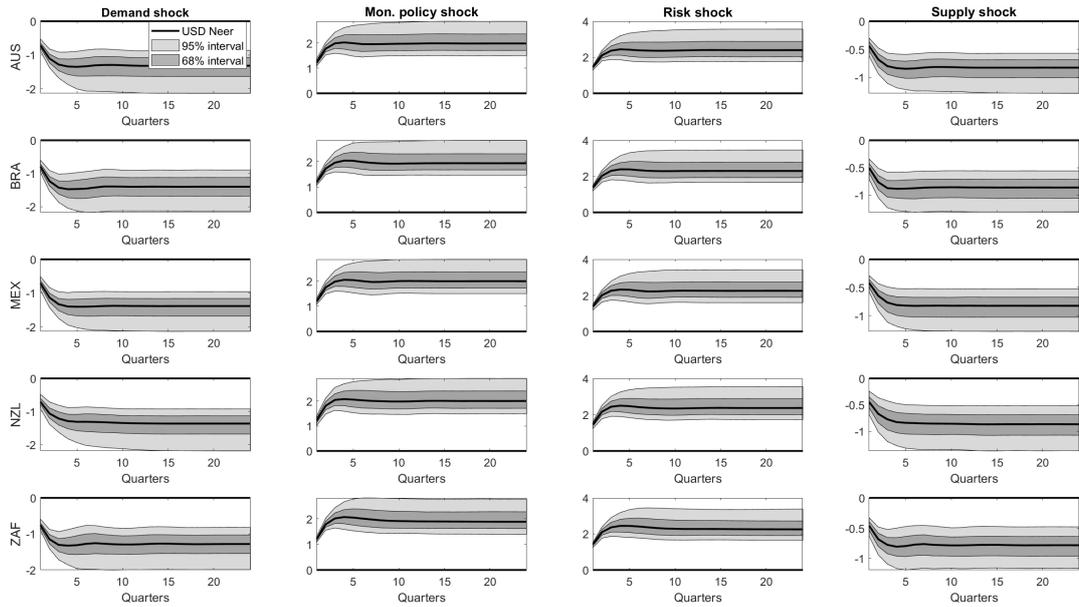
Continuation of [Figure B.9](#) – impulse responses (in percent) of the USD Neer.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



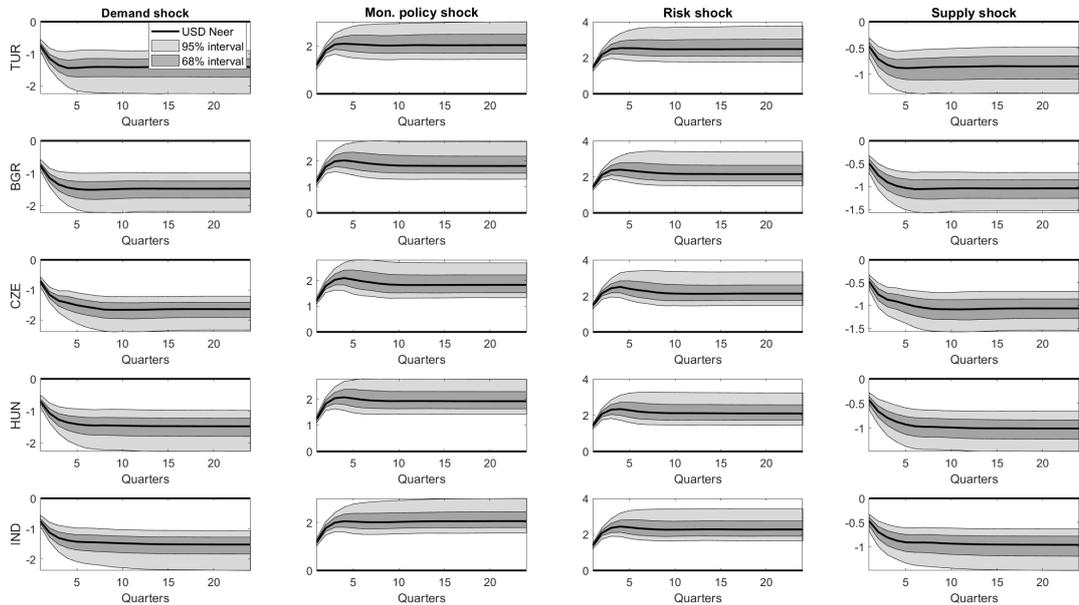
Continuation of [Figure B.9](#) – impulse responses (in percent) of the USD Neer.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



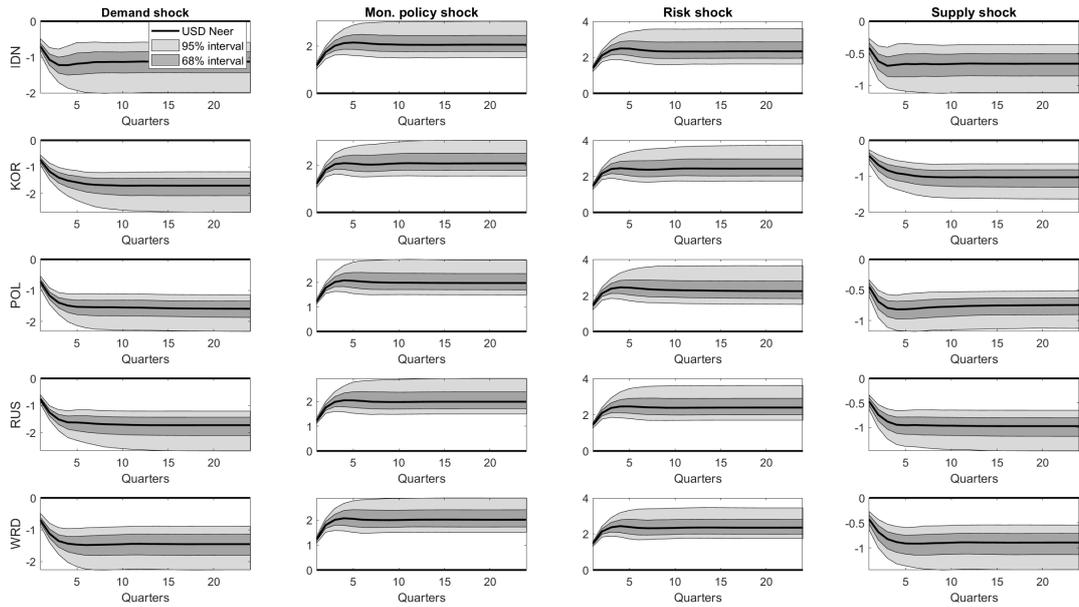
Continuation of [Figure B.9](#) – impulse responses (in percent) of the USD Neer.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



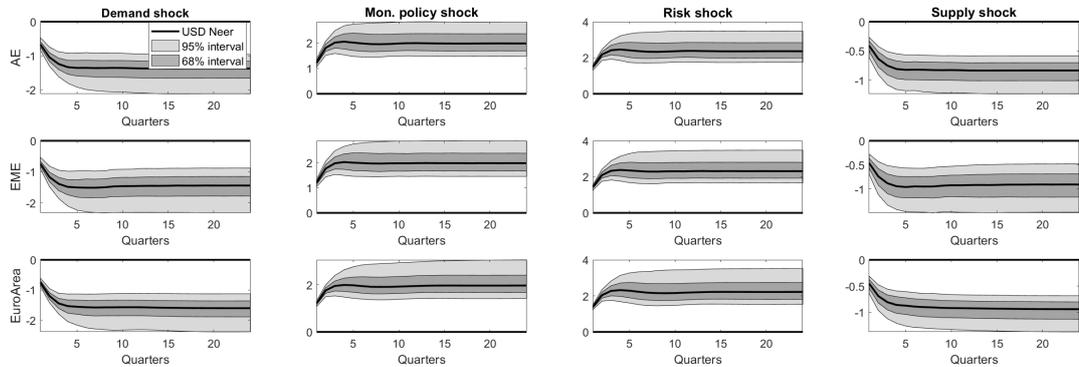
Continuation of [Figure B.9](#) – impulse responses (in percent) of the USD Neer.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.9](#) – impulse responses (in percent) of the USD Neer.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.9](#) – impulse responses (in percent) of the USD Neer.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).

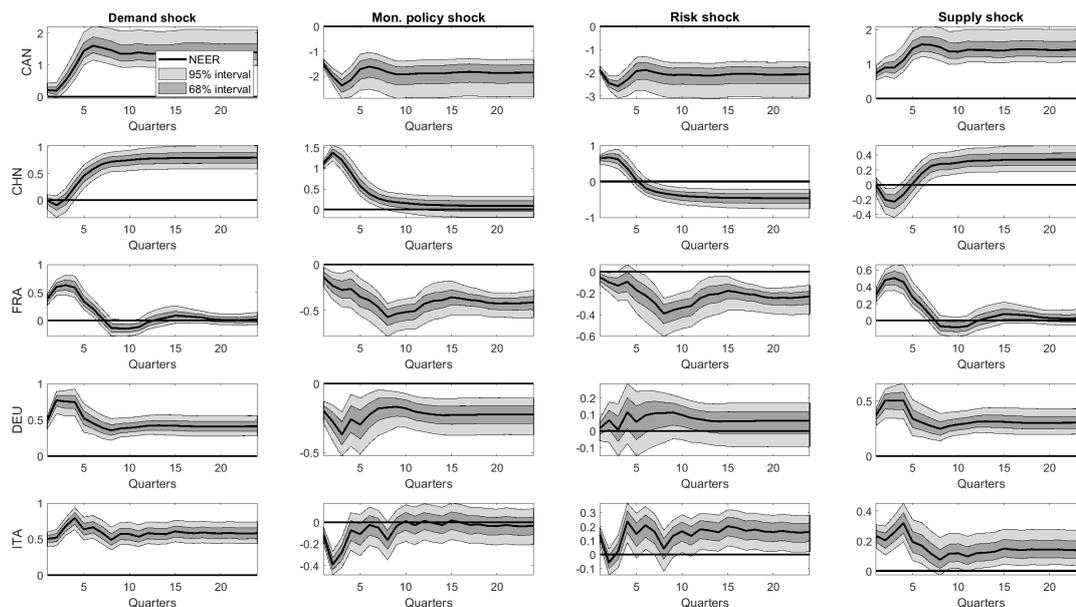
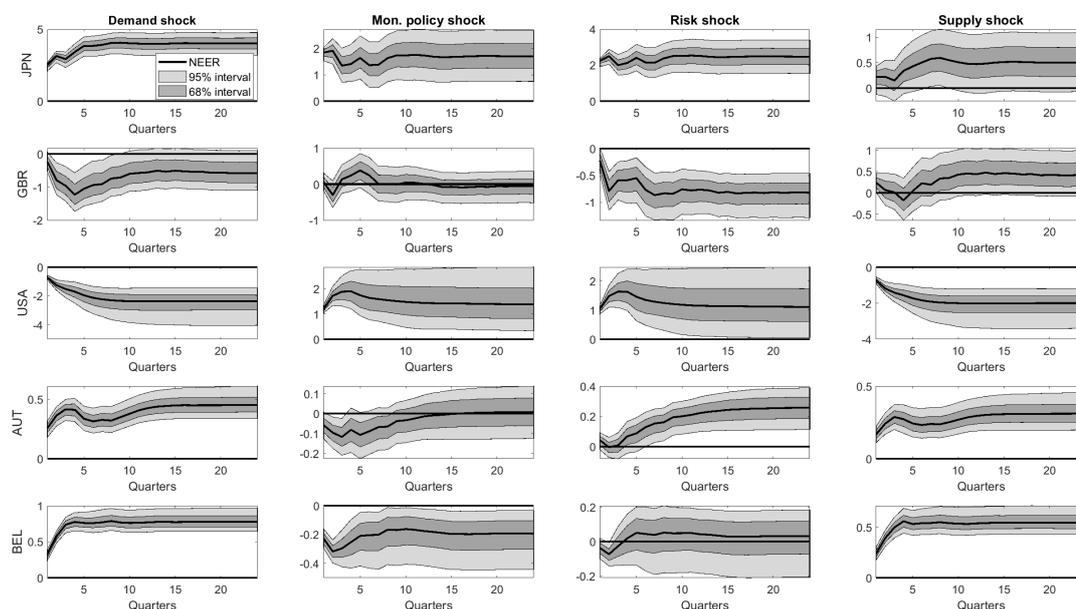
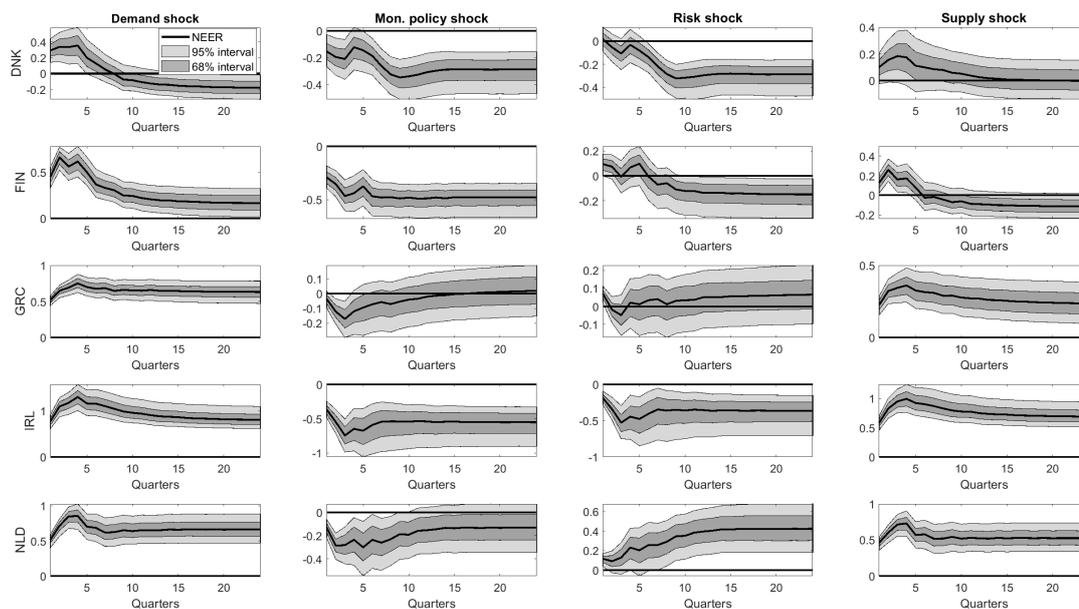


