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How macroprudential regulation shapes US monetary policy spillovers: a Bayesian GVAR analysis

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Abstract

We build a 26 country Bayesian Global VAR model to estimate the global spillovers of US monetary policy. Two alternative identification schemes are used (Cholesky, sign restrictions) to identify this shock. We assess its impact on domestic credit, interest rates, exchange rates and GDP growth. Once the IRFs are estimated, we compare them to macroprudential regulations, to understand whether those are effective in spillover mitigation. We manage to reproduce the stylized facts in international macroeconomics: US monetary contractions lead to a global decrease in output and credit, and depreciate foreign currencies. On macroprudential policy, results are mixed, and we find isolating properties only on credit. The iMaPP seems to amplify output and interest rate spillovers, and its effect depends on the trade channel too.

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1. Introduction

The global financial cycle (GFC) literature uncovers the central role of the USA in the world's financial system, driving the co-movement of financial variables around the globe in ways that could be asynchronous with local business and financial cycles, and thus deleterious. Financial integration also puts into question the Mundellian trilemma: flexible exchange rates are no longer sufficient to isolate an economy from global turmoil and allow for an independent monetary policy. Financial globalization has clear downsides, but also positives: FDI are a key driver of technological progress and propagation of knowledge and good practices, financial openness allows risk-sharing and generally optimal allocation of savings. Those positives are generally hampered by capital flow regulation. Some authors point to another dampener of global spillovers: macroprudential policy. Its effectiveness in the task could be granted by the international nature of the biggest banks, which intermediate USD liquidity and dispense internationally diversified credits. Here, we aim at verifying macroprudential regulation's effectiveness in shock isolation. The context of low interest rates and limited policy margins makes macroprudential policy even more attractive to regulate macroeconomic fluctuations.

The interconnected nature of the world economy means we must account for multilateral, back and forth interactions: the GVAR model fits this purpose. Our work is different from previous GVAR studies in that it tries to describe the role of macroprudential policy in shaping US monetary policy spillovers, a question as of yet untouched by GVAR modelers, to the best of our knowledge. From the perspective of macroprudential literature, we understand its connection to various international monetary policy transmission channels, in a framework that allows for complex multilateral interactions.

The results we obtain are mostly in line with the literature on US monetary policy shocks: positive shocks on the US short rate generate contractions in output and credit around the world, and depreciations of the foreign currencies. We have trouble confirming the hypothesis that macroprudential policy is a powerful tool in preventing global financial cycle contagion, on variables other than credit. Indeed, our results show the iMaPP rather amplifies spillovers.

The remaining of this work is structured as follows. Section 2 provides a review of the relevant literature. Section 3 presents the empirical framework, while Section 4 goes into more detail on the data and their inclusion into the specification of the models. In section 5, the results are analysed while Section 6 describes the diagnostics and robustness tests. Section 7 concludes.

2. Literature Review

2.1. The Global Financial Cycle and US monetary policy spillovers

Rey et al. (2020) established the existence of a global financial cycle (GFC)[1], which states that financial variables across the globe (asset prices, exchange rates, credit, capital flows) exhibit a strong co-movement. After extracting a global factor in world risky asset prices from a block-Dynamic Factor Model, they show it explains 31% of asset returns. The GFC has two key drivers: US monetary policy, due to the USA's dominant position in the financial system, and global investors' risk aversion. Spillovers of US monetary policy are found to be strong and to partly ignore the FX regime.

Two main channels of US monetary policy transmission to other countries are uncovered: the credit channel, linked to financial market frictions, and the risk-taking channel (lower USD rates imply a relaxing of VaR constraints for GSIBs, for example). These international transmission channels exist in part because banks are globalised, and USD financed. Credit is provided across borders. Banks are important players on asset markets, and they are risk neutral, meaning they asset buying behaviour depends on value at risk constraints.

[1] The original paper was published in 2015

The existence of those spillovers questions the validity of the Mundellian trilemma: a flexible exchange rate is no longer sufficient to isolate an economy from foreign shocks. The paper concludes however that using fixed exchange rates and reversing capital flow openness isn't the way to go. Macroprudential regulations might mitigate the GFC however, opening a path for future research. This thesis aims at continuing this research project.

Although the existence and influence of the GFC has been questioned, Rey (2021) reviews the literature which followed the first paper. They re-establish the importance of the GFC, and refine the asymmetric roles of different countries, and the different ways in which theey're linked: US monetary spillovers are more important, the ECB's role has grown, China is financially insignificant but drives a trade and commodity cycle. Proper modelling over interrelations is thus important.

An important strand of the literature is related to identifying different channels. The ECB's September 2021 report "The implications of globalisation for the ECB monetary policy strategy" provides a categorization of monetary policy's channels as well as a review of the recent literature on how globalization affects them. Five channels of monetary policy are laid out: interest rate, wealth effect, exchange rate, credit and risk-taking. We will provide additional comments on those channels when discussing our results.

2.2. Macroprudential regulation and international spillovers

Fendoglu (2017) find that portfolio inflows & credit cycles are smoothed by macroprudential regulation, whereas FX & financial-institution based measures are weaker. Epure (2021) for example also find dampening effects of macroprudential regulations. Most importantly Bergant et al. (2020) ask a question similar to ours, in a panel regression framework. They show that more stringent macroprudential regulations (they study bank capital, liquidity, FX mismatches, risky credit limitations) helps mitigate the negative effect of VIX, interest rate and capital flow shocks on GDP. They also find that macroprudential regulations are superior to capital controls, have positive spillovers on neighbouring countries and allow for a more countercyclical monetary policy.

Finally, regarding the choice of dataset to carry out the empirical analyses, we follow Alam (2019) for its simplicity and proven worth.

2.3. GVAR analyses of international monetary policy and financial spillovers

The Global VAR model spurred a vast literature: Galesi (2013) provides an interesting overview of what can be done in the framework. The macroprudential applications they cover are related to stress-testing. Here focus on more recent and relevant papers. Feldkircher and Hüber (2016) use a Bayesian GVAR model, implemented with a stochastic search variable selection (SSVS) prior which accounts for uncertainty in variables selection. They analyse US aggregate supply, aggregate demand and monetary policy shocks, identified with sign restrictions. The three are significant abroad, and monetary policy is the most important. Advanced economies have stronger and faster reactions. From GFEVD analyses, the USA's AD shocks seem to drive global output, AS shocks drive inflation and MP shock drive short term rates.

Georgiadis (2015) estimates a GVAR in first differences and studies the spillovers of US monetary policy. By studying the trough responses of GDP to US interest rate shocks, he finds that spillovers are even more negative outside the US. Trade integration, domestic financial market development, flexibility of exchange rates and labour markets mitigate the negative spillovers linked to rate increases. The effects depend on the emerging or advanced status of the economies and presents non-linearities.

Eickmeier (2015) study credit supply shocks and innovate in that they link countries via financial weights, not only trade. US credit supply shocks imply negative responses in GDP credit and equity prices around the world. They are very important for the EU and UK, but much less elsewhere. Exchange rate responses showcase a flight to quality in favour of the USD. Fadejeva (2016) study credit supply and demand, and aggregate demand shocks for the USA and Eurozone. Eurozone shocks yield smaller and more uncertain negative effects that those of the USA. Again, spillovers are bigger abroad than in the origin country.

Dées (2021) build a GVAR model with 26 countries to study the global spillovers of US monetary policy. Separating conventional and non-conventional monetary policy shocks via sign restrictions, they do find an important co-movement in global financial variables, corresponding to the GFC. Furthermore, the exchange rate regime doesn't seem to isolate from interest rate shocks. Accounting for time variation in the trade linkages between countries, they find that US monetary policy spillovers have increased with time, even though the USA is less important in trade. This suggests the higher role of financial integration with a US bias. Network effects outside the USA double the shock's total effect.

Our work differs from Bergant et al. (2020) in that we focus not only on the responses of GDP and interest rates, but also on banking credit and the exchange rate, which are essential in understanding the relations at hand. Our difference from them is that we model the various linkages between the nations and try to explore how the various channels of transmission for the US monetary policy shock play into the spillovers. We draw on Eickmeier et al. (2015) for the treatment of credit variables and the use of a financial weighting scheme. From Feldkircher et al. (2016), we repurpose the shock identification and the use of the Bayesian model. Georgiadis (2015) is our inspiration for spillover analysis. Relative to Dées (2021), we also investigate the GFC and its trilemma implications, but from the domestic credit perspective, that they ignore[2] in favour of foreign capital flows.

[2] On the basis that the external part of credit is the most important in transmitting the GFC.

3. Empirical framework

3.1. The GVAR

The GVAR method was originally proposed by Pesaran et al. (2004). The method aimed at proposing a comprehensive framework for Deutsche Bank's credit portfolio risk management, which required macroeconomic forecasts to account for the complexity of international linkages. Dées et al. (2007) extends the GVAR framework, notably by designing the orthogonalization procedures for the IRFs, allowing structural shock analysis. Among the benefits of this framework, we must mention the very large panel dataset, the fact that correlations between units are accounted for, and that parameters are variable for each unit, which allows cross-sectional heterogeneity. Georgiadis (2017) exposes the problems of two-country VARs when estimating spillovers, relative to GVARs (i.e. higher bias in coefficients & higher MSE), thanks to Monte-Carlo simulations.

The first step consists in estimating VARX* (p, q)[3] models:

$$y_{it} = a_{i0} + a_{i1} * t + \Sigma\Phi_{ip} y_{it-j} + \Sigma\Lambda_{iq} y^*_{it-j} + \Sigma\Gamma_{iq} \mathrm{x}_{t-j} + \varepsilon_{it},\ \ \varepsilon_{it} \sim \mathrm{N}(0, \Sigma_{it})$$

Summing by p from 1 to P and by q from 0 to Q: the y* enter the VARX* as lagged *and* contemporaneous variables. They are exogenous in the VARX*, but endogenous in the GVAR. The foreign variables, y*, allow for a personalized relation between a country and the world. They are defined as such:

$$y^*_{it} = \Sigma \mathrm{w}_{ij} y_{jt}\ ;\ \Sigma \mathrm{w}_{ij} = 1\ ;\ \mathrm{w}_{ii} = 0$$

For w_{ij}, we use both trade and financial weights.

The global variable, x (the oil price[4]), is included in the US model, where it is endogenous. Because each model includes a linear combination of all the other country variables, we can rewrite the VARX* in a way that makes them all appear:

[3] p is the domestic lag order, q is the foreign variable lag order

[4] oil prices are entered in part because they play the role of a global control variable.

$$G_{i0}y_t = a_i + b_i * t + \Sigma \mathrm{G}_{ip} y_{t-j} + \Sigma \Gamma_{iq} \mathrm{x}_{t-j} + u_{it},\ \ u_{it} \sim \mathrm{N}(0, \Sigma_{it})$$

After estimating each VARX* and the global model, we simply stack them on top of each other, to obtain the GVAR representation:

$$G_0 y_t = a + b * t + \Sigma \mathrm{G}_j y_{t-j} + \Sigma \Gamma_q \mathrm{x}_{t-j} + u_t$$

Furthermore, the x being endogenous in the US model, we can write:

$$H_0 Z_t = a' + b' * t + \Sigma \mathrm{H}_j Z_{t-j} + e_t;\text{ where: } Z_t = y_y, x_t$$

3.2. Bayesian estimation

In the wake of Feldkircher (2016), we resort to the Bayesian version of the GVAR. The motivation is we can handle more countries, more lags, more variables per country. We will also account for model uncertainty. The R BGVAR package[5] is used. Its main drawback is it gives no flexibility in the choice of the lag structure: it must be the same for all variables, in all VARX* models and for the global model too. To tackle this, we implement the SSVS prior, described in George et al. (2008) and implemented in the GVAR by Feldkircher (2016). The fact that some coefficients are shrinked to 0 helps avoiding overfitting. This prior also has a natural affinity with the BGVAR package: the elimination of useless lags allows for a finer specification[6].

The model is estimated with stochastic volatility because we have obvious periods with volatility spikes. As presented in Feldkircher (2019), the variance-covariance matrix of the VARX* is decomposed as follows:

$$\Sigma_{i,t} = U_i \mathrm{H}_{i,t} U'_i$$

[5] It permits all the standard post-estimation diagnostics and analyses, includes identification schemes by Cholesky orderings, sign & zero restrictions, and rationality conditions. Trends, stochastic volatility, stochastic search variable selection and normal gamma priors are also featured, along with flexible prior parametrization.
[6] The posterior inclusion probabilities of each coefficient of each equation can be computed and used to analyse which variables are important contributors to the others. We don't analyse them, for concision.

Where the U_i matrix is a lower diagonal matrix, with ones in the diagonal and $\mathrm{H}_{i,t}$ is a diagonal matrix with $\mathrm{H}_{i,t} = diag(e^{h_{i1,t}}, \ldots, e^{h_{ik_i,t}})$.

$$\mathrm{h}_{ij,t} = \mu_{ij} + \rho_{ij}(h_{ij,t-1} - \mu_{ij}) + \xi_{ij,t}$$

Where μ_{ij} is the mean of the log-volatility, ρ_{ij} is a persistence parameter and $\xi_{ij,t}$ is a white-noise error term. Finally, we estimate the model with two alternative sets of weights, in order to compare them and make a choice.

3.3. Identification strategy

In line with Dées (2007) and most of the subsequent literature, we only impose sign restrictions within the US model. Loosely following Feldkircher (2016), we identify three shocks: aggregate supply, aggregate demand, and monetary policy. We are interested in monetary policy, but identifying the other shocks will allow for finer identification of our shock of interest. Just like those authors, we impose no restriction on oil prices. We differ from them on the aggregate supply shock's definition: we don't restrict the short-term rate, because authorities may want to use forward guidance to dissipate price tensions, while lowering rates to counter the economy's output decrease. Similarly, credit might increase because of liquidity needs from firms, or decrease because of lowered solvency.

Table 1: Sign restrictions (underlined when also binding for 1 quarter after impact)

	oil	y	dP	credit	ltir	stir
Aggregate demand shock	?	+	+	+	?	+
Aggregate supply shock	?	$\underline{+}$	-	?	?	?
Monetary policy shock	?	-	$\underline{-}$	-	-	+

We impose all restrictions at the moment of shock impact. Implementing more restrictions complicated the obtention of rotation matrices.

In place of our ideal scheme[7], we simply require that the AS shock reduce output at t+0 and t+1, while the MP shock affects prices at t+0 and t+1. No restriction is imposed on the other countries: we are agnostic regarding their responses.

As an alternative, for robustness testing, we tried to implement a Cholesky decomposition scheme. Our ordering was based on Avdjiev-Zheng (2014), a common choice in the monetary VAR literature. Our difference is that we do not have the credit spread. It is replaced by the long-term interest rate. We also introduce the oil price, which is ordered first because its international nature makes it more exogenous. Our ordering is thus:

$$\text{poil} \rightarrow \text{y} \rightarrow \text{dP} \rightarrow \text{credit} \rightarrow \text{ltir} \rightarrow \text{stir}$$

The attempts yielded incoherent IRFs for the monetary policy shock: a puzzle appears for both output and inflation, meaning that the scheme cannot identify the monetary policy shock.

It is important to note that the shocks are only semi orthogonalized. The US shocks will be orthogonal among each other, but not with the other countries' residuals. However, the inclusion of the *contemporaneous*, US-specific foreign variables in the VARX* should help reduce the cross-sectional correlation of the shocks. The hypothesis of no cross-sectional correlation of the residuals is thus essential for shock identification.

[7] It would have included the following restrictions after impact: monetary policy affects GDP a t+0, t+1 and t+2, doesn't affect inflation at t+0, but decreases it at t+1 and t+2 to allow for price rigidities. The supply shock affects GDP up to six quarters after impact. The demand shock affects inflation and output at t+0 and t+1.

4. Data

4.1. VARX* specifications and global model: treatments and selection rationale

The Euro Area is modelled as an aggregate, using the changing composition series of output and inflation. Fadejeva 2017 finds that the alternative between fixed and changing EA composition doesn't affect the results much. Second, we include countries outside of the dataset compiled by Mohaddes (2020). We harmonize the concepts used for all the countries. A map of the 26 countries we included, and a table with the data sources, are available in the annex. Our countries represent between a stable 80 to 81% of world GDP in PPP over 1998-2019.

We must study how US monetary policy affects credit and respect an international macroeconomic framework. The VARX* models thus naturally include GDP, inflation, short-term interest rates and the nominal bilateral exchange rate. We also include the long-term rate: it is a closer representation of the cost of borrowing, which affects credit. However, the variable is available only for 11 countries, and only advanced economies: 15 country models will be mis-specified, notwithstanding the foreign long rate. The corporate bond rate would have been a better proxy of borrowing costs, but it suffers from worse problems of availability. This absence means we cannot identify credit supply[8] or demand shocks and model a simpler link between monetary policy and credit. We do not include equity prices either[9].

For credit, the main variable of this study, we use domestic banking credit to nonfinancial institutions from the BIS. It was chosen due to its wide coverage. It is labelled in Bn of the domestic currency and adjusted for breaks. As Eickmeier (2015), we put it in logs of real private credit[10]. We choose to focus on lending by banks to the private non-financial sector,

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[8] Those shocks required restricting two variables to move in the same direction but with one faster than the other. R BGVAR doesn't permit this type of restriction and we couldn't implement it in any case.

[9] They could have caught other effects (certain risks and expectations, a wealth effect caused by changes in asset prices…). The deciding argument against the inclusion of equity prices is this variable made it impossible to recover rotation matrices for identification via sign restriction. On those technical grounds, we did not include it.

[10] We deflate with the CPI we have.

because we aim at understanding whether of financial conditions transmit to a country via intra-national banking relations. Furthermore, macroprudential regulation specifically targets those institutions, so the variable is more adequate to check their effect. Fadejeva (2017) adjusts credit series for FX movements in countries which have big shares of FX denominated credit, but do not say how. We do not account for this and may thus suffer from a bias.

Because all exchange rates are relative to the USD, we do not include this variable in the US model. It will however include a trade-weighted average of the other exchange rates, which is akin to an effective exchange rate. Our set of variables is transformed as follows:

Macroeconomic variables: $y_{it} = \ln(RGDP_{it});\ p_{it} = \ln(CPI_{it});\ ner_{it} = \ln(NER_{it})$

Financial variables: $credit_{it} = ln\left(\frac{CREDIT_{it}}{CPI_{it}}\right);\ r_{it} = 0{,}25ln(1 + \frac{r_{it}}{100})$

Global variable: $poil_t = \ln(BRENT_t)$

A major difficulty for us is that, in contrast to Eickmeier (2015) and Fadejeva (2017), we don't end the sample in 2009 or 2013. We could have two distinct regimes for credit dynamics. Fadejeva (2017) includes a dummy for 2009-2013, because the post-crisis period implied a structural change. We abstain from including a dummy, because in our case it would probably be too long. The best solution is to split the sample in two and estimate two different models to see whether the relations have changed before and after the crisis.

In our baseline specification, all the variables are included in first differences of their logarithms, as pioneered by Georgiadis (2015) and Georgiadis (2016).

Dummy variables were tested but they did not add much stability and caused problems of residuals. They were discarded.

4.2. Link Matrices

The link matrices we use come from the R BGVAR package and are described in the package documentation. Our choice of countries is thus restricted: we must include countries for which the weighting scheme is available, and for which the credit series are too.

Eickmeier et al. (2015) uses mixed-weights matrices, combining trade weights and financial weight schemes. Some examples of financial weighting schemes they use are inward banking claims (BCin), outward banking claims (BCout) and FDI, inward and outward too. Following Eickmeier 2015 and Fadejeva 2016, we use bilateral banking sector exposures as a complement to trade-based weights, according to the BCin + BCout scheme. The values taken are the averages of 2007 and 2008. The trade matrices we use are those computed by Feldkircher (2016), and they use the trade flows of 2012.

5. Results

The model we selected has only one lag, for all types of variables. The selection process is presented in the annex. We keep the estimation parameters relatively simple. Following the suggestion of Litterman (1986), we modify the AR(1) term's hyperparameter at 0.35 so as to fit the data better. We only use one lags, as the extension to two lags doesn't yield extreme improvements in specification, while being costly in term of computation time and memory. The estimation is conducted using 30000 draws[11] and 30000 burnins. We do not include any dummy variable, as their performance proved disappointing. 71.63% of the model's residuals don't suffer from autocorrelation. 27 have an average cross-correlation between 0.1 and 0.2, only four have one above 0.2, which we deem acceptable by the standards of Dées (2021).

5.1. Domestic impact of the monetary policy shock

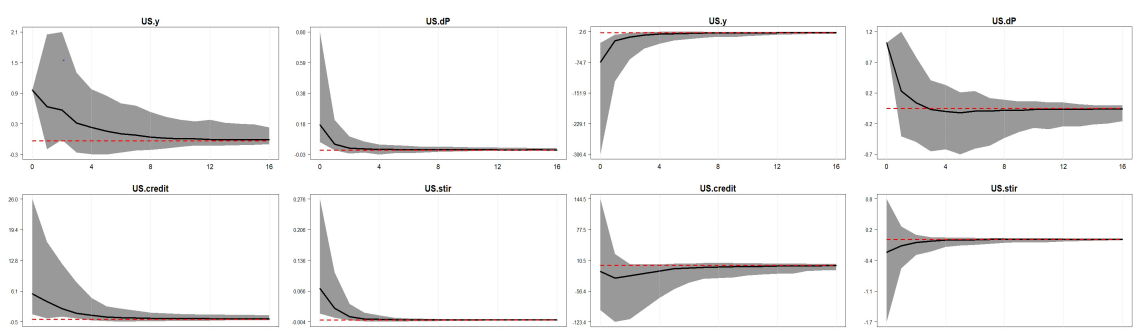
We then go on to apply the sign restrictions and try to recover rotation matrices to recover the IRFs. Out of our successful draws, we set the function to attempt 4500 tries at a rotation matrix for each draw. 208 draws yielded successful rotation matrices[12].

[11] We retain one tenth of them, to ensure that MCMC simulated draws aren't correlated with each other.
[12] In the model without the long rate and with restrictions imposed only on impact, 1500 tries 690 yielded successful rotation matrices.

The next step is then to verify that the impact of each shock on the US variables is coherent with macroeconomic theory. All our IRFs are reported with 68% quantiles. However, Feldkircher & Siklos (2019) note that for highly parametrized models such as the one at hand, a 50% interval could be more adequate. Hence, even when our responses are not significant, we include them in the later analyses.

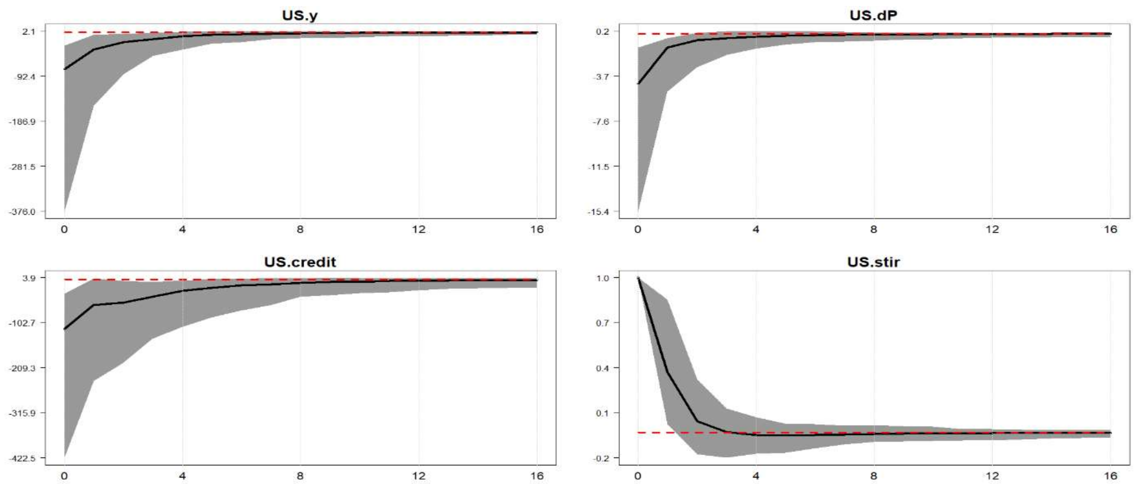
As expected, the sign restrictions are fulfilled. Shocks generally have a low persistence. We did not restrict the responses of credit and the short rate for the US supply shock. Their responses are interesting. The interest rate goes down, suggesting that monetary authorities leave price control to forward guidance, and prefer to stimulate the economy. This response contradicts the sign restrictions imposed by Feldkircher (2016) but not Fadejeva (2016). Credit goes down, as in Fadejeva (2016). Finally, we reported the Cholesky decomposition results in the annex. The monetary policy shock seems poorly identified, as we have both an output and a price puzzle. Thus, we don't report all foreign IRFs there.