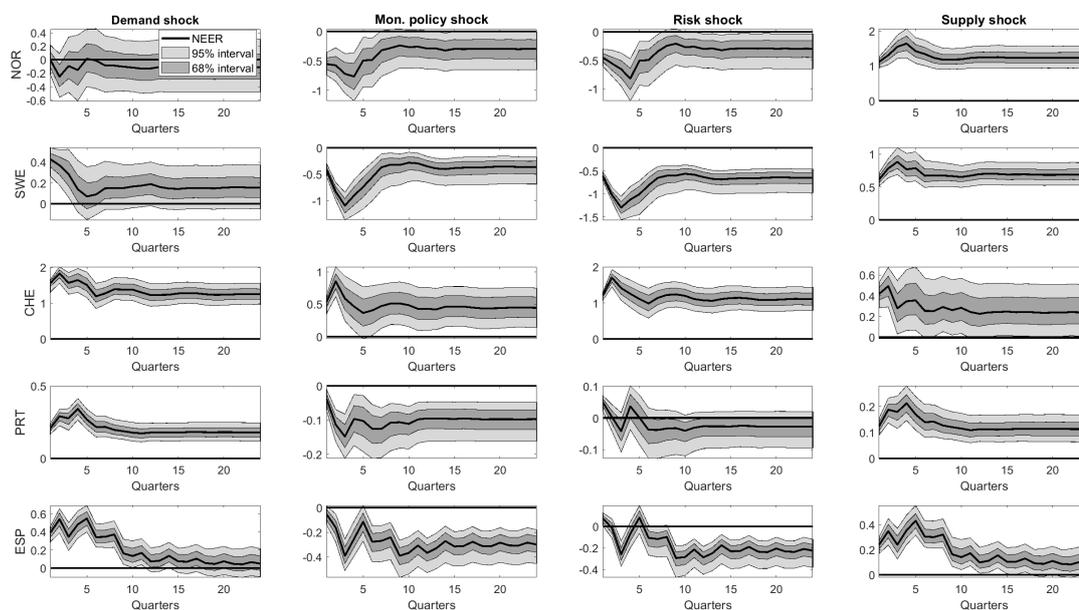
Figure B.10: Accumulated impulse responses (in percent) of the domestic Neer.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of Equation (3.2).



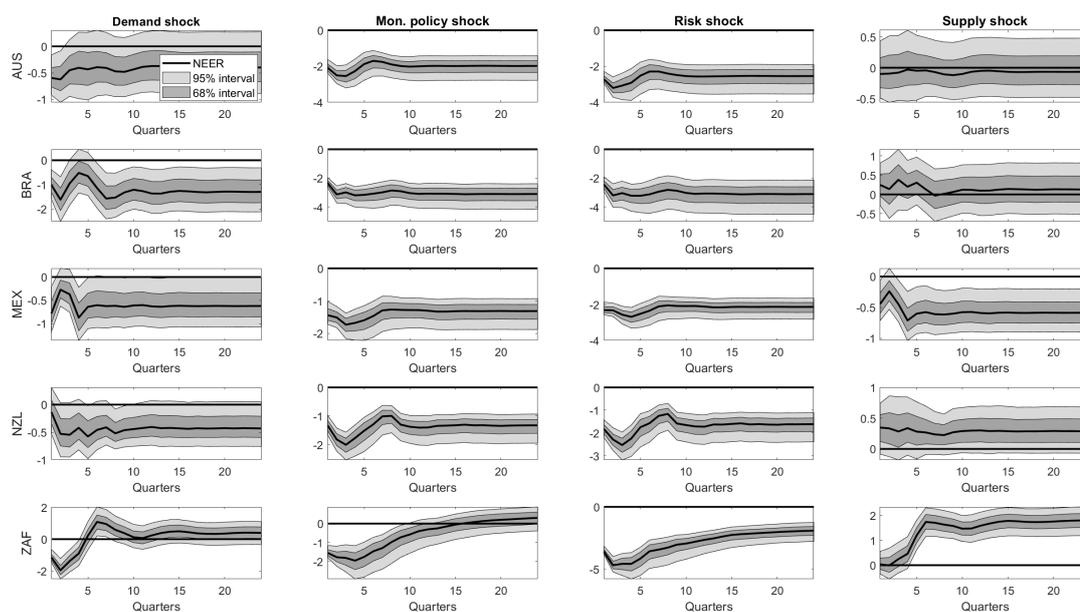
Continuation of Figure B.10 – impulse responses (in percent) of the domestic Neer.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of Equation (3.2).



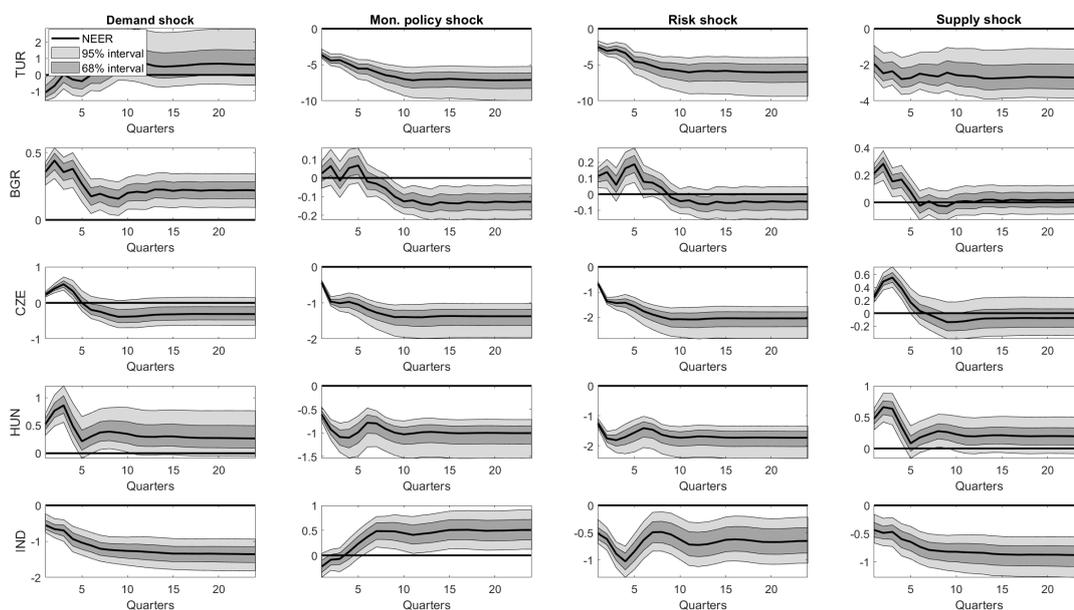
Continuation of [Figure B.10](#) – impulse responses (in percent) of the domestic Neer.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



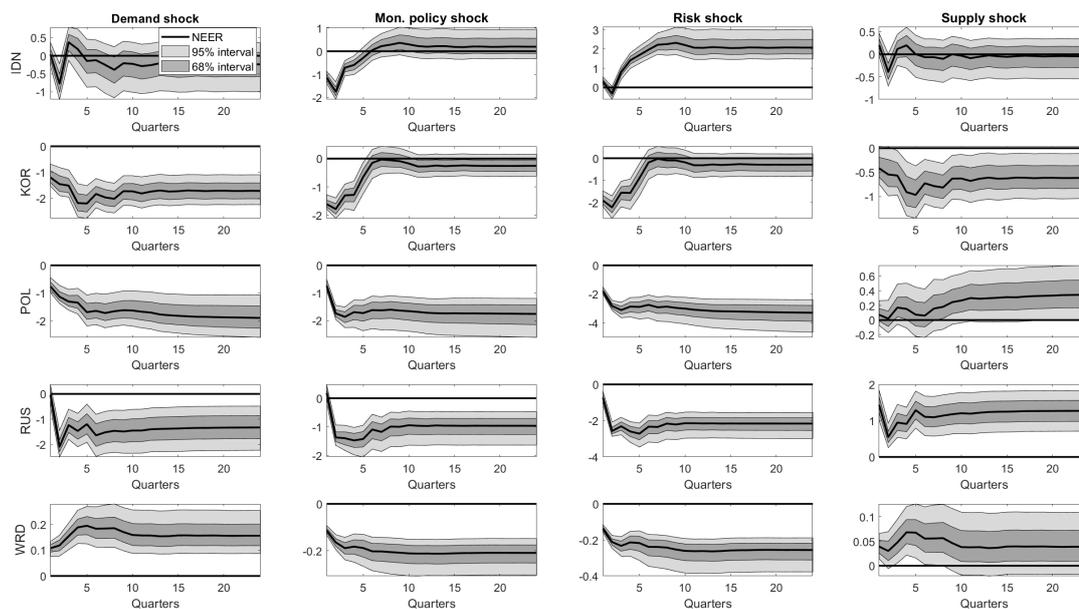
Continuation of [Figure B.10](#) – impulse responses (in percent) of the domestic Neer.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



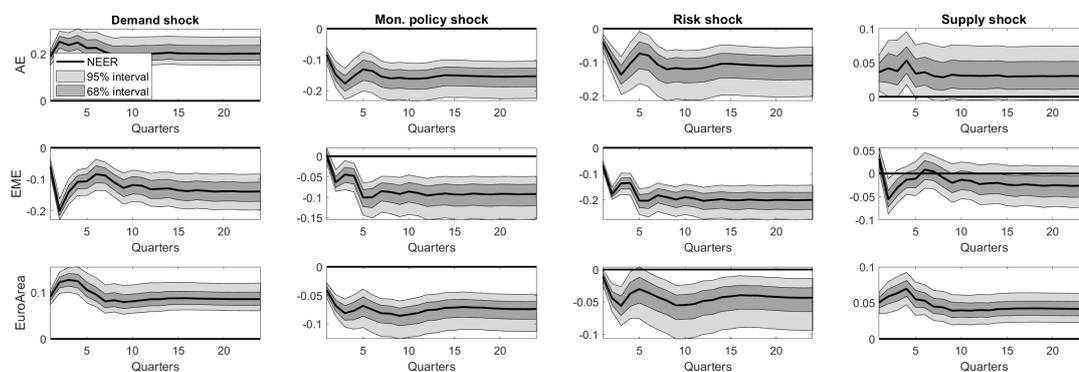
Continuation of [Figure B.10](#) – impulse responses (in percent) of the domestic Neer.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.10](#) – impulse responses (in percent) of the domestic Neer.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.10](#) – impulse responses (in percent) of the domestic Neer.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.10](#) – impulse responses (in percent) of the domestic Neer.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).

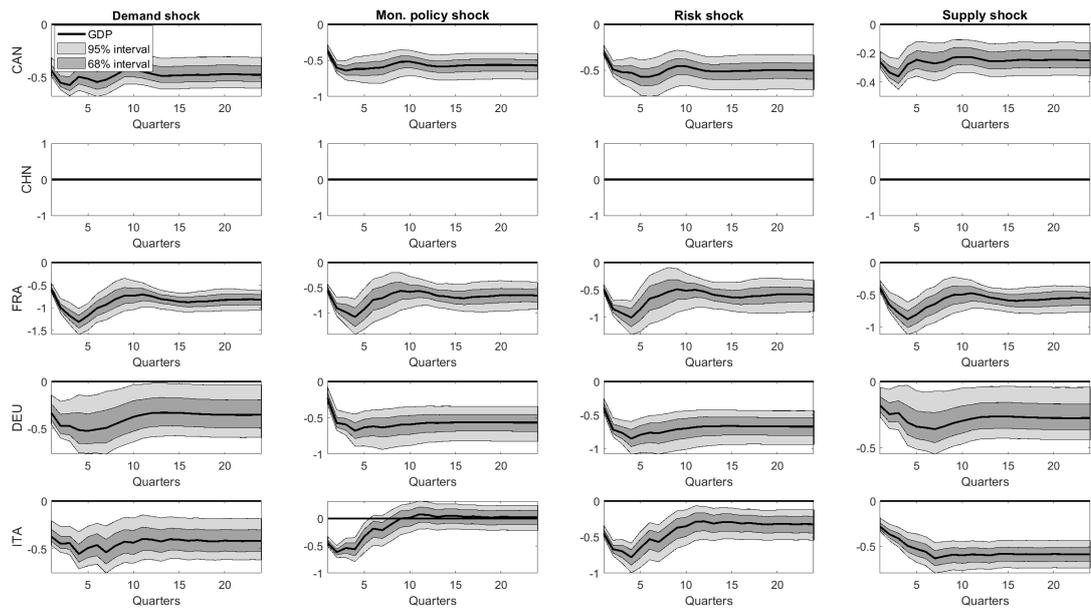
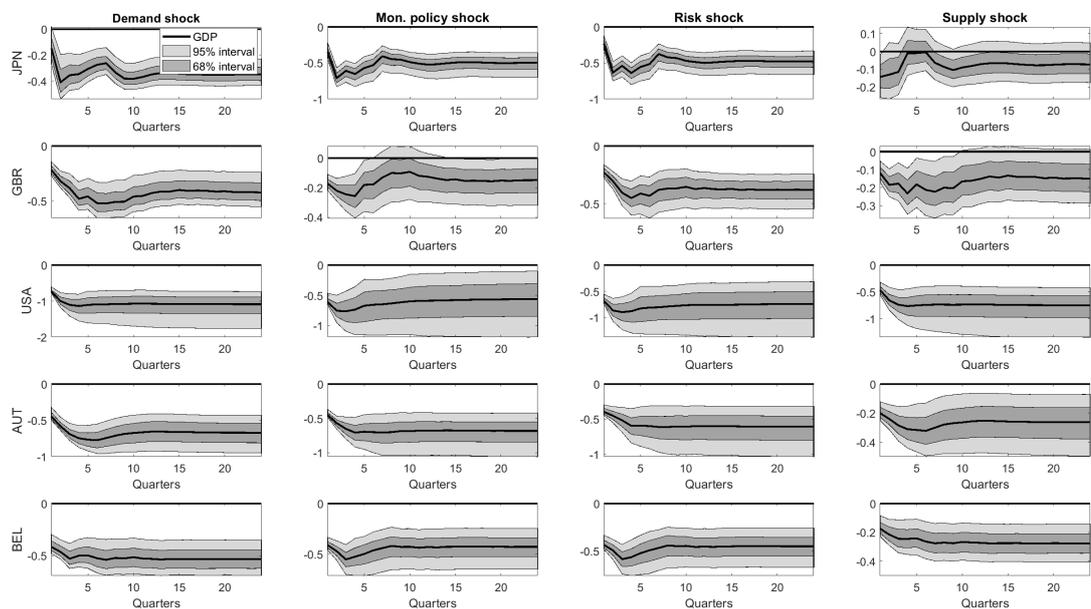


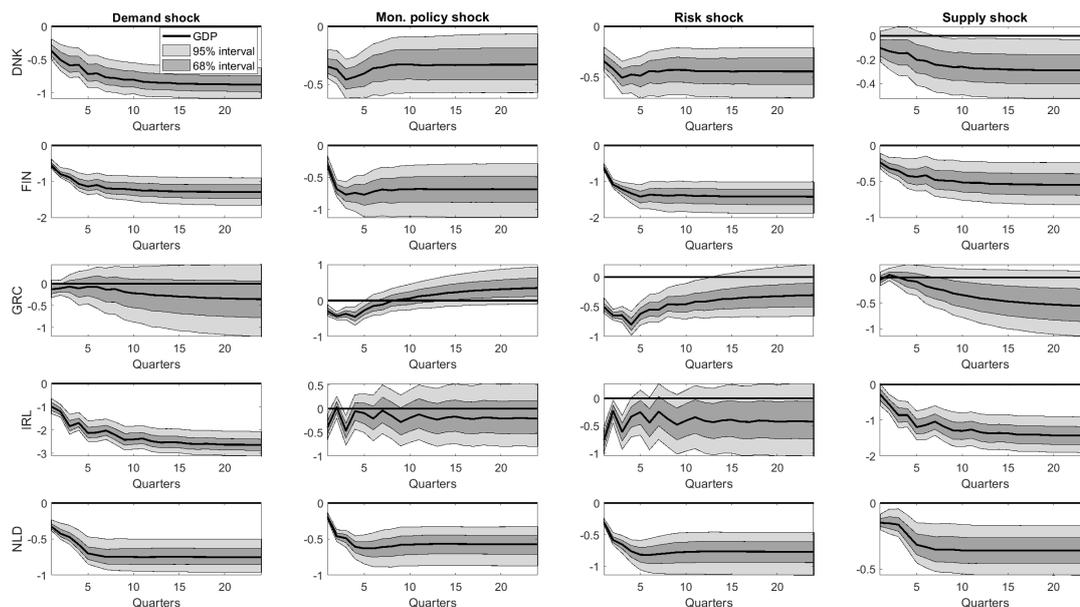
Figure B.11: Accumulated impulse responses (in percent) of the domestic real GDP growth.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



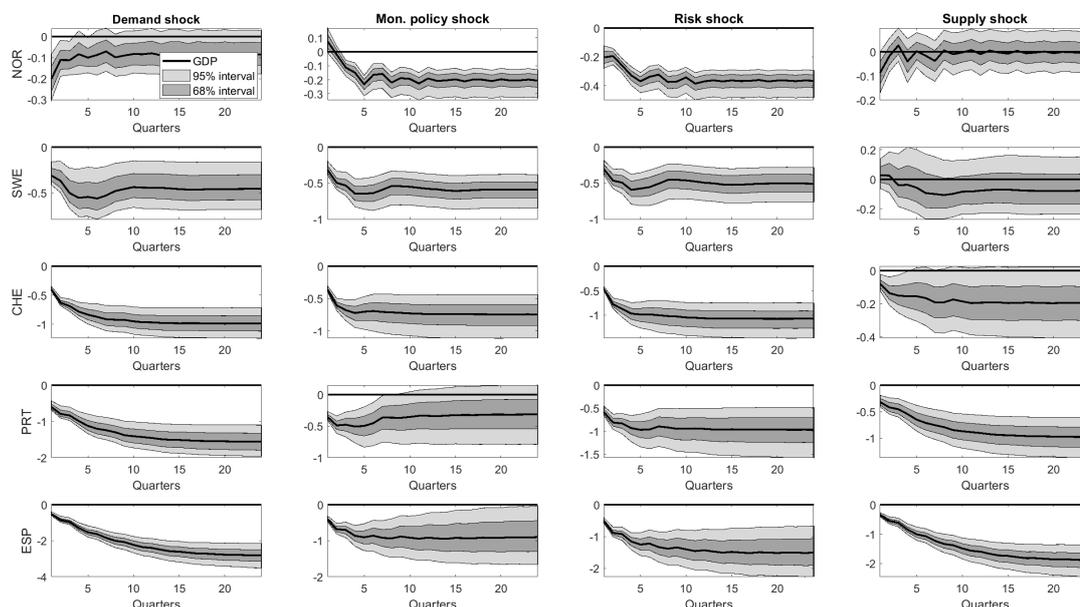
Continuation of [Figure B.11](#) – impulse responses (in percent) of the domestic real GDP growth.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



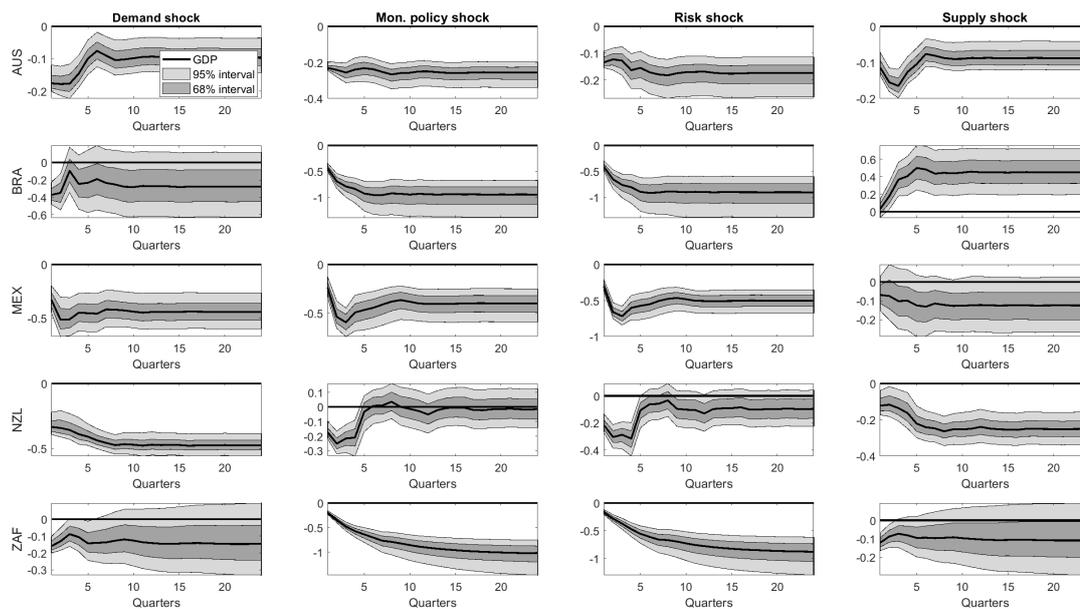
Continuation of [Figure B.11](#) – impulse responses (in percent) of the domestic real GDP growth.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



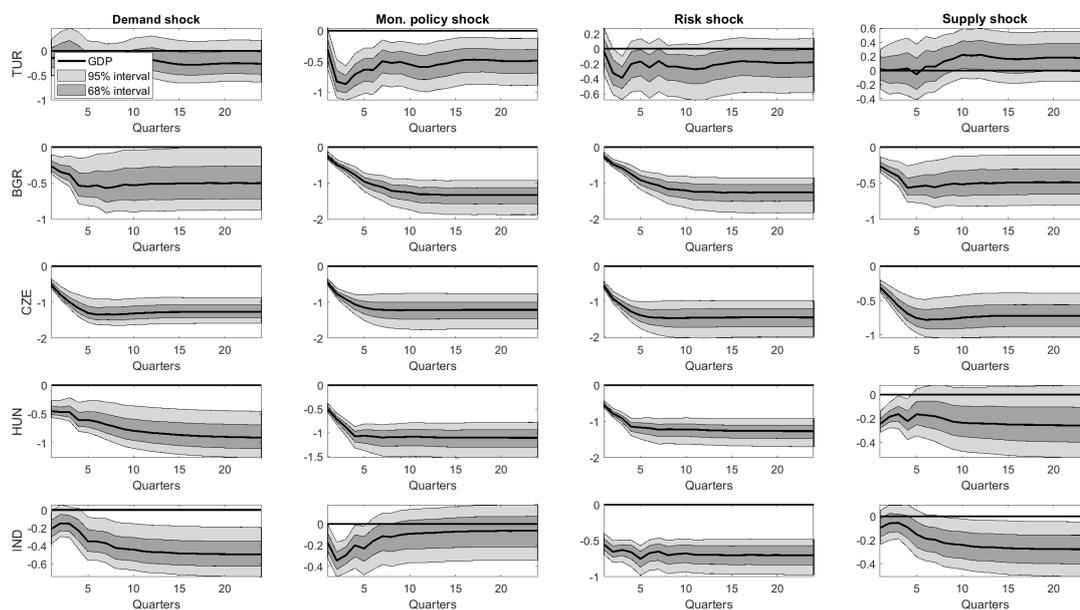
Continuation of [Figure B.11](#) – impulse responses (in percent) of the domestic real GDP growth.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



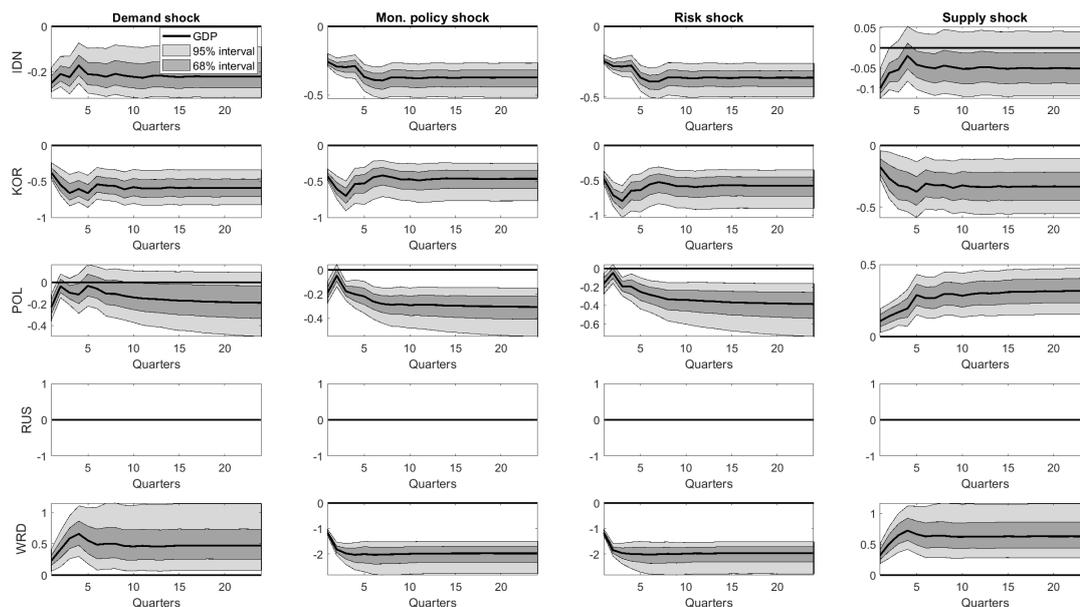
Continuation of [Figure B.11](#) – impulse responses (in percent) of the domestic real GDP growth.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



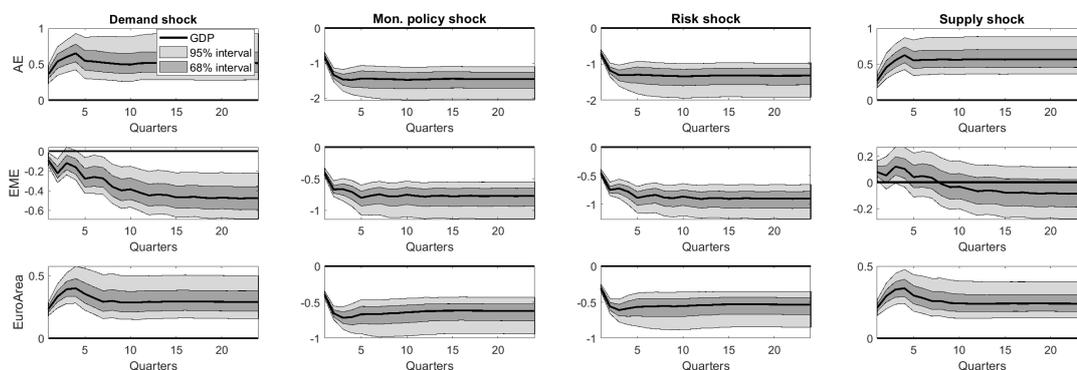
Continuation of [Figure B.11](#) – impulse responses (in percent) of the domestic real GDP growth.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.11](#) – impulse responses (in percent) of the domestic real GDP growth.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.11](#) – impulse responses (in percent) of the domestic real GDP growth.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).