Figure 1: Impact of the US demand shock (size = 0.01[13]) and the US supply shock (size = 0.01 to the dP variable, a contractionary supply shock)



[13] This is badly dimensioned, knowing the rates were entered as 0.25*log(1+r/100). We don't rescale it because we are interest in relative effects and correlations.

Figure 2: Impact of the US monetary policy shock (size = 0.01)



5.2. Global spillovers of US monetary policy

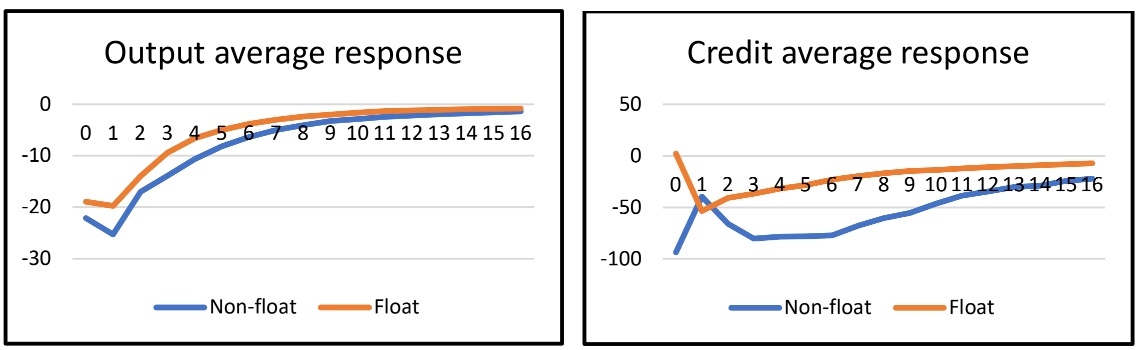
We now turn to the transmission of US monetary policy shocks across the world. The IRFs are reported in the annex. We will analyse the impact of US monetary policy on credit, output, the exchange rate and the exchange rate in the 25 other countries of our sample. For all variables, we will plot some statistic of the IRFs against our index of macroprudential policy.

We chose the iMaPP index because of its simplicity, and successful use in several other papers (cf Bergant (IMF, 2020)). The monthly indicator takes the value of 1, 0 or -1 when macroprudential policy tightens, stagnates or loosens, respectively. The series starts in 1990 and covers 27 types of macroprudential regulation (e.g. capital ratio, reserve requirements…). If in any one month, two regulatory areas suffer a tightening, the value of the indicator is 2. To build our indicator, we simply sum the values of the monthly indicator over the 30 years of the dataset, or use use the average value over the summed value over the 20 years of our sample as an alternative. The results of both are systematically very close, and so we report only the former. The indicator has several downsides. First, it is only an indicator of policy decisions being taken. As such it doesn't reflect intensity of the policy changes. The loan-to-value ratio and dollarisation rates were also potential indicator candidates, which we ignore for the sake of simplicity and comparability to Bergant (2020). We will always compare the iMaPP's impact with that of capital controls. The series on capital control is the "overall restrictions index" to capital flows (in and outflows) proposed by Fernandez (2015). We take its average value from 1999 to 2019. Argentina, Brazil and Turkey were eliminated from all subsequent analyses, since their credit response is ten times stronger than the other countries.

Here, identification relies on cross-sectional variation only. A further extension would break the sample in two, pre-2008 crisis and post-crisis, estimate two models and add a time-variation to our sample of IRF-iMaPP relations.

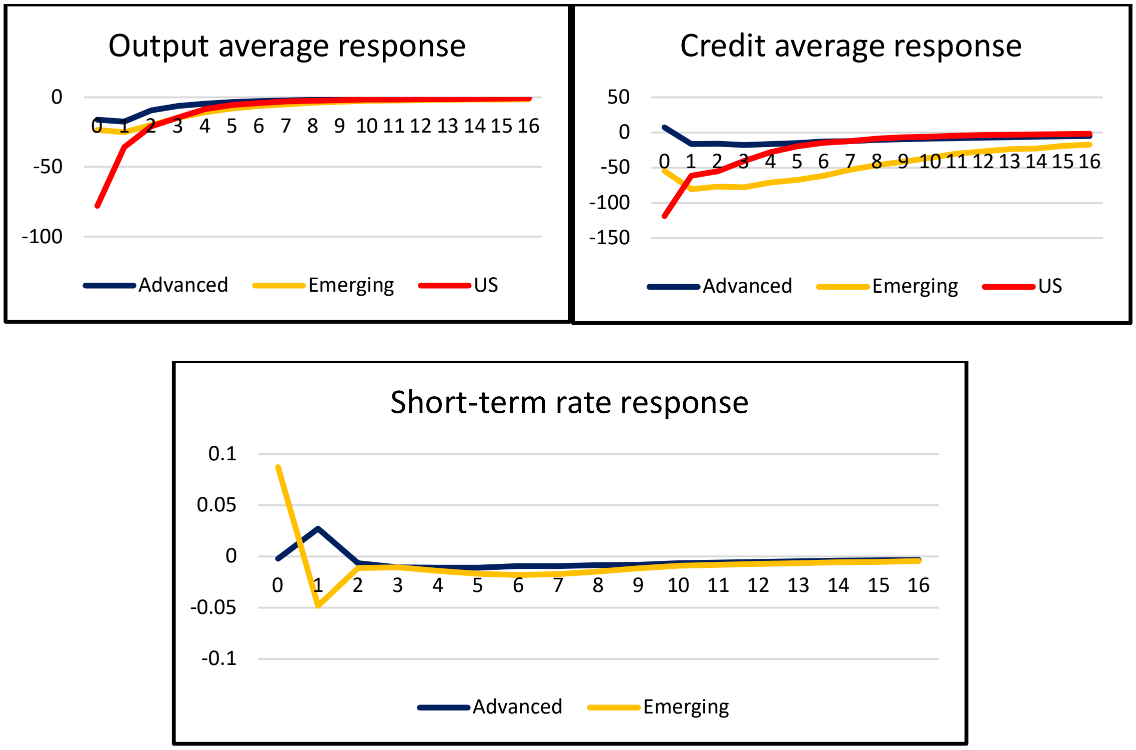
IRF aggregated per country groups

Figure 3: IRFs for the fixed vs. floating exchange rate countries [14]



[14] We defined fixed and floating countries based on our judgement. The question of defining floating and fixed ER regimes must relate to the shock we're studying: Denmark is pegged to the Euro and will thus be floating towards the USD. The rest of the classification is done by consulting the 2008 exchange rate regimes and seeing how the regime evolved from there and before, to assign a country to a group.

Figure 4: IRFs for the advanced vs. emerging economies

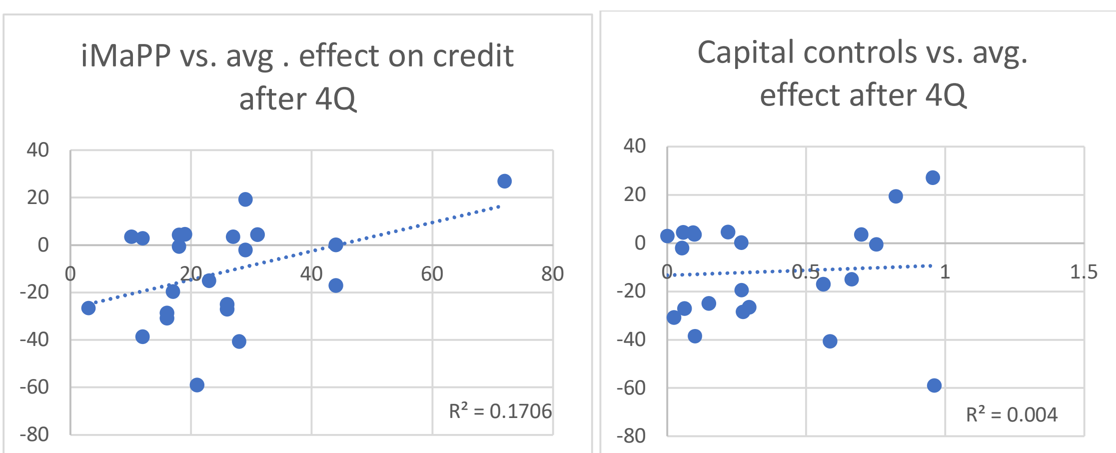


According to the Mundell-Fleming predictions, a floating exchange rate allows shock isolation: those countries indeed behave better than those with non-floating regimes. However, as stated by the GFC literature, a floating regime is insufficient to fully isolate a country from external shocks. Here, non-floaters suffer around +25% more than floaters, whereas Dées' (2021) finding is closer to +100%. We find that the impact of the shock on credit is stronger in emerging countries than in the US after one quarter. Regarding output, we see that, contrary to most papers, the USA is more affected by its own shock than the other countries. We also see that emerging countries' interest rates respond more strongly to the shock, suggesting a fear of destabilizing capital flight, followed by a need for monetary easing to stimulate output. Our IRFs generally reflect the stylized facts of international macroeconomics.

IRFs of domestic credit

Our main question is about macroprudential regulation's efficiency at preventing fluctuations in credit. For that purpose, we start by seeing whether country-level IRFs are driven by the iMaPP index, with simple univariate correlations. Those analyses are purely descriptive, and endogeneity problems may be present: we can't deduce causality from them. We are faced with one problem: on impact, 16 countries show an increase in credit, and 9 are clear increases. On the next quarter however, the situation is reversed: only 6 countries see an increase (19 credit decreases), versus 2 after 5 quarters (23 decreases). Upon computation of cumulative impulse responses, we see that only four countries (Malaysia, Japan, China, Canada) have a long-term increase in credit after the shock. The problem is too important to be ignored. Hence, our analysis of the spillover-iMaPP will not be limited to the trough of the response as in Georgiadis (2015), but it will consider the average of the four first quarters[15]. The two methods aren't very different, however.

Figure 5 : IRFs on credit (vertical axis) vs. iMaPP and capital controls (horizontal axis)



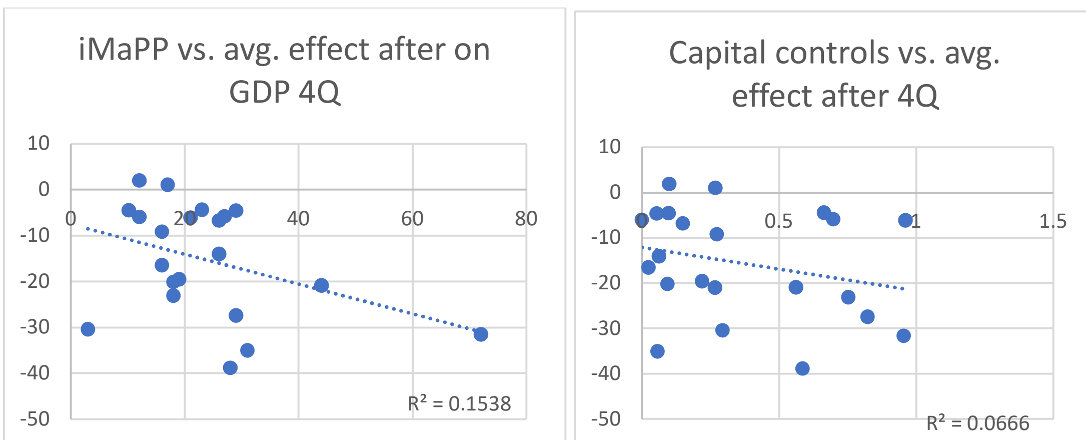
[15] That is to say : t+0, t+1, t+2 and t+3 after the shock

We see that macroprudential policy is correlated to the shock's effect over the first 4 quarters: it does have a dampening effect. We have an R^2 of 17%[16]. There is a substantial isolation effect, much more important than that achieved by capital controls.

IRFs of GDP

Now that we have verified the macroprudential impact on credit spillovers, we tackle the spillovers most often examined by the literature.

Figure 6: IRFs on output (vertical axis) vs. iMaPP and capital controls (horizontal axis)



This result is very puzzling: macroprudential regulation seems to *increase* the harmful effects of the US shock. However, as Georgiadis (2015) puts it, "Euro area economies in which a higher share of aggregate output is accounted for by sectors servicing interest rate sensitive demand exhibit a stronger transmission of monetary policy to real activity." We thus emit the hypothesis that macroprudential regulation's power is dependent with the share of interest rate sensitive sectors in a country, an endogeneity problem (omitted variable) which may explain the discrepancy. Further, he adds: "Also, economies with stronger institutions experience larger spillovers; this last result is similar to the findings of Giannone et al. (2011), who find that countries with better regulatory quality in credit markets experienced stronger spillovers from

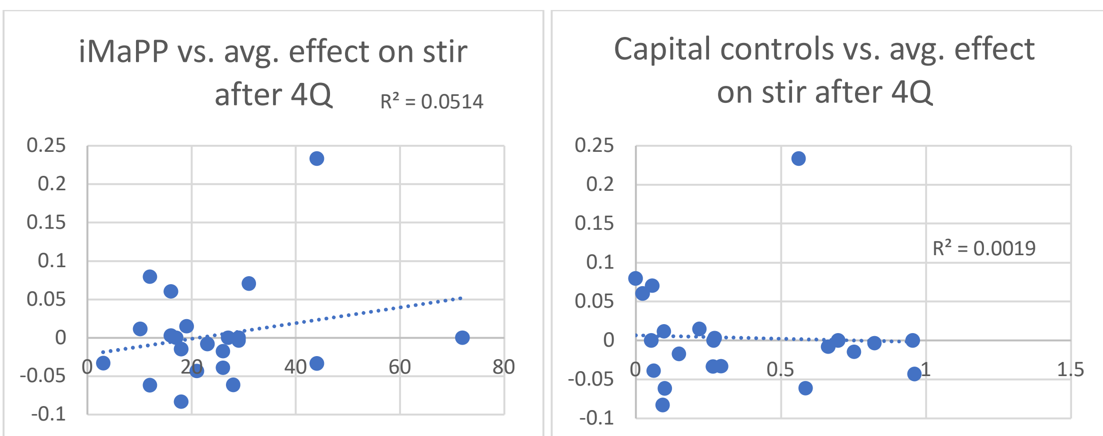
[16] For comparison, in the regression inspiring us, Georgiadis (2016) obtains an R^2 of 72% with 15 variables, for the GDP trough response.

the global financial crisis in 2008/09." Macroprudential regulation may have come hand in hand with more liberalized markets, and thus more risks. Another hypothesis remark of this author is that the monetary contraction lowers exports: spillovers should be stronger where manufactured goods are a bigger share of GDP. We set out to analyse it in section 5.3.

IRFs of local interest rates

The Mundellian trilemma posits that the flexible exchange rate allows for an independent monetary policy, i.e. a domestic interest rate which doesn't respond to foreign rate movements. This has been challenged, in part by the GFC literature. Can macroprudential regulation make up for it? And again, how does it compare to capital flow regulation?

Figure 7 : IRFs on interest rate (vertical axis) vs. iMaPP and capital controls (horizontal axis)

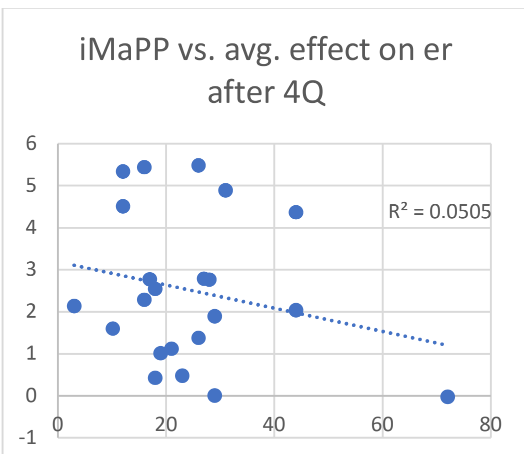


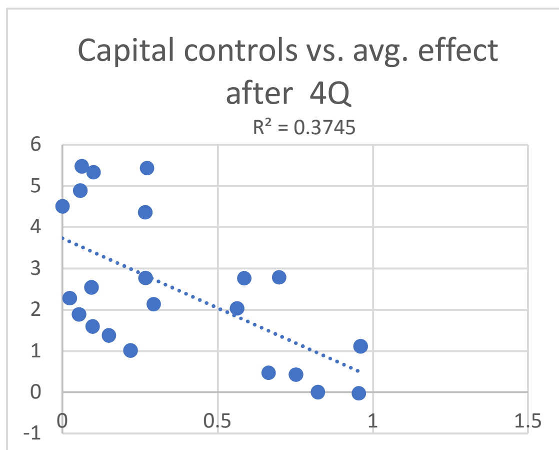
We see a modest positive relation between macroprudential policy and the interest rate reaction. We can't say whether monetary policy becomes more independent: as some countries react by raising their rate and other react by decreasing it. The scatterplot realized for the maximum of the absolute value over 4 quarters tells a different story: interest rates move more with higher macroprudential regulation, which argues in against an insulation effect (R^2=2.5%). Capital controls seem powerless on both measures.

IRFs of the exchange rate

Interest rate parity theory suggests that, given a fixed domestic interest rate, foreign interest rate increases should trigger a depreciation of the domestic currency. ECB (2021) describes the exchange rate channel this way: a currency depreciation leads to expenditure switching from foreign to domestic goods and increasing net exports: this would have a positive effect on GDP. The balance sheets of banks are also affected by the exchange rate. Trade integration and financial integration can increase or decrease this channel's strength. Here, we aim at determining the contribution of macroprudential policy on the potential of the channel, proxied by the exchange rate's variation.

Figure 8 : IRFs on the exchange rate (vertical axis) vs. iMaPP and capital controls (horizontal)





Here, the situation is reversed: capital controls play a substantial role in mitigating the currency depreciation brought by US monetary contractions. This is negative for GDP, however: preventing exchange rate depreciation means that expenditures can't switch to domestic goods. The exchange rate channel of US monetary policy is weakened by capital controls, and by macroprudential regulations as well.

5.3. The iMaPP versus other spillover determinants

The iMaPP-GDP relation is puzzling. We will try to control for other characteristics here.

The last exercise we should do is a multivariate regression at country-level for each IRF of the following form:

$$IRF = \alpha * iMaPP + \beta * KA + \gamma * C + \varepsilon$$

Where C includes interaction terms and other spillovers determinants. We draw the list of spillover determinant controls directly from Georgiadis (2016). We start by analyzing the significance of the correlations we found above. The relations between iMaPP and IRFs are significant at the 10% threshold only for GDP and credit. Next, we decide which spillovers to consider, based on their R^2 with the output IRF. Manufacturing has a 2.78% R^2 and market capitalization has 12.6%. They both have a dampening effect on the IRF. We then run a regression featuring the new variable, the iMaPP, their interaction and also capital controls. Including the manufacturing share reduces the negative effect of the iMaPP. The interaction term is negative: more manufacturing means macroprudential regulations become amplifiers. Including market capitalization increases the negative effect of the iMaPP. The interaction term is positive. We interpreted this as meaning that higher financial integration leads to a higher power of macroprudential regulation, meaning the financial market channels should not be disregarded. However, we have only 22 observations, and nothing here is significant.

6. Discussions of the results and possible extensions

6.1. Robustness tests

We only conducted two alternative model specifications. We built an alternative in which the VIX and the oil price are modelled as global variables, in a separate model as in Georgiadis (2016). The goal was to improve identification of interest rate shocks, avoiding confusion with shocks to risk-aversion and uncertainty. The fit and diagnostics were poorer than our current model, so it was rejected. The second consisted in replacing domestic credit with total credit, in order to capture foreign sources of credit. We simply obtained Cholesky IRFs, and noted that their behaviour didn't showcase a t+0 increase, that their decrease was more pronounced and that the use of those series allowed for IRFs with an acceptable shape, notably for monetary policy. Due to the weight of the computations, we didn't pursue sign-restrictions on that alternative. We didn't re-estimate the model normal rates instead of shadow rates to evaluate the differences.

6.2. Discussion of the results and extensions to the project

This draft version is currently incomplete, and could see the following extensions:

-re-do the exercice, but instead of using "domestic credit" as a credit variable, use "all credit" (i.e. credit including non-resident sources). This will allow us to evaluate the importance of foreign sources of credit, which could explain why the literature finds dampening effects for macroprudential regulation. We could separately include a capital flows variable.

-estimating the model before and after the 2008 crisis, then computing IRFs before and after. This would and double the sample size for the iMaPP regressions. Furthermore, we would tackle the obvious structural breaks in regulatory environment and financial linkages.

-use extended sign restrictions. Including corporate spreads would allow identifying credit shocks, which could currently be mixed up with monetary policy shocks.

-using an intensity-adjusted indicator of macroprudential policy

-adding more countries, disaggregating the Euro Area and modelling of the ECB's monetary policy. First, as in Georgiadis (2015), we could disaggregate the Euro Area block into its component countries and model the ECB separately. We would obtain more material for the IRF-macroprudential relation. This would also help us with the problem of matrix weights not being small.

-estimating the model in levels, maybe a GVECM, so that we can exploit cointegration relations. In particular we have eliminated the credit-to-GDP ratio, which is essential to our problem.

-A supplementary exercise could be the analysis of movements in credit via forecast error variance decompositions. The main question we ask here is whether credit dynamics are explained more by the local, or the US and foreign interest rates, and whether iMaPP data can help explain their respective shares. If such is the case, macroprudential policy could reinforce the credit channel of domestic monetary policy. For this, we would compute the FEVD up to 4 or 8 quarters. We will then make the ratio of domestic rate variance to foreign rate variance, and see the correlations with iMaPP.

7. Conclusion

This paper sought to uncover the global spillovers of US monetary policy on credit in 25 countries. We found that spillovers are strong and confirm theoretical expectations given by the GFC literature: US monetary policy shocks trigger synchronous responses throughout the globe. As for policy recommendations our results are in contradiction with Bergant (2020), and find an amplification effect of macroprudential policy on output and the domestic interest rate. Regarding capital controls, we find that their increase reduces the mitigation channel of exchange rate depreciation. Only credit benefits from isolation effects in our study. The effect of macroprudential regulations on domestic credit is a dampening effect, however. We partly explained the GDP-iMaPP puzzle by pointing out that the trade channel plays a role in negatively shaping the impact of macroprudential regulations.

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Model selection

Several hypotheses must be verified for the proper estimation of a GVAR model: we describe the preliminary verifications here.

Data stationarity

Only two series are non-stationary in 1st differences are stationary to the pp test at the 5% threshold, against 41 (out of 141) for an ADF test. This difference may be the sign that our data suffers from heteroskedasticity, a problem which we solve by estimating a model including stochastic volatility.

Georgiadis (2015) estimates a model in first-differences, and justifies it with three arguments: stability is ensured (this is the most important in our case), elimination of the need to test for the weak exogeneity of the country-specific foreign variables[17] and finally the fact that GVECMs are often mis-specified anyways because the adequate cointegration rank can't be applied because it leads to instability.

Smallness of link matrix weights

The weights linking the models (reported in the annex) are globally acceptably small. Regarding banking exposures, the Eurozone and the USA stand out, and don't respect the hypothesis: they're overweighted in their neighbour countries. The same goes for the UK and

[17] This hypothesis matters for cointegrating relationships, which are eliminated by the differentiation.

some of its partners. The situation is better with the trade weights matrix: only Mexico and Canada are overweighted for the USA, and 10 Eurozone neighbours. These problems could be avoided by including a disaggregated Eurozone model. Just like Dées (2021), we consider the cases we pointed out to be inconsequential anomalies.

Weak exogeneity hypothesis

We rely on the argument made by Feldkircher (2016): the SSVS prior automatically selects the relevant variables and dispenses us from testing this. If a country doesn't respect the "small open economy" hypothesis, the star variables shouldn't be in its VARX* because they're not weakly exogenous. If the foreign variables are irrelevant, the prior shrinks their coefficients to zero, and we don't need to deal with this problem.

Stability of the global model

This hypothesis is granted from the outset, because we automatically reject any draw whose eigenvalue is above or equal to 1.

We must then choose the right model specification: several specification tests were conducted, all of them with 25000 burnins and 1000 model draws. We set the prior value of the AR(1) term to 0.35, after some experimentation.