## B.4 IRFs for the financial model

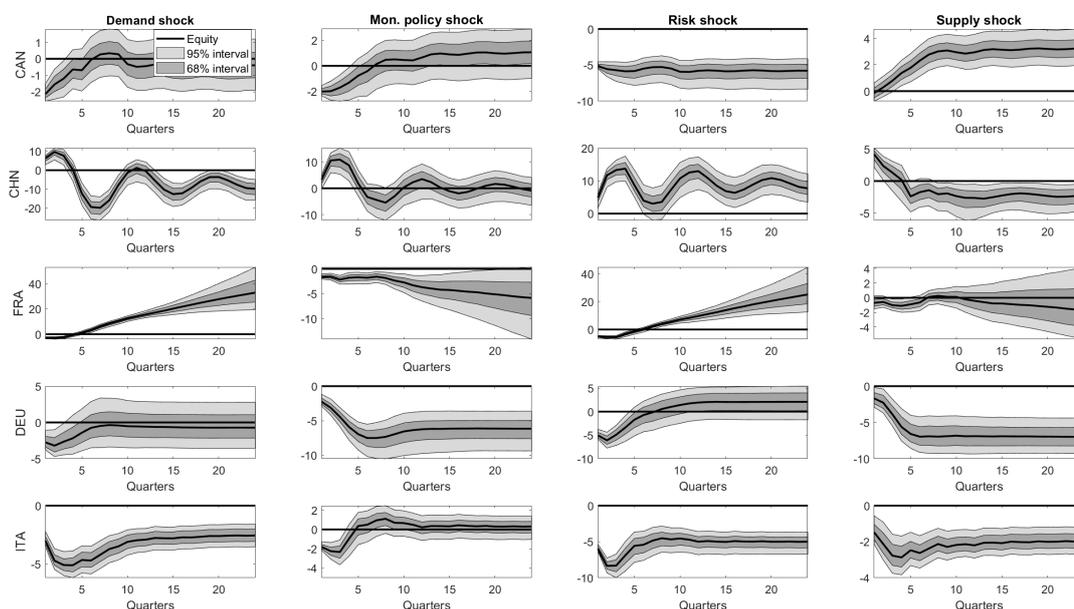
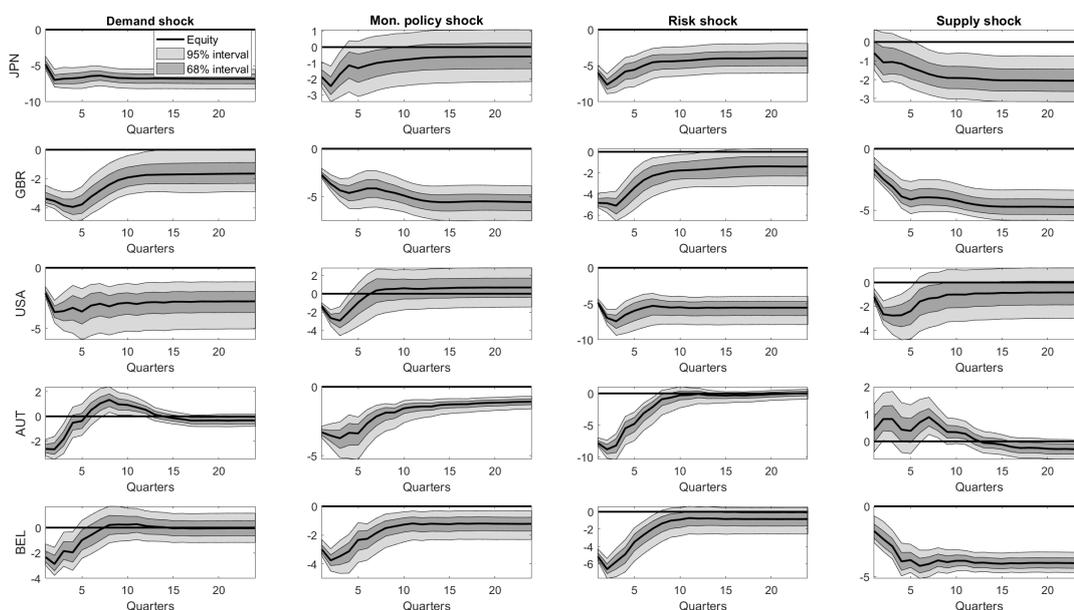


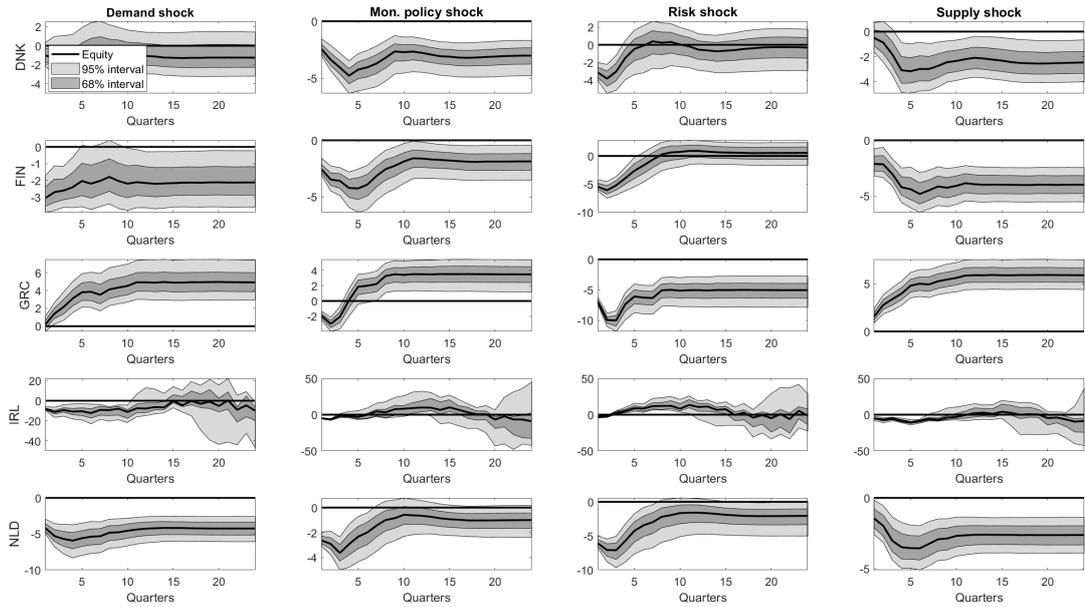
Figure B.12: Accumulated impulse responses (in percent) of equity indices.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



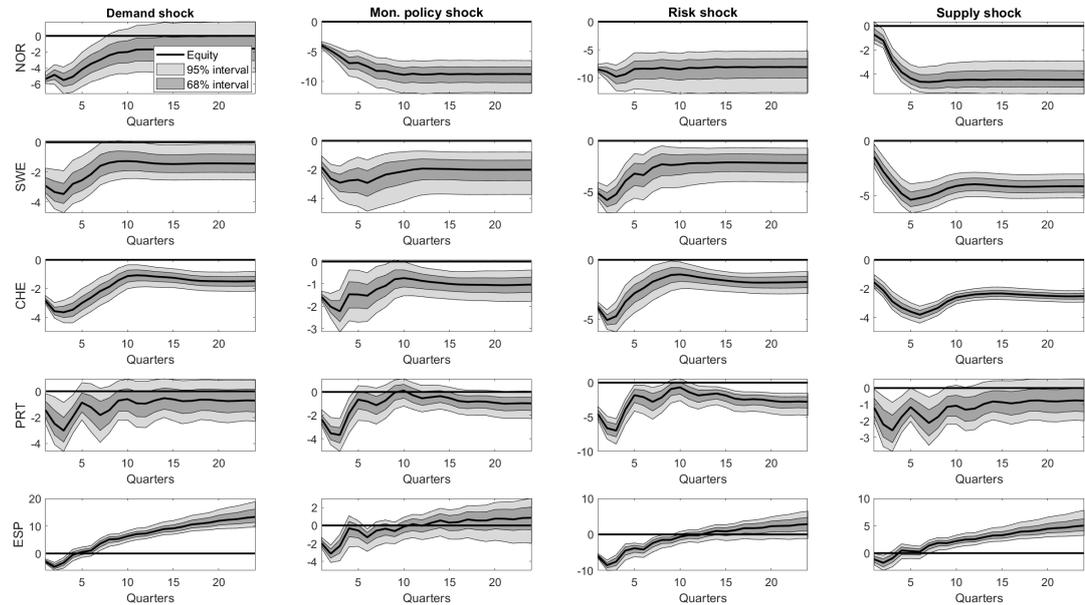
Continuation of [Figure B.12](#) – impulse responses (in percent) of equity indices.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



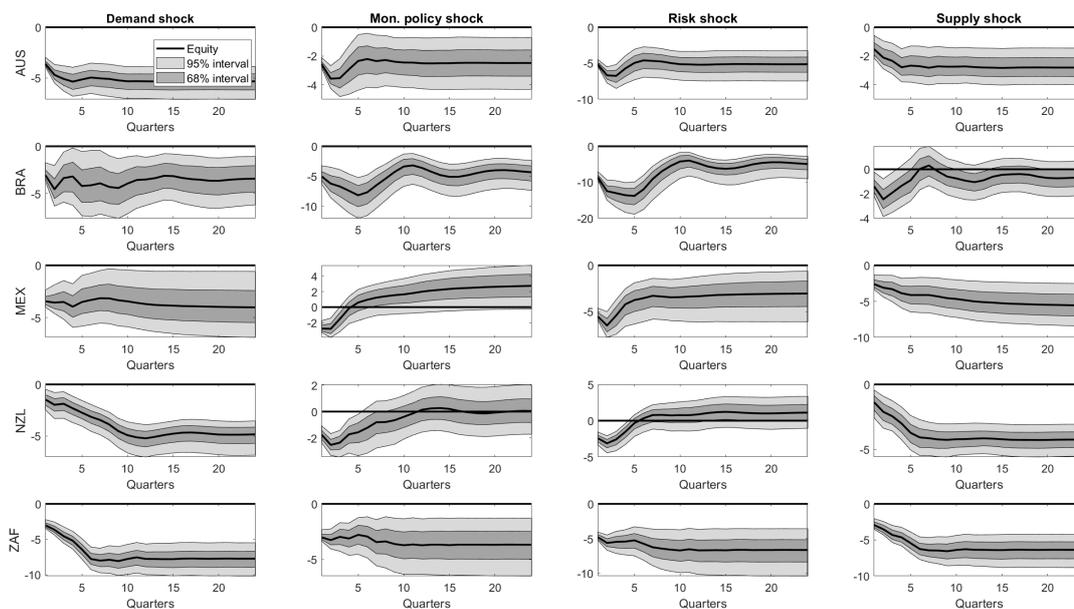
Continuation of [Figure B.12](#) – impulse responses (in percent) of equity indices.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).

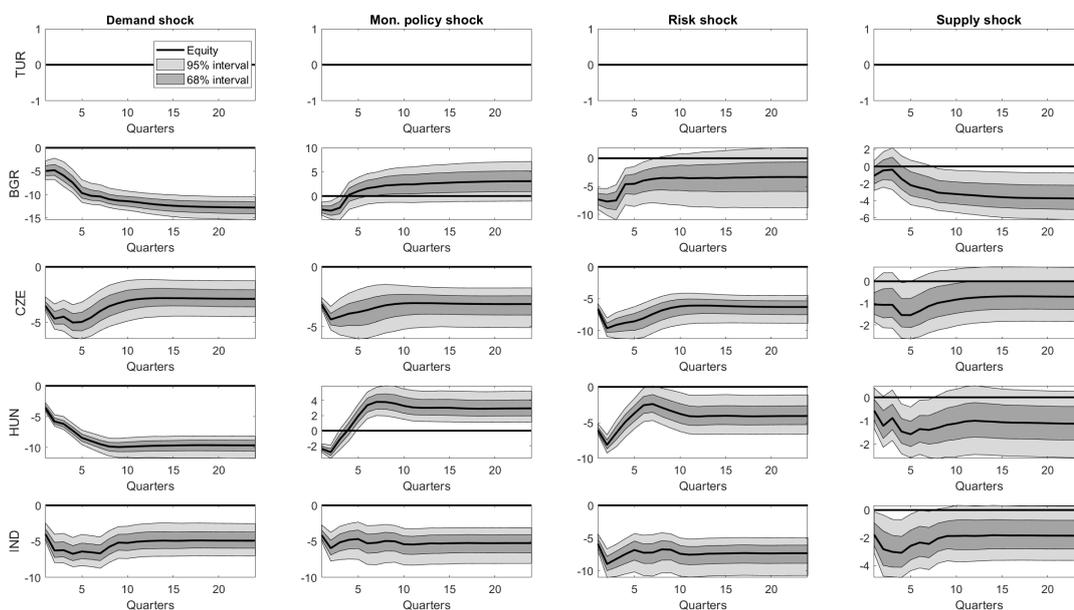


Continuation of [Figure B.12](#) – impulse responses (in percent) of equity indices.

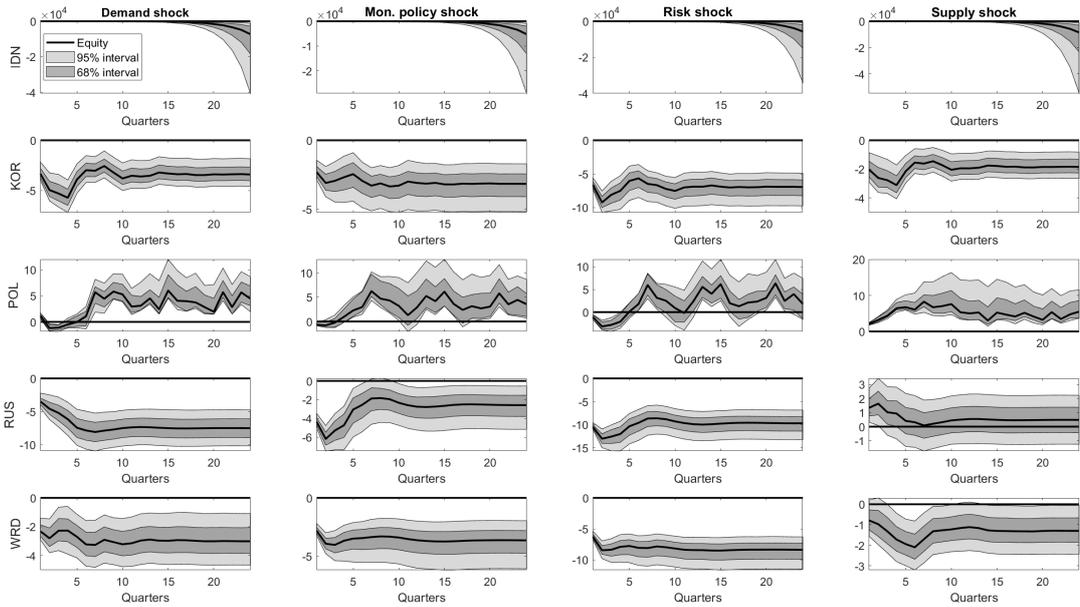
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.12](#) – impulse responses (in percent) of equity indices.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).

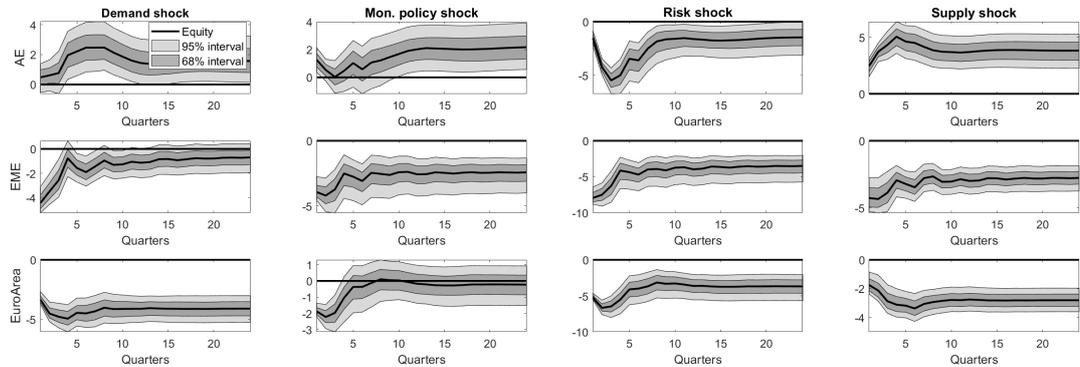


Continuation of [Figure B.12](#) – impulse responses (in percent) of equity indices.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.12](#) – impulse responses (in percent) of equity indices.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.12](#) – impulse responses (in percent) of equity indices.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).

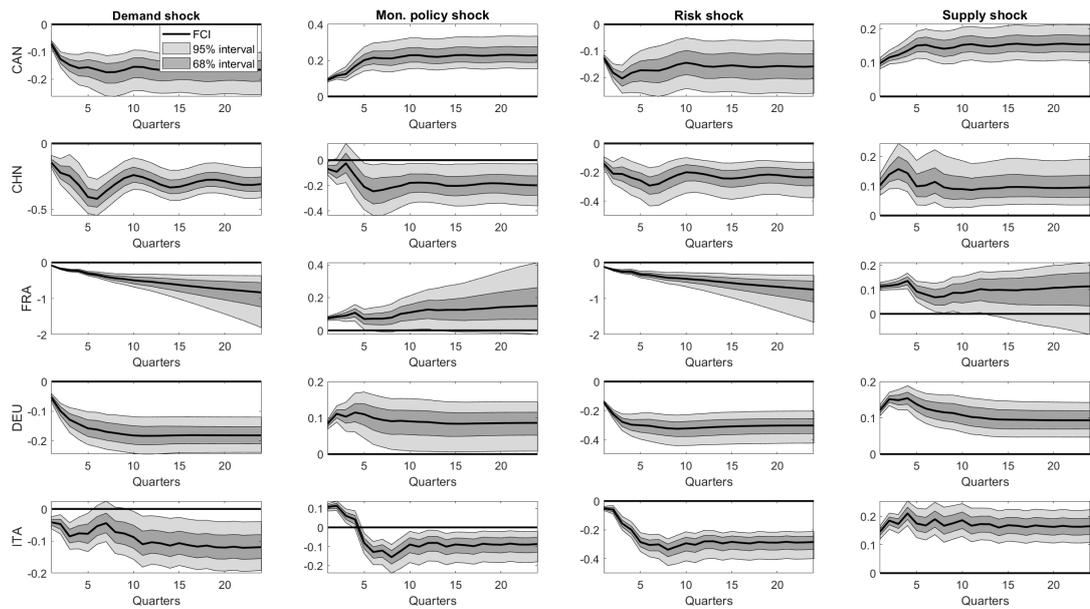
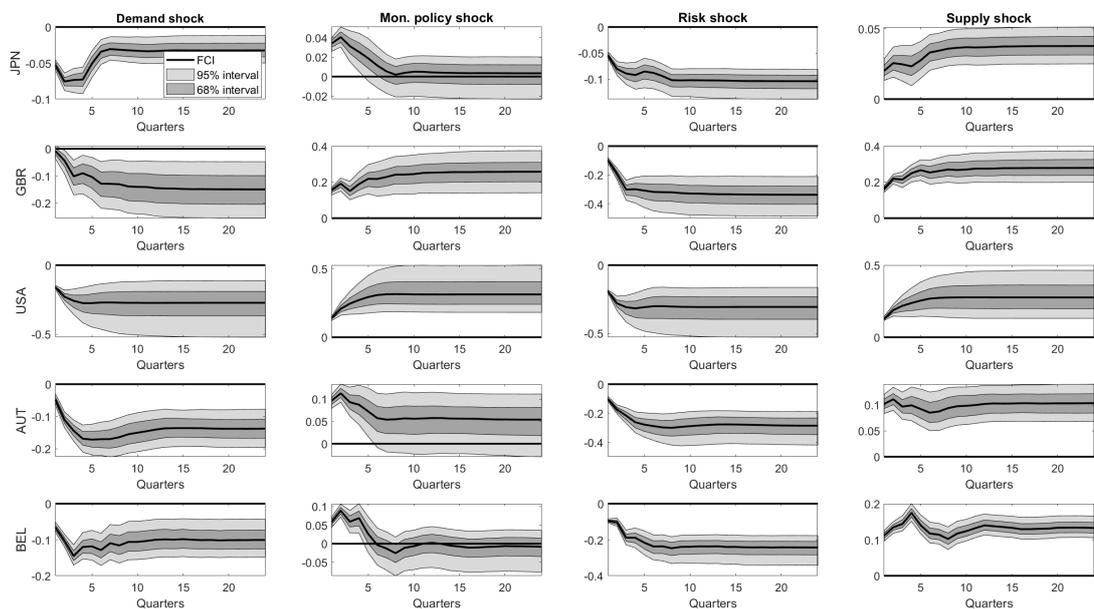


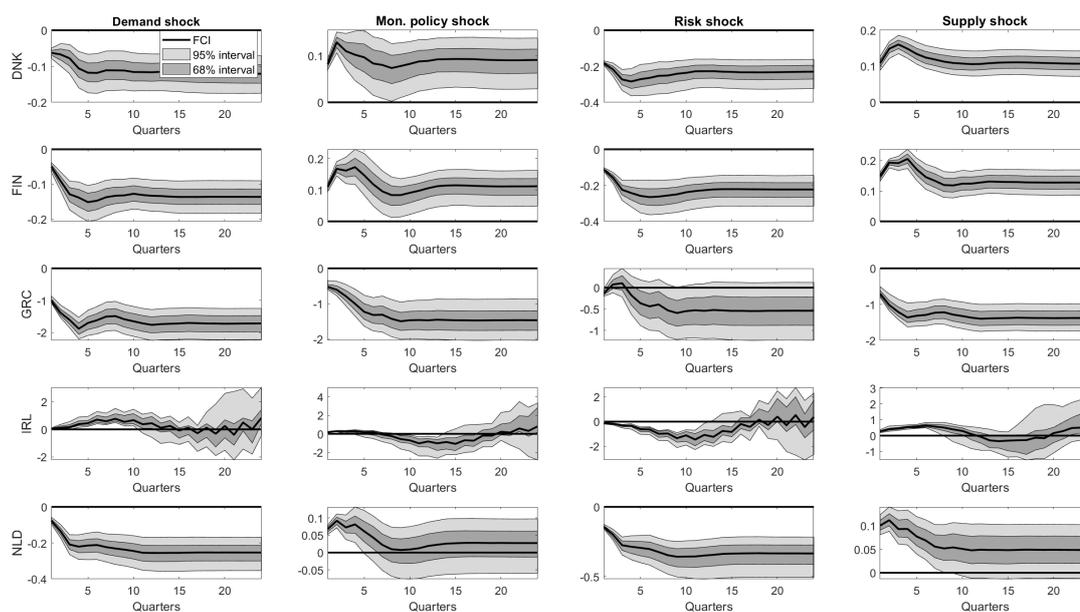
Figure B.13: Accumulated impulse responses (in percent) of 10-year yields.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).

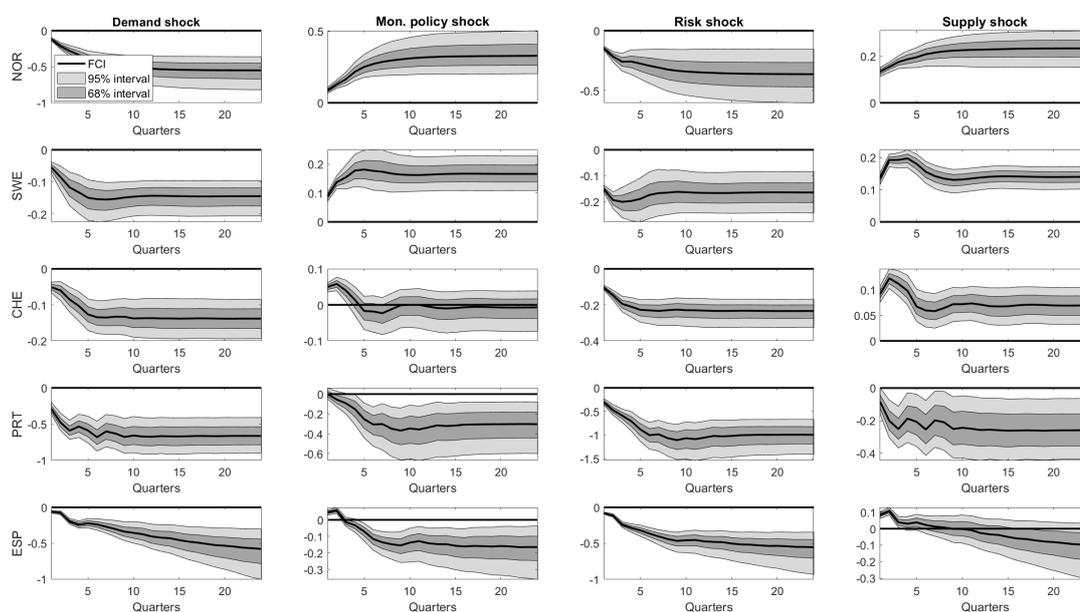


Continuation of [Figure B.13](#) – impulse responses (in percent) of 10-year yields.