We first determine the lag order of the model. With one lag, 72.3% of the residuals are free from autocorrelation at the 5% threshold; 31 residuals suffer from cross country correlation, including 17 for the exchange rate. Only 4 series (exchange rate) have cross-country correlations above 0.2. The log-likelihood is -1.449159e+34. With two lags, the log-likelihood is -2.984096e+33. 79.23% of the residuals are free from autocorrelation at the 5% threshold; 27 residuals suffer from cross country correlation, including 16 for the exchange rate. Only 3 series (exchange rate) have cross-country correlations above 0.2. With three lags, the log-likelihood is -7.233787e+31. 77.69% of the residuals are free from autocorrelation at the 5% threshold; 24 residuals suffer from cross country correlation, including 15 for the exchange rate. 4 series (exchange rate) have cross-country correlations above 0.2. With four lags, diagnostics are unambiguously worse. 22 series suffer from cross-country correlation, but only 73.07% ae free from autocorrelation.

The two-lags specification seems to be better. However, another concern determines us: with one lag, we find 92.3% of stable draws, versus 53.1% with two lags and 34.0% with three lags and 4% with four lags.

Using dummies doesn't improve the situation. Knowing the difficulty in finding rotation matrices for sign identification later on, we decide to give up on the 2 lags modest improvements and stick with the one lag specification.

Then, we compare the trade weights to the mixed financial and trade weights. We choose the mixed-weights scheme because its likelihood of -1.449159e+34 is lower than the -1.250612e+34 of the trade weights scheme.

Data appendix

GDP series are real, seasonally adjusted and in local currencies. We copied GDP from Mohaddes (2020) for most countries. They were imported from dbnomics, via OECD's MEI database for the countries we added to the original GVAR dataset (Poland, Czechia, Denmark and Hungary)

Russian GDP was obtained from Bloomberg (Q1 1999 – Q2 2021, ticker: BCMPRUSA INDEX), because the CBR series cover the periods 1995-2011 NSA, 2003-2011 SA and 2011-2021 SA. Data for the 1995-2002 were not revised and harmonized with the later periods. To compute our RGDP series for Russia, we proceed in the following way:

-deseasonalize the 1995-2011 vintage

-compute its QoQ growth rates

-iterate backwards on the Bloomberg series with those growth rates, in order to obtain the RGDP series starting in Q1 1998.

CPI series come from Mohaddes (2020). We used the quarterly growth rates provided by the dataset to reverse engineer CPI series, with a basis of 100 in Q1 2010.

For the countries we added, we used the IMF's CPI repository, found on dbnomics. We deseasonalized them with rdbnomics' integrated deseasonalization function.

Bank credit to domestic NFIs is from the BIS. It was deseasonalized via R's "seasonal" package, implementing X-13 ARIMA SEATS, with an additive decomposition. They are in local currency and adjusted for breaks. The variables were passed in logs before de-seasonalization, and retransformed after the process.

Interest rates, both long and short, are taken from Mohaddes (2020). For the 5 countries we added, we used the same provider, IMF's IFS. Poland, Czechia and Denmark have the policy related rate series. Russia has the money market rate. Norway has its rates in Mohaddes (2020). When calculating the spread, we simply substracted the short-term rate from our long rate series.

We used the short shadow rates built by the Bank of New Zealand's Leo Krippner (2020) for the USA, Eurozone, UK, New Zealand, Japan, Australia, Canada and Switzerland. Because this series has negative values, we cannot apply the log transformation from Mohaddes (2020). In order for those series to be harmonized with the rest, we apply to them the inverse hyperbolic sine transformation.

Bilateral exchange rates (local currency per 1 USD), come from the BIS. They were imported via dbnomics and we used quarterly averages.

Equity prices come from MSCI indices are normalized by the author to have index = 100 in Q1 2010 (Bloomberg ticker: MXUS INDEX for the USA, always using the 2 digits ISO country codes.)

Table 2: Sources and availability of the GVAR data :

Variable	y	dP	stir	ner	equities	credit	ltir	Trade-Φ weights
US	K. M.	K. M.	Bloom	BIS	Bloom	BIS	K. M.	
CN	K. M.	K. M.	K. M.	BIS	Bloom	BIS		
EA	MEI	IMF	Bloom	BIS	Bloom	BIS	K. M.	
UK	K. M.	K. M.	Bloom	BIS	Bloom	BIS	K. M.	
JP	K. M.	K. M.	Bloom	BIS	Bloom	BIS	K. M.	
BR	K. M.	K. M.	K. M.	BIS	Bloom	BIS		
CA	K. M.	K. M.	Bloom	BIS	Bloom	BIS	K. M.	
CL	K. M.	K. M.	K. M.	BIS	Bloom	BIS		
TR	K. M.	K. M.	K. M.	BIS	Bloom	BIS		
IN	K. M.	K. M.	K. M.	BIS	Bloom	BIS		
AU	K. M.	K. M.	Bloom	BIS	Bloom	BIS	K. M.	
ID	K. M.	K. M.	K. M.	BIS	Bloom	BIS		
KR	K. M.	K. M.	K. M.	BIS	Bloom	BIS	K. M.	
MY	K. M.	K. M.	K. M.	BIS	Bloom	BIS		
NZ	K. M.	K. M.	Bloom	BIS	Bloom	BIS	K. M.	
PH	K. M.	K. M.	K. M.	BIS	Bloom			
SG	K. M.	K. M.	K. M.	BIS	Bloom	BIS		
TH	K. M.	K. M.	K. M.	BIS	Bloom	BIS		
MX	K. M.	K. M.	K. M.	BIS	Bloom	BIS		
AR	K. M.	K. M.	K. M.	BIS	Bloom	BIS		
PE	K. M.	K. M.	K. M.	BIS	Bloom			
SA	K. M.	K. M.		BIS				
ZA	K. M.	K. M.	K. M.	BIS	Bloom			
SE	K. M.	K. M.	K. M.	BIS	Bloom	BIS	K. M.	
CH	K. M.	K. M.	Bloom	BIS	Bloom	BIS	K. M.	
NO	K. M.	K. M.	K. M.	BIS	Bloom	BIS		
PL	MEI	IMF	IMF	BIS	Bloom	BIS		
CZ	MEI	IMF	IMF	BIS	Bloom	BIS		
RU	CBR	IMF	IMF	BIS	Bloom	BIS		
DK	MEI	IMF	IMF	BIS	Bloom	BIS		

Problem countries in Mohaddes (2020) are South Africa and Saudi Arabia, which don't have the financial exposure weights, and the Philippines and Peru which do not have the credit series. New countries we included as replacements are Norway, Poland, Czechia, Denmark and Russia. **Feldkircher (2016)** include banking weights for many countries in the CESEE and the former Soviet Union. However, we do not have the corresponding credit data, and can't exploit most of those countries, except for Russia, Poland, Czechia and Denmark.

Table 3: Weights based on banking exposures (assets + liabilities); green if bilateral weight below 20%, and shades of yellow if between 20 and 40%, orange-red if above 40% (NB: country in question is in lines, partner in columns)

	US	CN	EA	UK	JP	BR	CA	CL	TR	IN	AU	ID	KR	MY	NZ	TH	MX	AR	SE	CH	NO	PL	CZ	RU	DK	HU
US	0	0.01	0.24	0.49	0.06	0.01	0.05	0.01	0	0	0.01	0	0.01	0	0	0	0.02	0	0	0.05	0.01	0	0	0.01	0	0
CN	0.24	0	0.3	0.22	0.1	0	0.01	0	0	0.01	0.02	0	0.07	0	0	0	0	0	0.01	0.02	0	0	0	0	0.01	0
EA	0.19	0.01	0	0.54	0.03	0	0.01	0	0.01	0	0.01	0	0.01	0	0	0	0	0	0.02	0.08	0.01	0.01	0.01	0.02	0.02	0.01
UK	0.24	0.01	0.53	0	0.05	0	0.02	0	0	0	0.01	0	0	0	0	0	0	0	0.01	0.07	0.01	0	0	0.01	0.01	0
JP	0.37	0.01	0.26	0.24	0	0	0.01	0	0	0	0.02	0	0.01	0	0	0	0	0	0	0.03	0	0	0	0	0	0
BR	0.38	0	0.26	0.24	0.05	0	0.03	0.01	0	0	0	0	0.03	0	0	0	0	0	0	0.01	0	0	0	0	0.01	0
CA	0.65	0	0.08	0.21	0.01	0.01	0	0.01	0	0	0	0	0	0	0	0	0.01	0	0	0.01	0	0	0	0	0	0.01
CL	0.56	0.02	0.2	0.1	0.02	0.04	0.04	0	0	0.01	0	0	0.01	0	0	0	0	0.01	0	0.01	0	0	0	0	0	0
TR	0.16	0	0.53	0.27	0.01	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.01	0	0	0	0	0	0.01
IN	0.52	0.02	0.16	0.22	0.02	0	0.02	0	0	0	0.01	0	0.01	0	0	0	0	0	0	0.01	0	0	0	0	0	0
AU	0.2	0.01	0.14	0.51	0.05	0	0.01	0	0	0	0	0	0	0	0.05	0	0	0	0	0.02	0	0	0	0	0	0
ID	0.17	0	0.34	0.13	0.19	0	0	0	0	0.01	0.03	0	0.05	0.03	0	0	0	0	0.01	0.04	0	0	0	0	0	0
KR	0.23	0.08	0.21	0.23	0.1	0	0.01	0	0	0.01	0.02	0.01	0	0.02	0	0	0	0	0	0.05	0	0	0	0.01	0	0
MY	0.2	0.02	0.16	0.33	0.05	0	0.01	0	0	0.01	0.03	0.03	0.1	0	0	0.03	0	0	0	0.01	0	0	0	0	0.01	0
NZ	0.09	0	0.08	0.15	0.09	0	0	0	0	0	0.55	0	0	0	0	0	0	0	0	0.04	0	0	0	0	0	0
TH	0.19	0	0.23	0.24	0.19	0	0.01	0	0	0.01	0.01	0	0.02	0.02	0	0	0	0	0.03	0.05	0	0	0	0	0.01	0
MX	0.7	0	0.17	0.08	0.02	0	0.02	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AR	0.35	0	0.24	0.14	0.03	0	0.01	0	0	0	0	0	0	0	0	0	0	0	0	0.22	0	0	0	0	0	0
SE	0.06	0	0.36	0.2	0	0	0	0	0	0	0.01	0	0	0	0	0	0	0	0	0.02	0.14	0.01	0	0.01	0.18	0
CH	0.14	0	0.39	0.36	0.04	0.01	0	0	0.01	0	0	0	0	0	0	0	0.01	0.01	0	0	0	0	0	0.01	0	0
NO	0.11	0	0.32	0.28	0.03	0	0	0	0	0	0	0	0	0	0	0	0	0	0.17	0.01	0	0	0	0	0.09	0
PL	0.07	0	0.73	0.12	0.03	0	0	0	0	0	0	0	0	0	0	0	0	0	0.02	0.01	0	0	0	0	0.01	0
CZ	0.04	0	0.81	0.12	0.01	0	0	0	0	0	0	0	0.01	0	0	0	0	0	0	0.02	0	0	0	0	0	0
RU	0.11	0	0.51	0.32	0.01	0	0	0	0	0.01	0	0	0	0	0	0	0	0	0.01	0.03	0	0	0	0	0	0
DK	0.04	0.01	0.4	0.18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.21	0.03	0.09	0	0	0.01	0	0
HU	0.01	0	0.81	0.1	0.01	0	0.03	0	0	0	0	0	0.01	0	0	0	0	0	0	0.01	0	0	0	0	0.01	0

Table 4: Weights based on trade (exports+imports); green if bilateral weight below 20%, and shades of yellow if between 20 and 40%, orange-red if above 40% (NB: country in question is in lines, partner in columns)