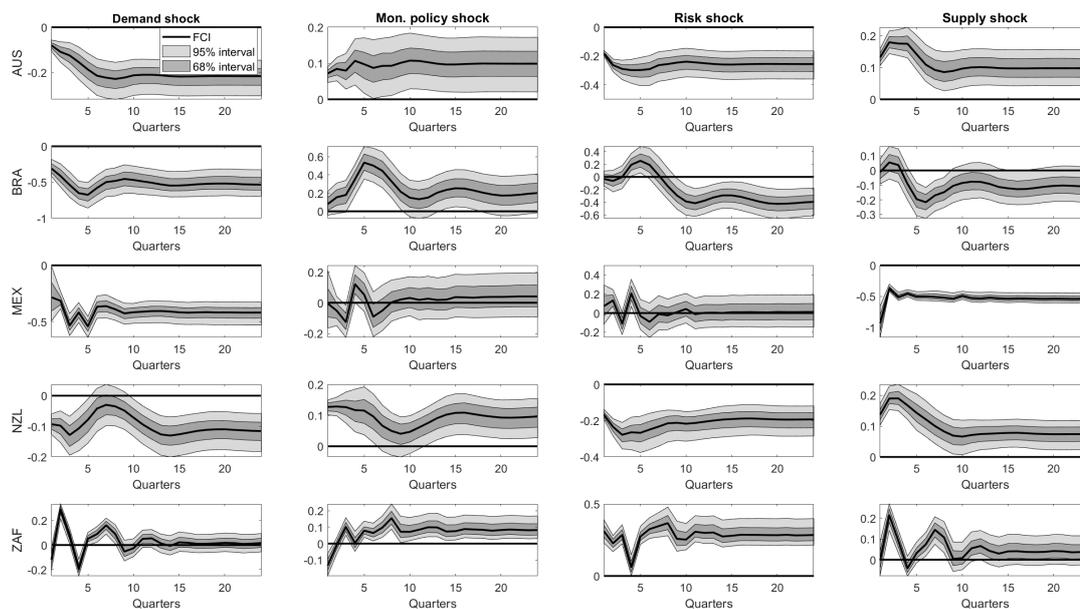
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



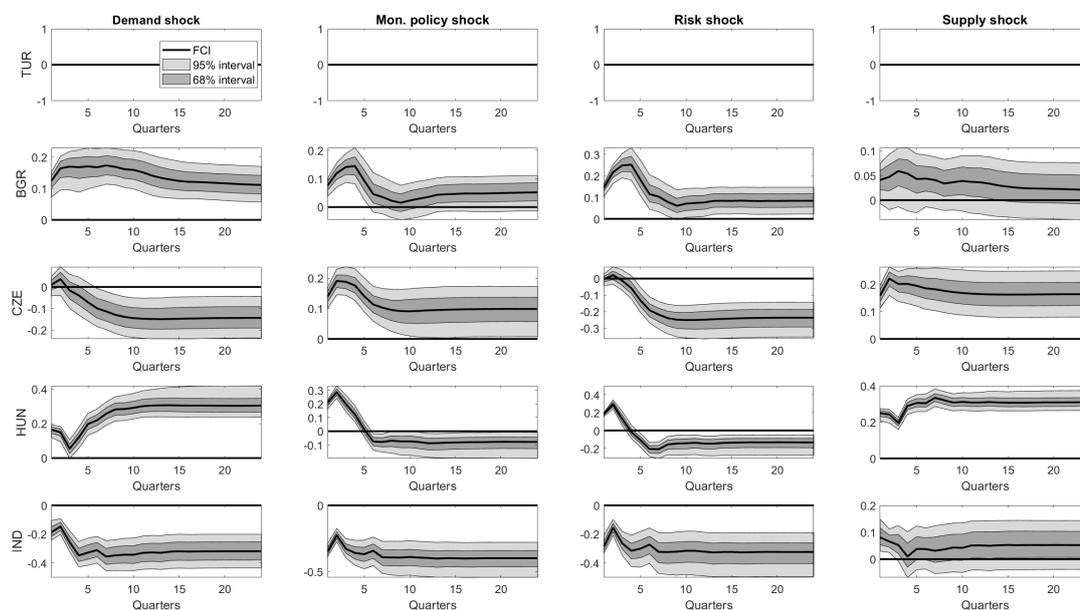
Continuation of [Figure B.13](#) – impulse responses (in percent) of 10-year yields.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



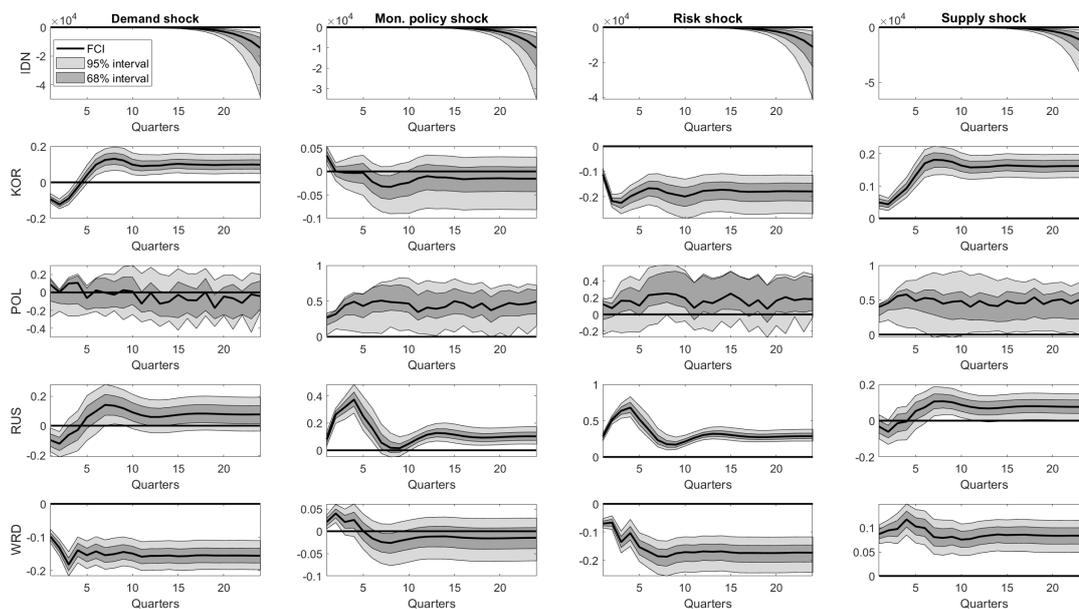
Continuation of [Figure B.13](#) – impulse responses (in percent) of 10-year yields.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



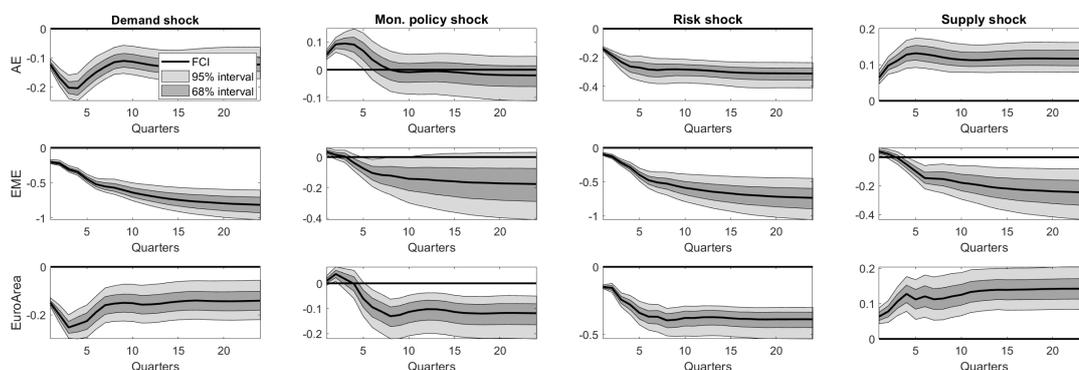
Continuation of [Figure B.13](#) – impulse responses (in percent) of 10-year yields.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.13](#) – impulse responses (in percent) of 10-year yields.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.13](#) – impulse responses (in percent) of 10-year yields.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



Continuation of [Figure B.13](#) – impulse responses (in percent) of 10-year yields.  
**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).

## B.5 Pass-through at different horizons

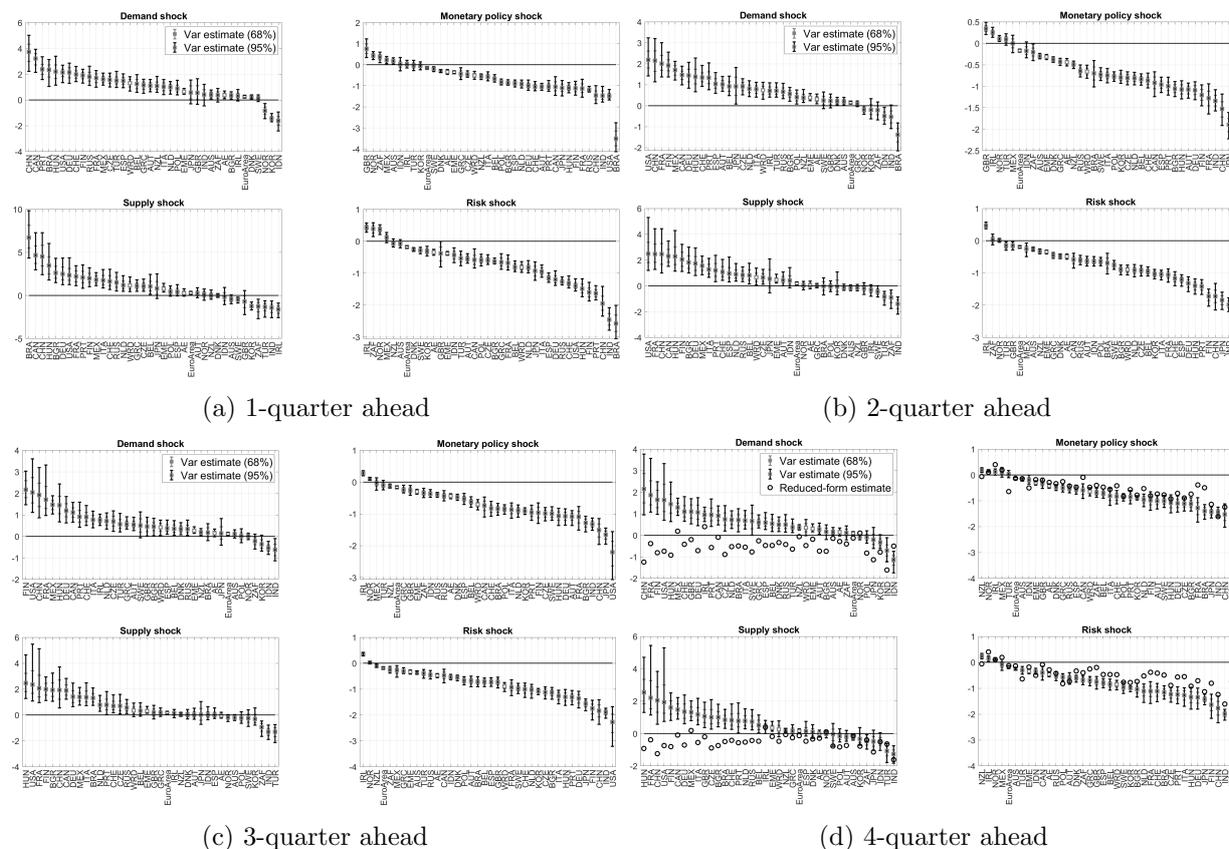


Figure B.14: Country-specific estimates of the pass-through to export volumes from the VAR in Equation (3.3) at different horizons.

**Notes:** pass-through coefficients are estimated separately for each country and describe the elasticity of exports (in percent points) to a 1% USD appreciation. Lines report 68% and 95% confidence intervals over the estimates obtained bootstrapping 1000 draws from the posterior distribution of identified US shocks. Black dots are the reduced-form pass-through estimates from Equation (2.1).

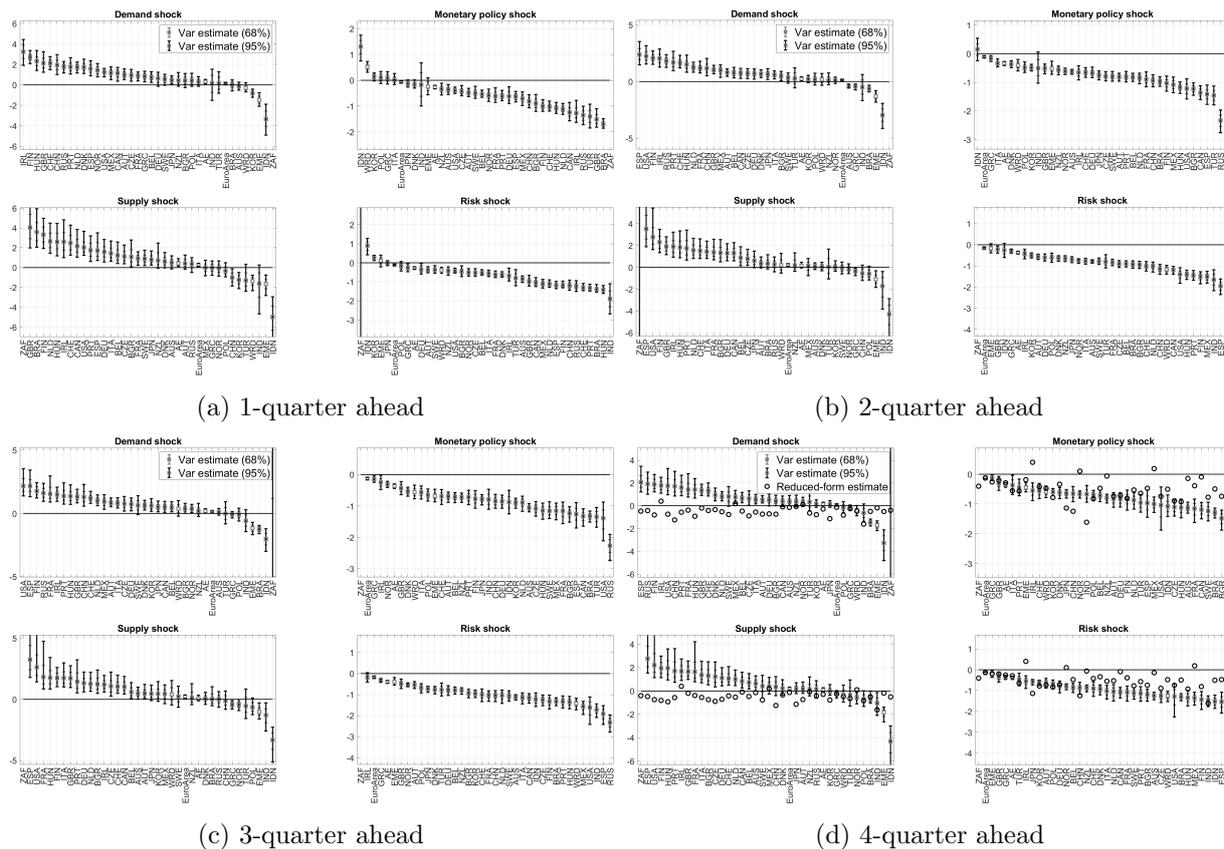


Figure B.15: Country-specific estimates of the pass-through to import volumes from the VAR in Equation (3.3) at different horizons.

**Notes:** pass-through coefficients are estimated separately for each country and describe the elasticity of imports (in percent points) to a 1% USD appreciation. Lines report 68% and 95% confidence intervals over the estimates obtained bootstrapping 1000 draws from the posterior distribution of identified US shocks. Black dots are the reduced-form pass-through estimates from Equation (2.1).

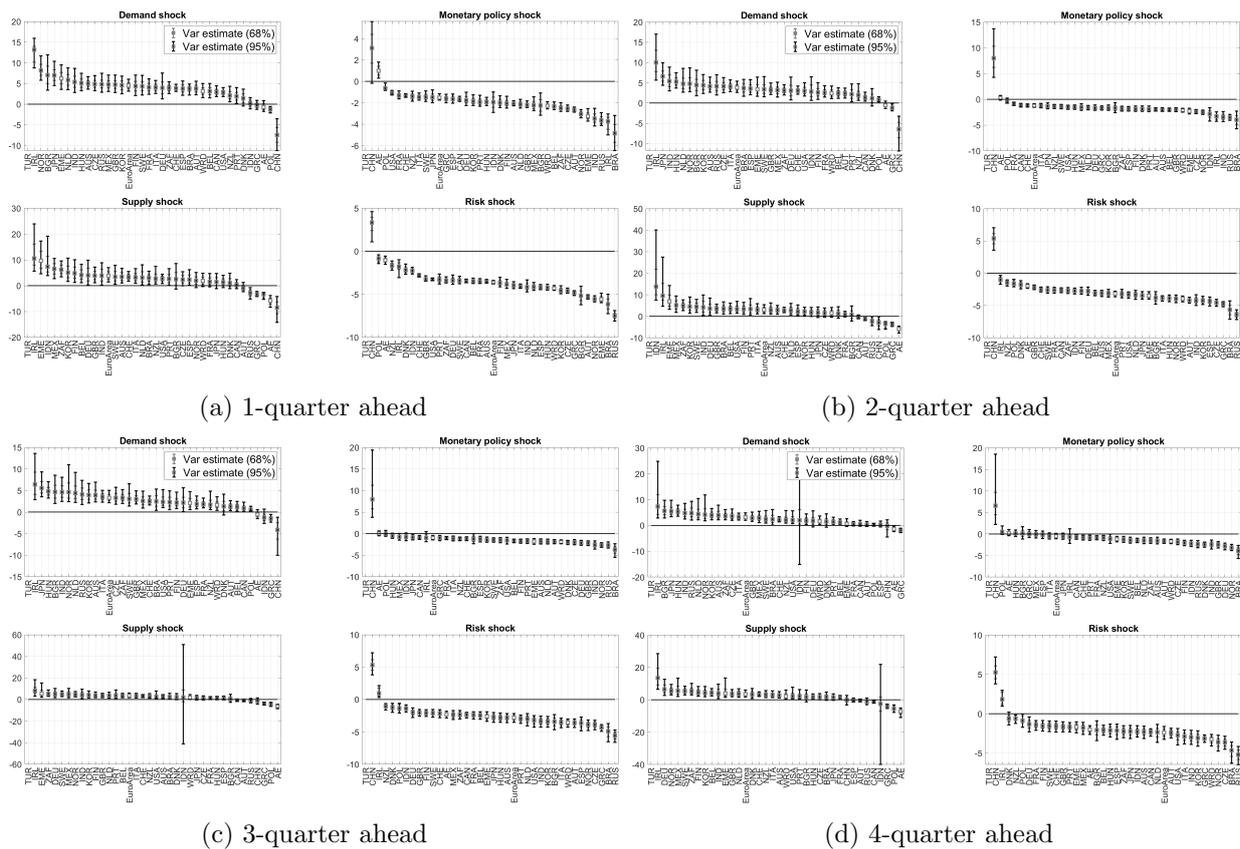


Figure B.16: Country-specific estimates of the pass-through to equity indices from the VAR in Equation (3.3) at different horizons.

**Notes:** pass-through coefficients are estimated separately for each country and describe the elasticity of equity indices (in percent points) to a 1% USD appreciation. Lines report 68% and 95% confidence intervals over the estimates obtained bootstrapping 1000 draws from the posterior distribution of identified US shocks.

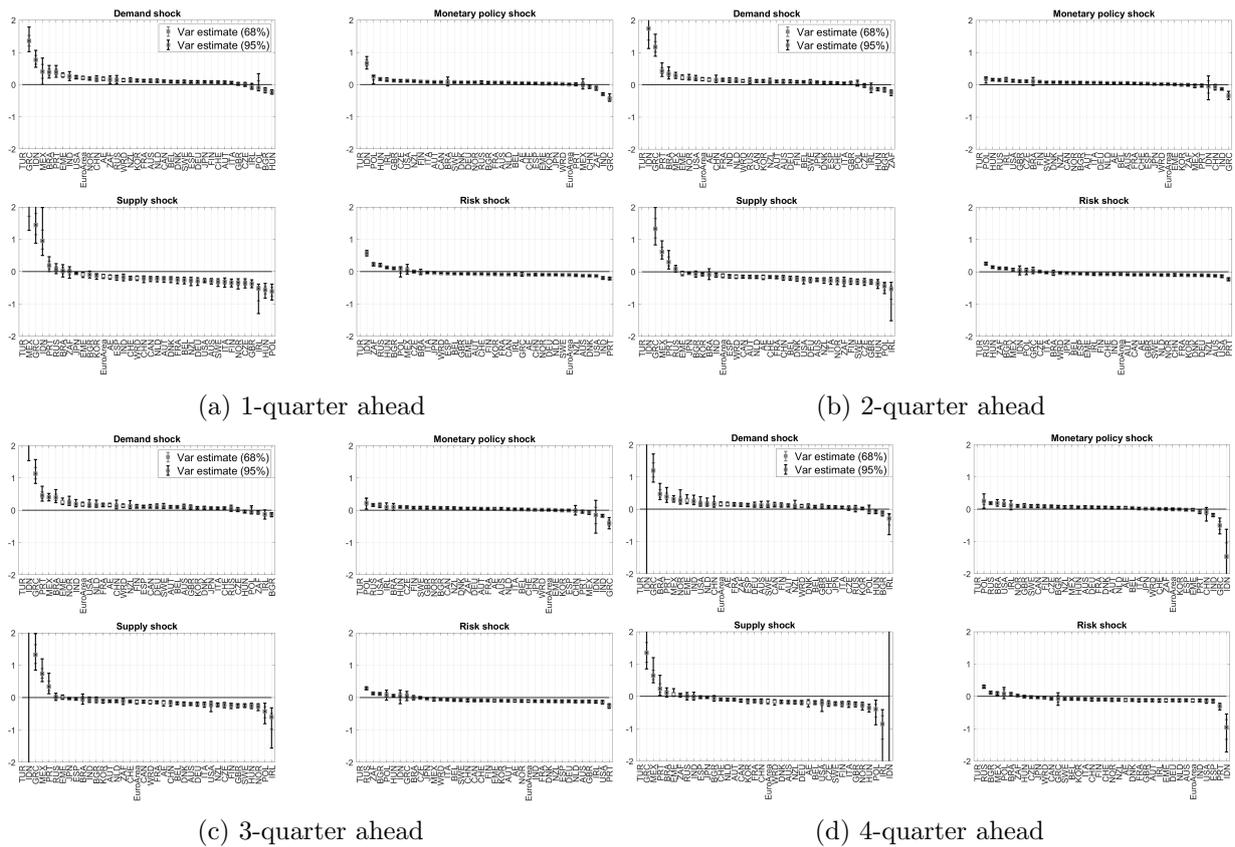


Figure B.17: Country-specific estimates of the pass-through to 10-year yields from the VAR in Equation (3.3) at different horizons.

**Notes:** pass-through coefficients are estimated separately for each country and describe the elasticity of 10-year yields (in percent) to a 1% USD appreciation. Lines report 68% and 95% confidence intervals over the estimates obtained bootstrapping 1000 draws from the posterior distribution of identified US shocks.

## B.6 IRFs of 2-year yields to US shocks

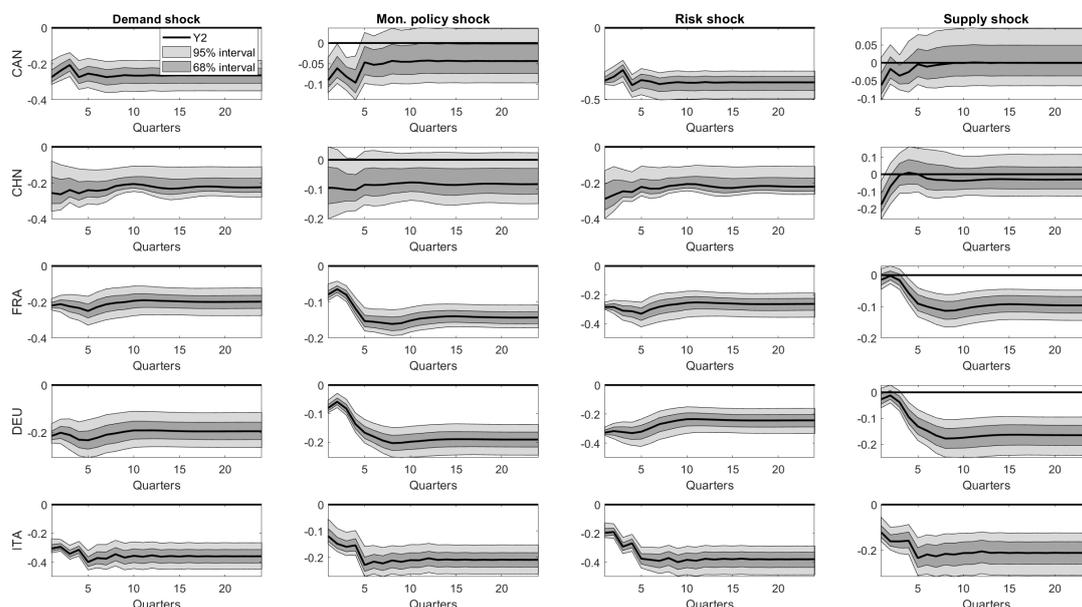
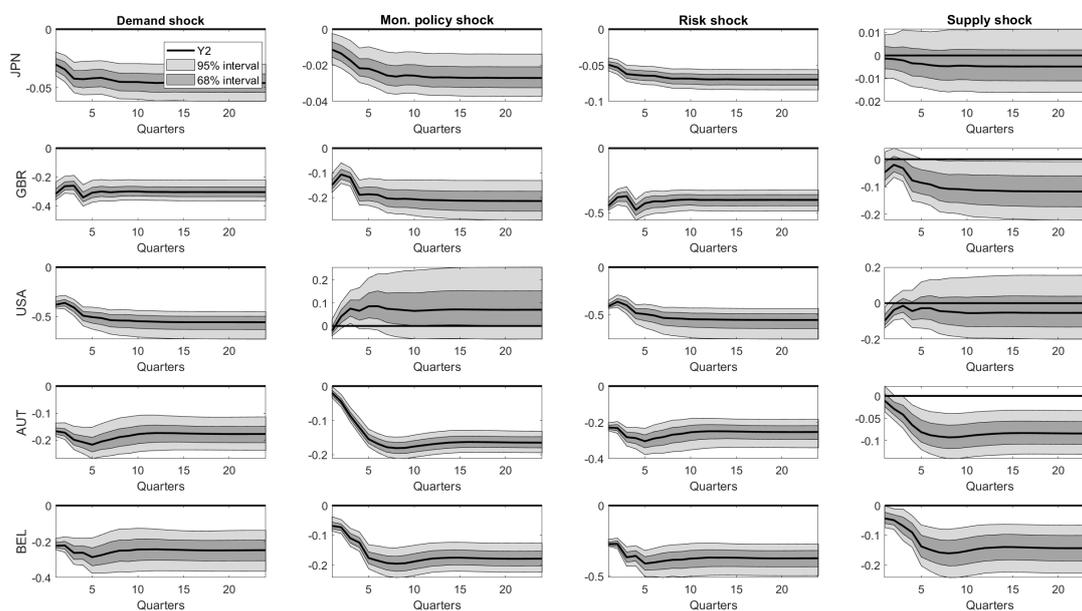