	US	CN	EA	UK	JP	BR	CA	CL	TR	IN	AU	ID	KR	MY	NZ	TH	MX	AR	SE	CH	NO	PL	CZ	RU	DK	HU
US	0.00	0.15	0.17	0.04	0.09	0.02	0.22	0.01	0.01	0.02	0.01	0.01	0.03	0.02	0.00	0.01	0.15	0.00	0.01	0.01	0.00	0.00	0.00	0.01	0.00	0.00
CN	0.21	0.00	0.19	0.03	0.17	0.03	0.02	0.01	0.01	0.03	0.04	0.02	0.11	0.04	0.00	0.03	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.03	0.00	0.00
EA	0.15	0.10	0.00	0.18	0.04	0.02	0.01	0.01	0.03	0.02	0.01	0.01	0.02	0.01	0.00	0.01	0.01	0.01	0.05	0.07	0.03	0.05	0.04	0.07	0.03	0.03
UK	0.12	0.05	0.55	0.00	0.03	0.01	0.02	0.00	0.01	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.02	0.03	0.03	0.01	0.01	0.02	0.01	0.01
JP	0.23	0.24	0.13	0.02	0.00	0.01	0.02	0.01	0.00	0.01	0.05	0.04	0.08	0.04	0.01	0.05	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.02	0.00	0.00
BR	0.20	0.14	0.24	0.03	0.05	0.00	0.02	0.03	0.00	0.02	0.01	0.01	0.03	0.01	0.00	0.01	0.03	0.11	0.01	0.01	0.01	0.00	0.00	0.02	0.00	0.00
CA	0.72	0.06	0.06	0.03	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
CL	0.19	0.18	0.18	0.02	0.09	0.08	0.02	0.00	0.01	0.02	0.01	0.00	0.06	0.00	0.00	0.01	0.04	0.07	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
TR	0.08	0.07	0.46	0.07	0.02	0.01	0.01	0.00	0.00	0.02	0.00	0.01	0.02	0.01	0.00	0.01	0.00	0.00	0.01	0.03	0.01	0.02	0.01	0.12	0.01	0.01
IN	0.16	0.16	0.23	0.05	0.05	0.02	0.01	0.01	0.01	0.00	0.04	0.04	0.04	0.03	0.00	0.02	0.01	0.01	0.01	0.06	0.00	0.00	0.00	0.02	0.00	0.00
AU	0.12	0.21	0.12	0.05	0.18	0.01	0.01	0.00	0.00	0.04	0.00	0.03	0.07	0.04	0.05	0.04	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
ID	0.12	0.15	0.11	0.02	0.22	0.01	0.01	0.00	0.01	0.05	0.04	0.00	0.09	0.07	0.01	0.05	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.00	0.00
KR	0.17	0.26	0.12	0.02	0.17	0.02	0.02	0.01	0.01	0.02	0.04	0.03	0.00	0.03	0.00	0.02	0.01	0.00	0.00	0.00	0.01	0.01	0.00	0.02	0.00	0.00
MY	0.19	0.15	0.13	0.02	0.18	0.01	0.01	0.00	0.00	0.03	0.04	0.05	0.06	0.00	0.01	0.08	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
NZ	0.14	0.13	0.13	0.04	0.11	0.00	0.02	0.00	0.00	0.01	0.25	0.02	0.04	0.03	0.00	0.02	0.01	0.00	0.01	0.01	0.00	0.00	0.00	0.01	0.01	0.00
TH	0.14	0.15	0.11	0.03	0.23	0.01	0.01	0.00	0.00	0.02	0.05	0.05	0.04	0.08	0.00	0.00	0.01	0.00	0.01	0.03	0.00	0.00	0.00	0.01	0.00	0.00
MX	0.72	0.06	0.07	0.01	0.03	0.01	0.03	0.01	0.00	0.00	0.00	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR	0.13	0.11	0.18	0.01	0.02	0.31	0.01	0.07	0.00	0.02	0.01	0.01	0.02	0.01	0.00	0.01	0.03	0.00	0.00	0.01	0.00	0.01	0.00	0.01	0.01	0.00
SE	0.07	0.03	0.47	0.08	0.02	0.01	0.01	0.00	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.10	0.03	0.01	0.03	0.09	0.01
CH	0.09	0.03	0.67	0.05	0.03	0.01	0.01	0.00	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.01
NO	0.06	0.03	0.42	0.20	0.02	0.01	0.03	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.10	0.01	0.00	0.02	0.01	0.01	0.05	0.00
PL	0.02	0.03	0.62	0.05	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.03	0.01	0.01	0.00	0.05	0.08	0.02	0.03
CZ	0.02	0.04	0.66	0.05	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.02	0.02	0.00	0.07	0.00	0.04	0.01	0.03
RU	0.05	0.12	0.47	0.04	0.04	0.01	0.00	0.00	0.05	0.02	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.02	0.03	0.01	0.05	0.02	0.00	0.01	0.02
DK	0.05	0.04	0.48	0.08	0.02	0.00	0.01	0.00	0.01	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.15	0.01	0.06	0.03	0.01	0.02	0.00	0.01
HU	0.03	0.05	0.63	0.04	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.05	0.04	0.06	0.01	0.00

Figure 9: values of the iMaPP index

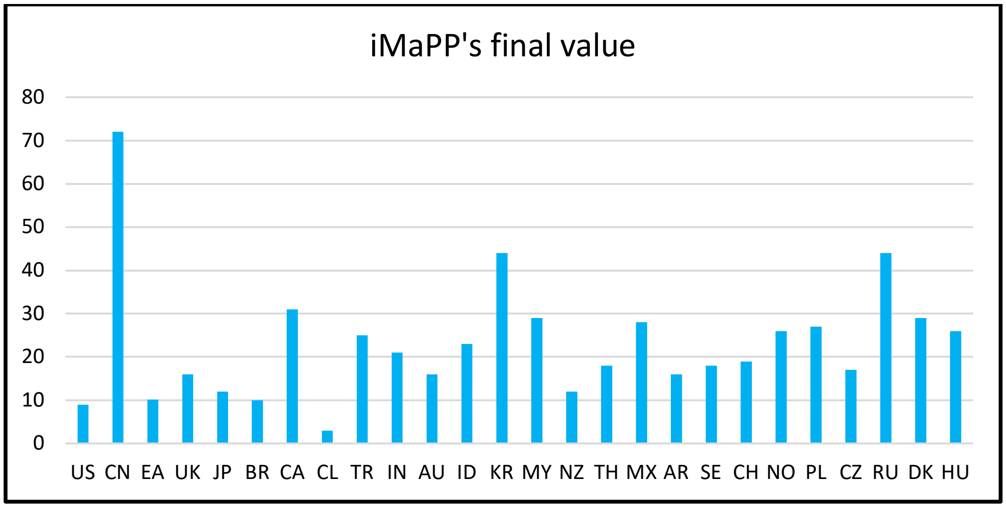
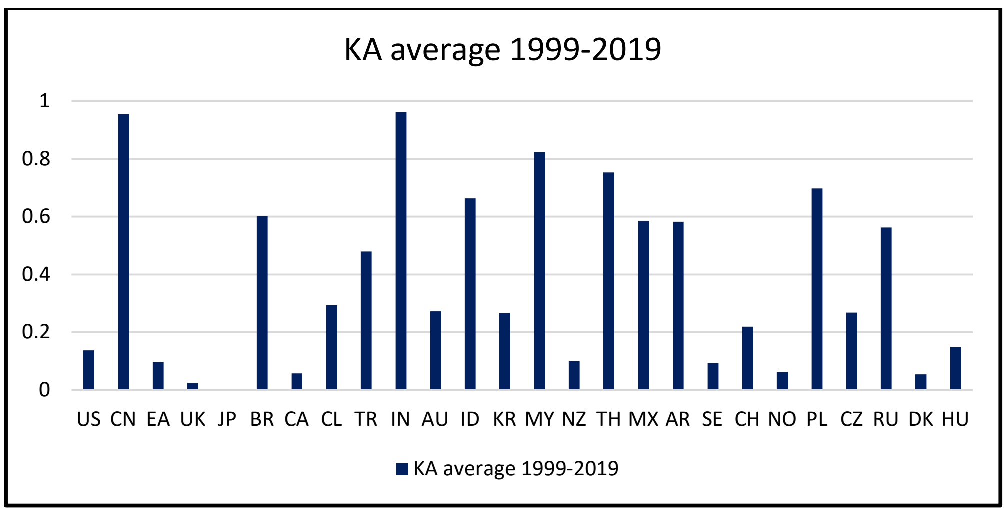


Figure 10: values of the capital controls index (Fernandez 2015)



Detail on regulatory indices computations for the Euro Area value:

We face the problem of aggregating the EA countries. We will answer it in a simple manner. Although we used a changing composition GDP for the EA, we will take the final iMaPP for each EZ member on 2019, and average them according to the country's GDP weight in the EA in 2007[18].

[18] The date choice is justified by the use of 2007-2008 values for banking exposures

For the euro area, we take an average of each country's indicator value, based on GDP weights. We neglect the 8 post-2001 adhesions, since they represent 2.19% of the region's 2019 GNI. Luxembourg is also left out, due to its size.

Map of the countries included:

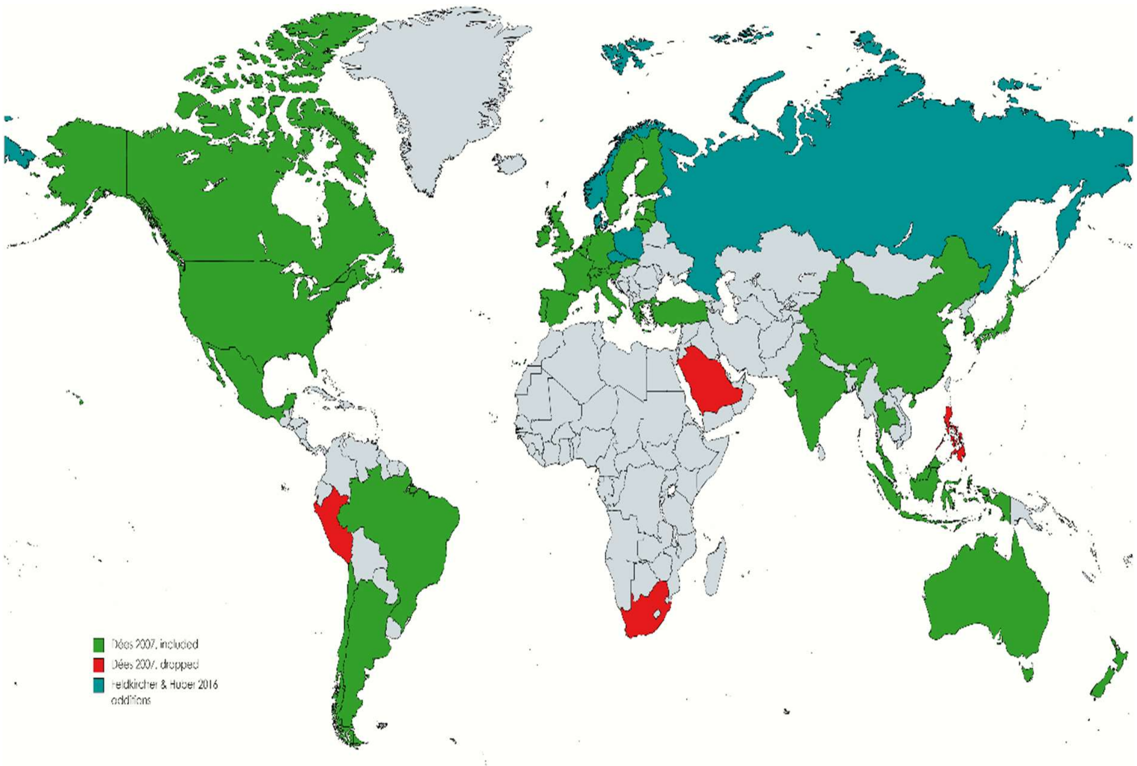


Table of spillover determinants:

Group	Country characteristics	Measurement	Source
Openness/integration	De jure financial openness	Omitted	Omitted
	Trade integration	(X+M)/GDP	WDI
	Financial integration	Gross foreign assets & liabilities over GDP, proxied by gross portfolio equity & debt assets/liabilities	Global financial development database
Economic structure	Industry structure	Manufacturing share in total value added	WDI
	Financial system competition	H-statistic	Global financial development database
	Financial depth	Domestic credit / GDP or stock market capitalisation relative to GDP	Global financial development database
	Financial liberalisation	Omitted	Omitted
	Labour market rigidities	Strictness of employment protection	OECD
Vulnerabilities	Institutional quality	Not available - paying source	Omitted
	Exchange rate regime	Dummies (0 or 1)	Author's judgement
	Advanced/ emerging status	Dummies (0 or 1)	iMaPP typology
	Public debt burden	Public debt/GDP	Global financial development database
Regulation	Capital controls	Overall restrictions index	Fernandez (2015)
	Macroprudential regulation	iMaPP's final value	Alam (2019)

The database on financial liberalization comes from a paper published in 2008: it thus ignores the regulatory developments post-crisis. Because we do not split our sample, we do not include this information, although it could be the key to our puzzle.