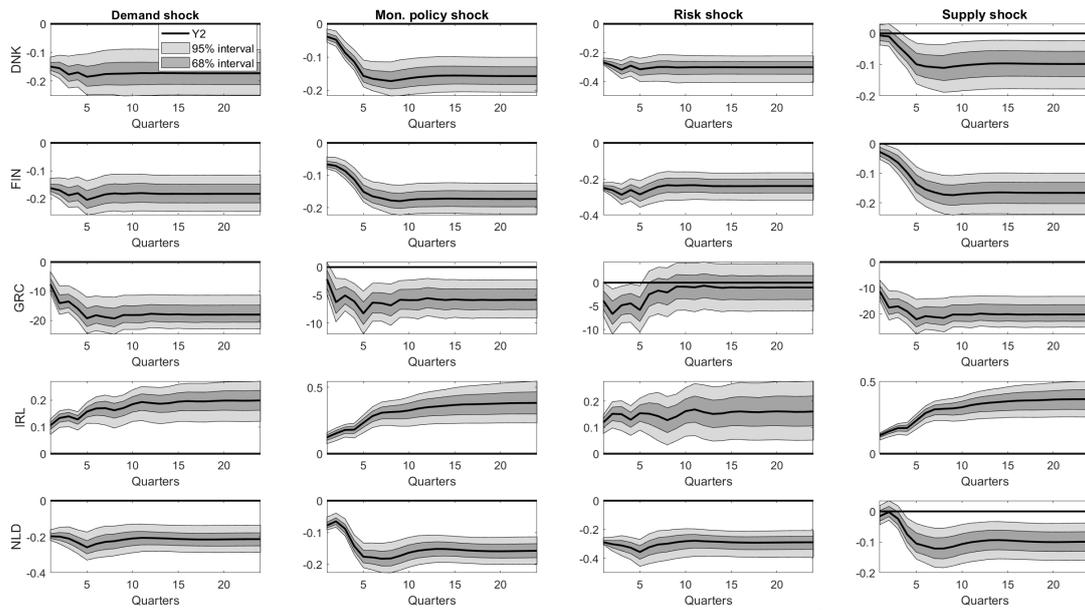
Figure B.18: Accumulated impulse responses (in percent) of 2-year yields.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



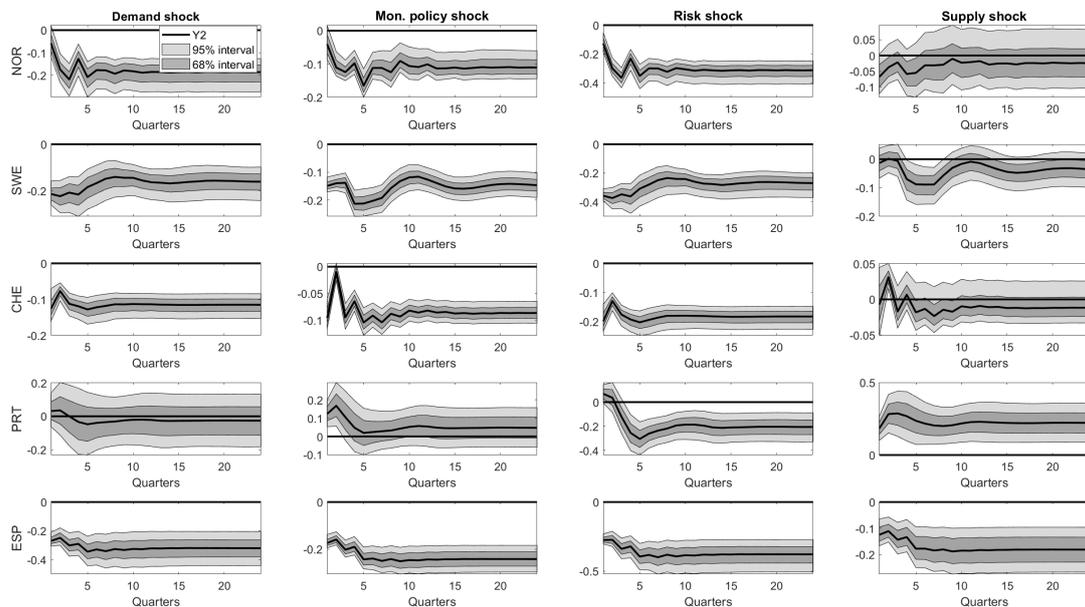
Continuation of [Figure B.18](#) – impulse responses (in percent) of 2-year yields.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).



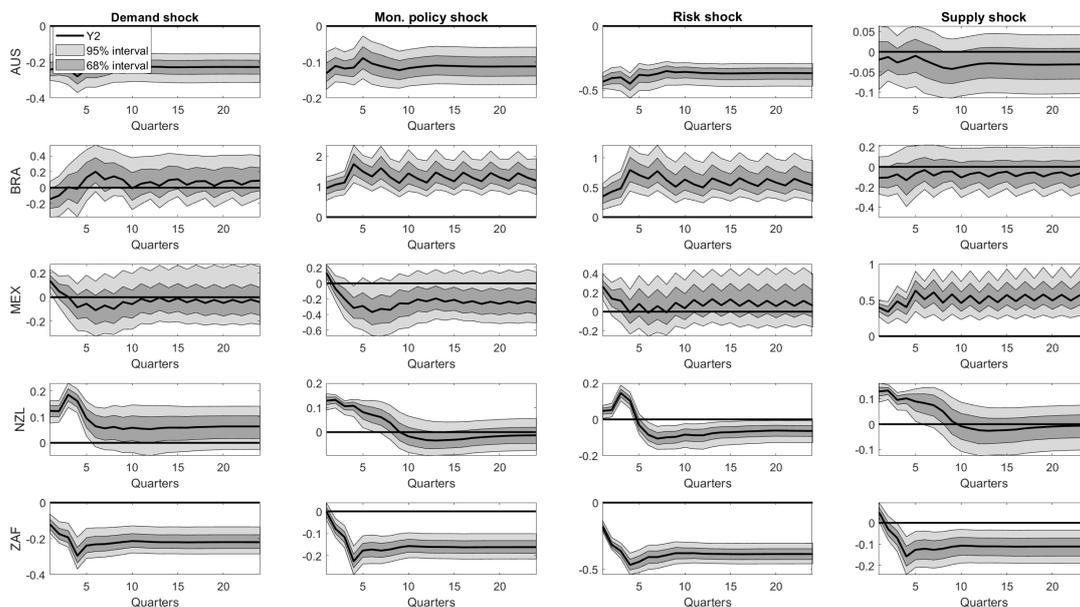
Continuation of Figure B.18 – impulse responses (in percent) of 2-year yields.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of Equation (3.2).



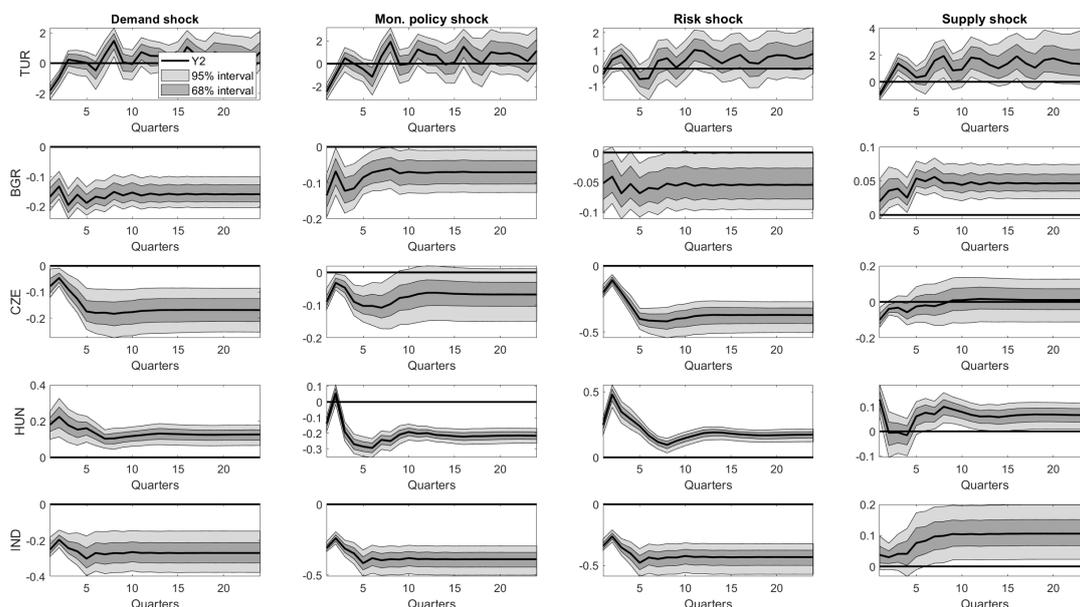
Continuation of Figure B.18 – impulse responses (in percent) of 2-year yields.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of Equation (3.2).



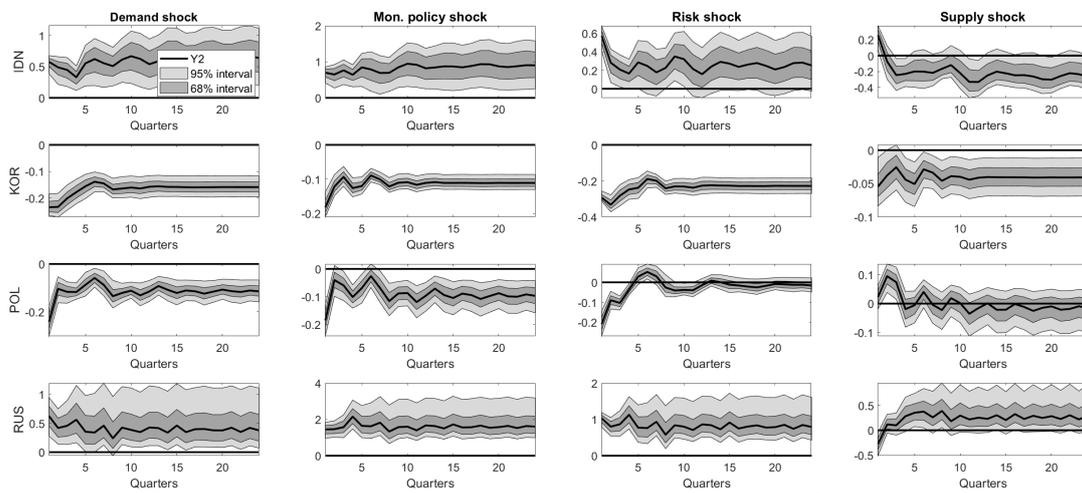
Continuation of Figure B.18 – impulse responses (in percent) of 2-year yields.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of Equation (3.2).



Continuation of Figure B.18 – impulse responses (in percent) of 2-year yields.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of Equation (3.2).



Continuation of [Figure B.18](#) – impulse responses (in percent) of 2-year yields.

**Notes:** Accumulated impulse responses (solid line) reported separately for each shock. Confidence intervals are bootstrapped using 1000 draws from the posterior distribution of [Equation \(3.2\)](#).

### Acknowledgements

We thank M. Ca' Zorzi, G. Georgiadis, D. Lodge, P. McQuade, A. Mehl, M. Mlikota and participants to the BoE, ECB and DAFM (King's College London) conference on Advanced Analytics, the Workshop on Applied Macroeconomics and Monetary Policy organized by the University of St. Gallen and APOYO Consultoría, the 2022 Finance Research Letters Annual Conference, the 2022 International Trade and Finance Association Annual Conference and seminars at the European Central Bank. The views expressed here are those of the authors and do not necessarily reflect those of the European Central Bank or the Eurosystem.

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ISBN 978-92-899-5268-2

ISSN 1725-2806

doi: 10.2866/381744

QB-AR-22-049-EN-N