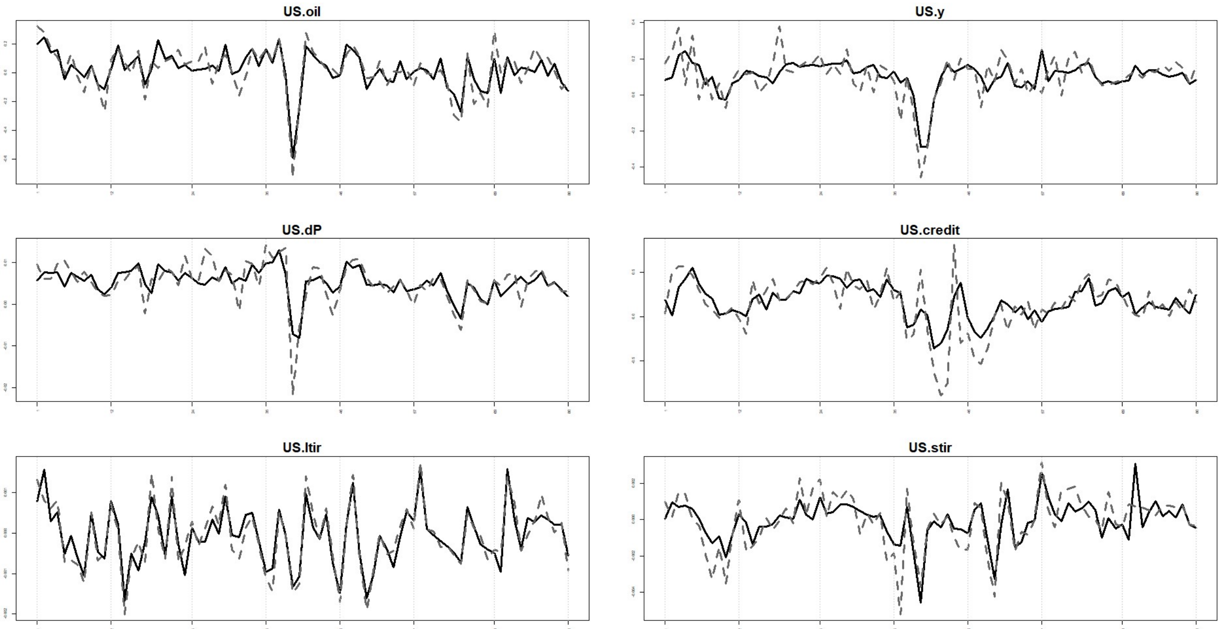
Outputs of the final estimation:

Model: oil in the US model, 1 lag, AR(1) coefficient set to 0.35, SSVS prior

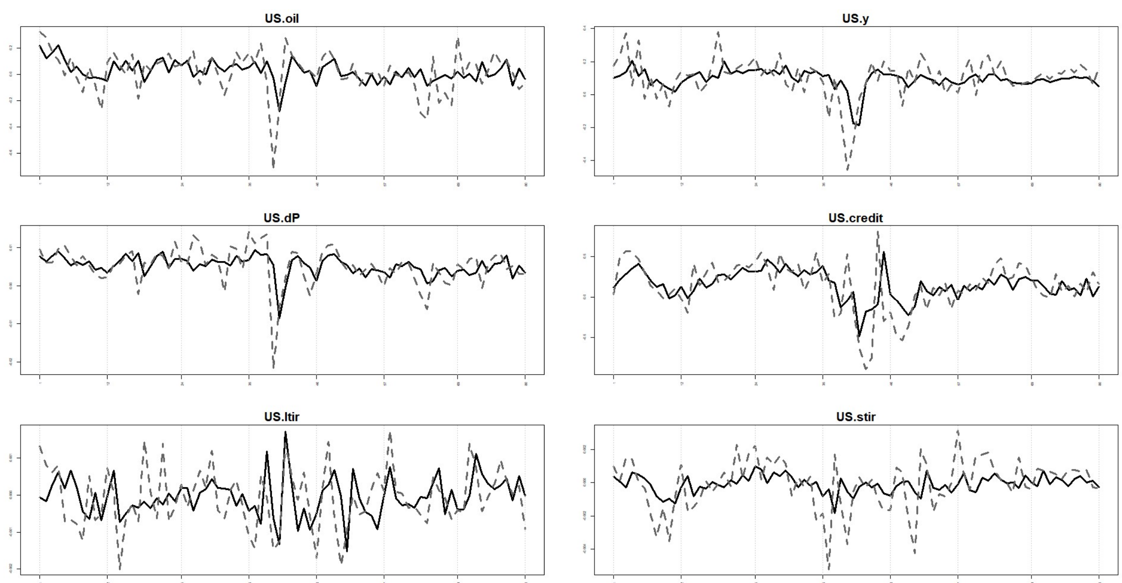
Diagnostic tests:

```
---------------------------------------------------------------------------
Model Info:
Prior: Stochastic Search Variable Selection prior (SSVS)
Number of lags: 1
Number of posterior draws: 30000/10=3000
Number of stable posterior draws:  2455
Number of cross-sectional units: 26
---------------------------------------------------------------------------
Convergence diagnostics
Geweke statistic:
1912 out of 20022 variables' z-values exceed the 1.96 threshold (9.55%).
---------------------------------------------------------------------------
F-test, first order serial autocorrelation of cross-unit residuals
Summary statistics:
=========  ==========  ======
\          # p-values  in %
=========  ==========  ======
>0.1       91          64.54%
0.05-0.1   10          7.09%
0.01-0.05  21          14.89%
<0.01      19          13.48%
=========  ==========  ======
---------------------------------------------------------------------------
Average pairwise cross-unit correlation of unit-model residuals
Summary statistics:
=======  ===========  ===========  =========  ===========  ===========  ========
\        y            dP           credit     ltir         stir         er
=======  ===========  ===========  =========  ===========  ===========  ========
<0.1     25 (96.15%)  22 (84.62%)  26 (100%)  10 (90.91%)  18 (69.23%)  8 (32%)
0.1-0.2  1 (3.85%)    4 (15.38%)   0 (0%)     1 (9.09%)    8 (30.77%)   13 (52%)
0.2-0.5  0 (0%)       0 (0%)       0 (0%)     0 (0%)       0 (0%)       4 (16%)
>0.5     0 (0%)       0 (0%)       0 (0%)     0 (0%)       0 (0%)       0 (0%)
=======  ===========  ===========  =========  ===========  ===========  ========
```

In sample fit of the USA’s VARX*:



In-sample fit of the GVAR, US variables:



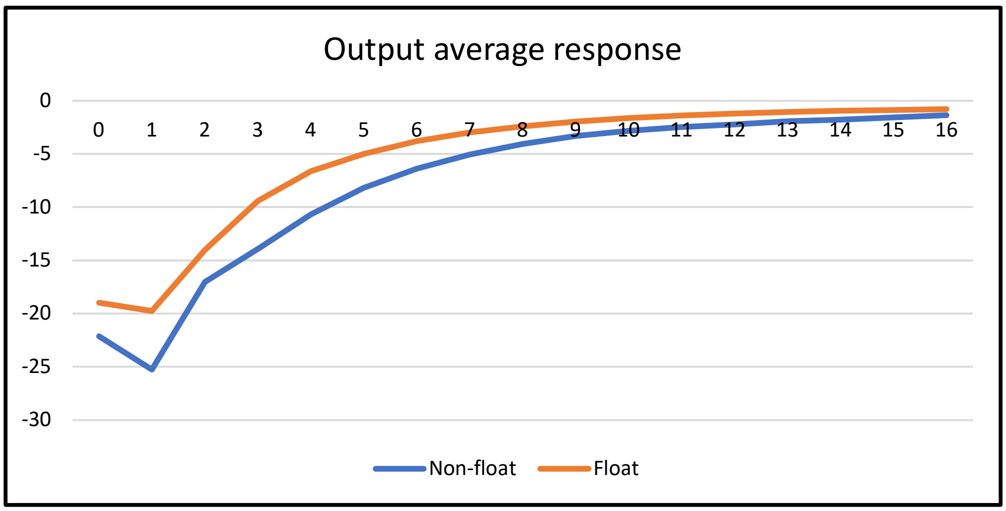
Impulse response functions

Here, we report the non-cumulative IRFs. For the international responses, we divide our 25 countries into five geographical areas: Europe, America, CESEE (Central, Eastern and South Eastern Europe), East and South Asia, and South-East Asia.

IRFs from sign restrictions:

Responses of aggregates:

Figure X: IRFs for the fixed vs. floating exchange rate countries



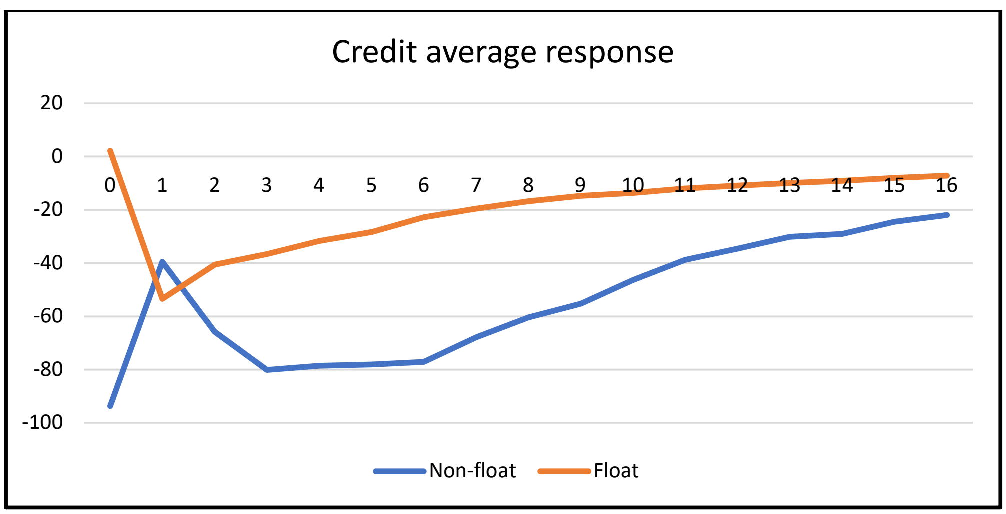
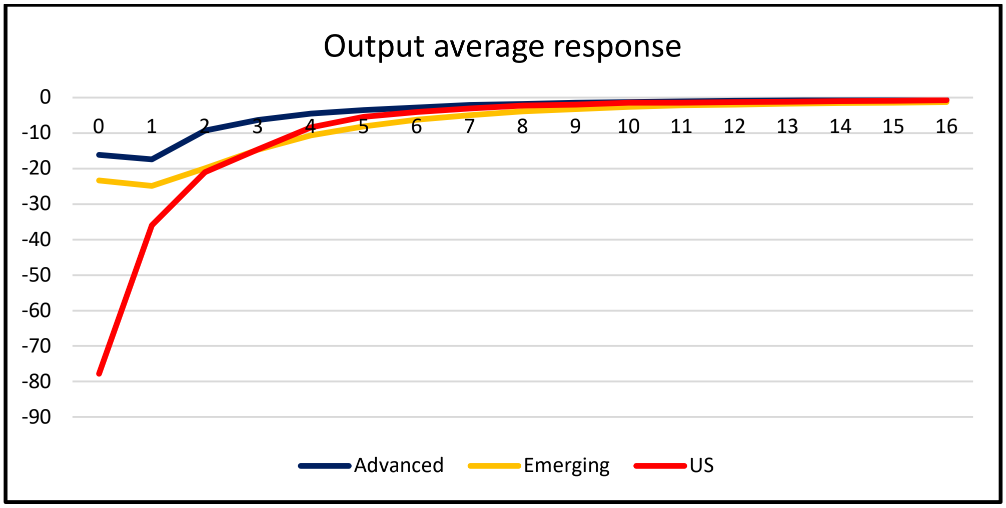
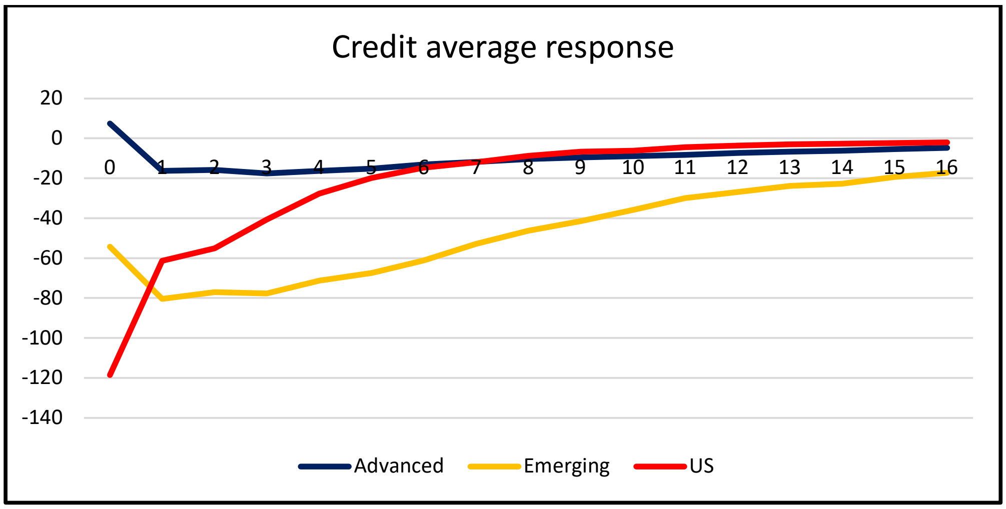
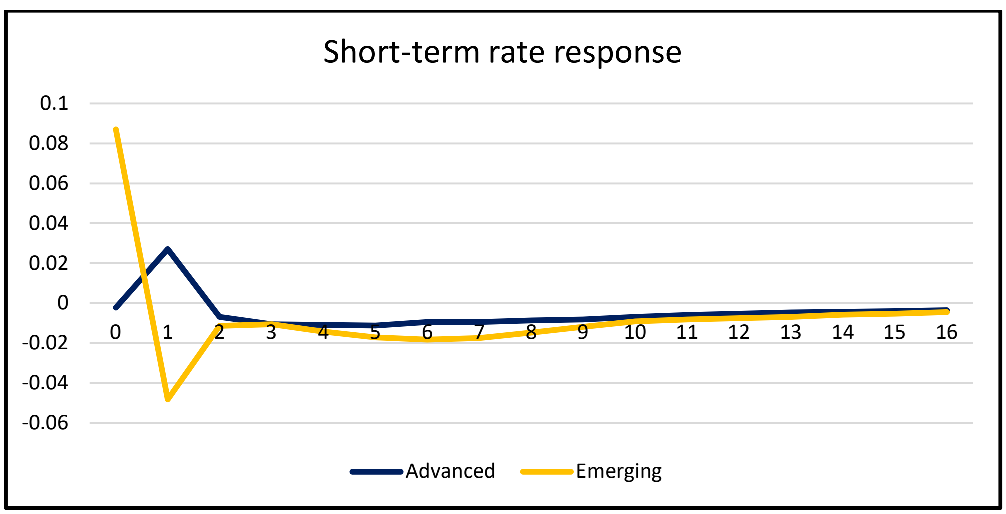


Figure X: IRFs for the advanced vs. emerging economies


Output average response
0
-10
-20
-30
-40
-50
-60
-70
-80
-90
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Advanced
Emerging
US


Credit average response
20
0
-20
-40
-60
-80
-100
-120
-140
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Advanced
Emerging
US


Short-term rate response
0.1
0.08
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Advanced
Emerging

Domestic responses of the USA:

Figure X: Impact of the US demand shock (size = 0.01[19])

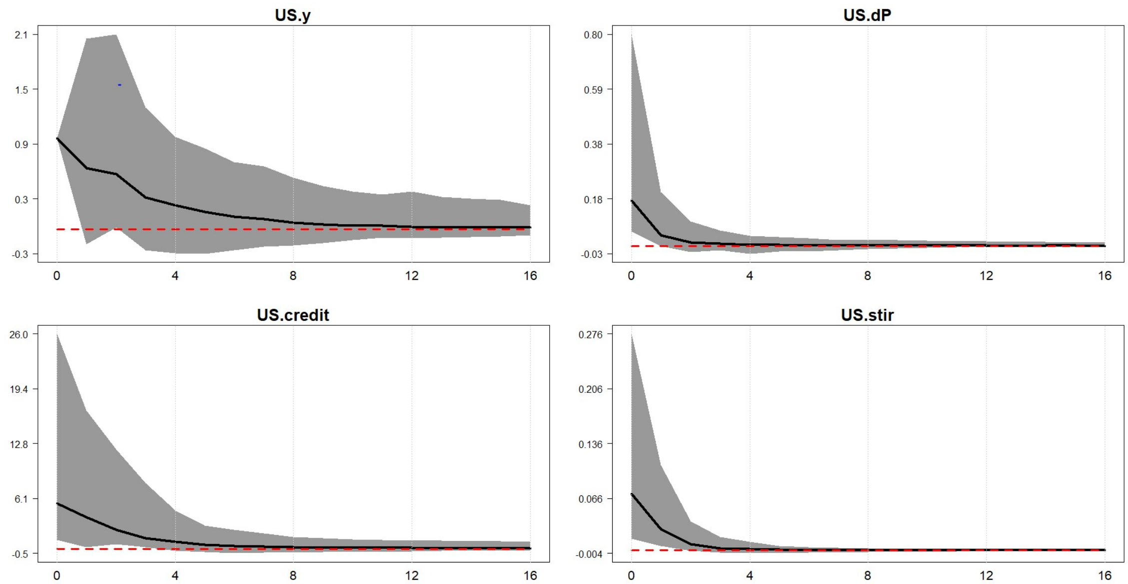


Figure X: Impact of the US supply shock (size = 0.01)

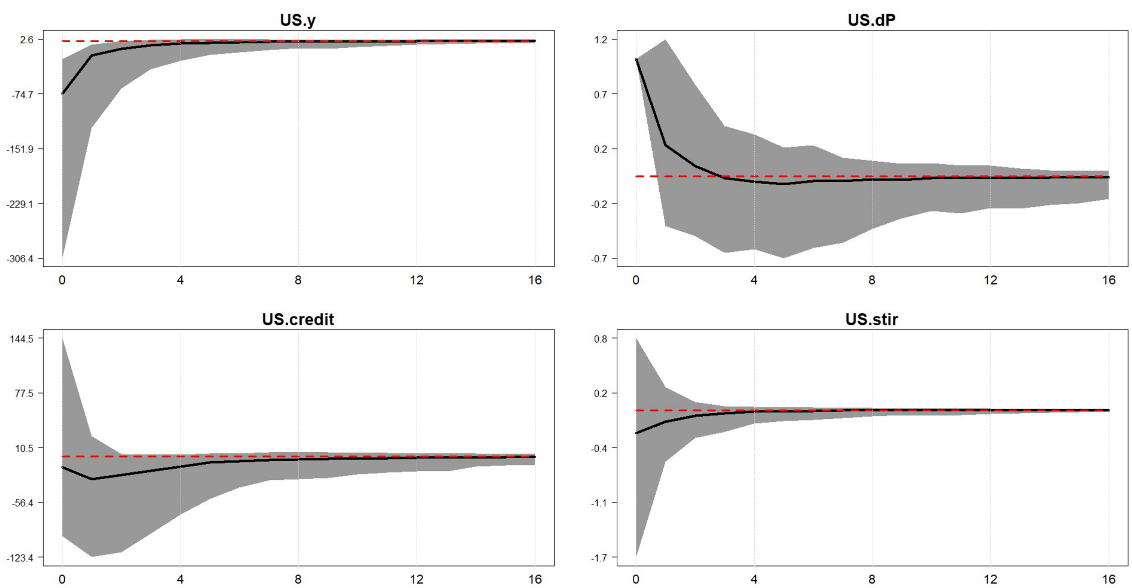
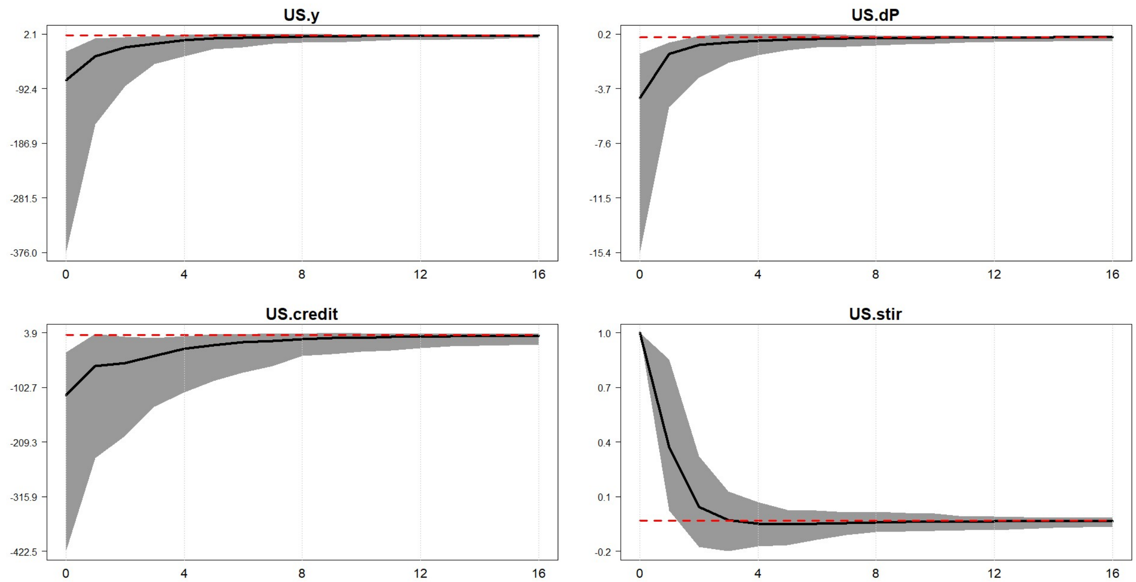


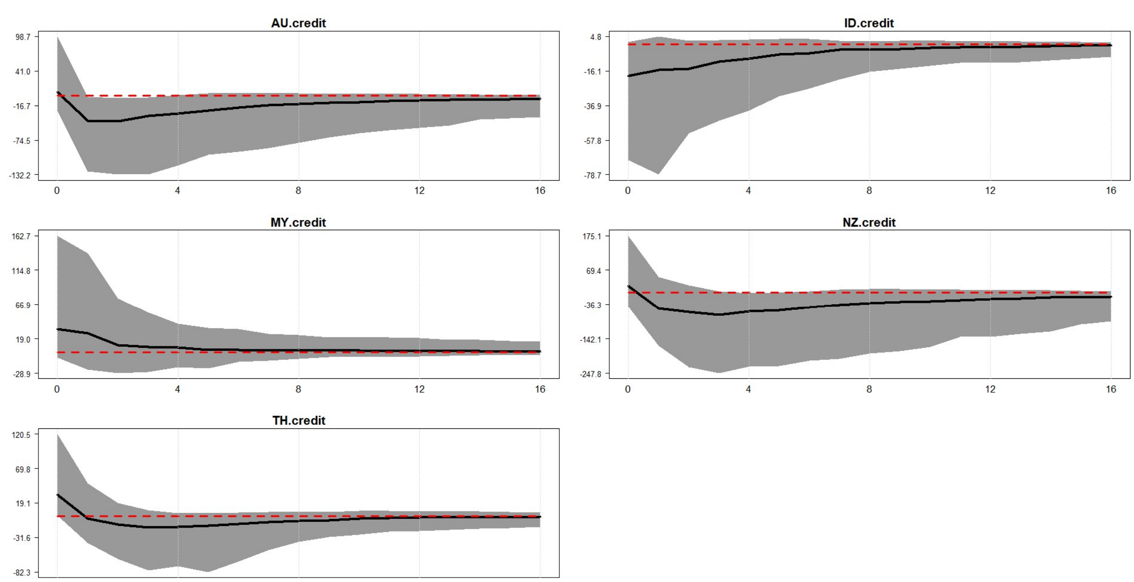
Figure X: Impact of the US monetary policy shock (size = 0.01)

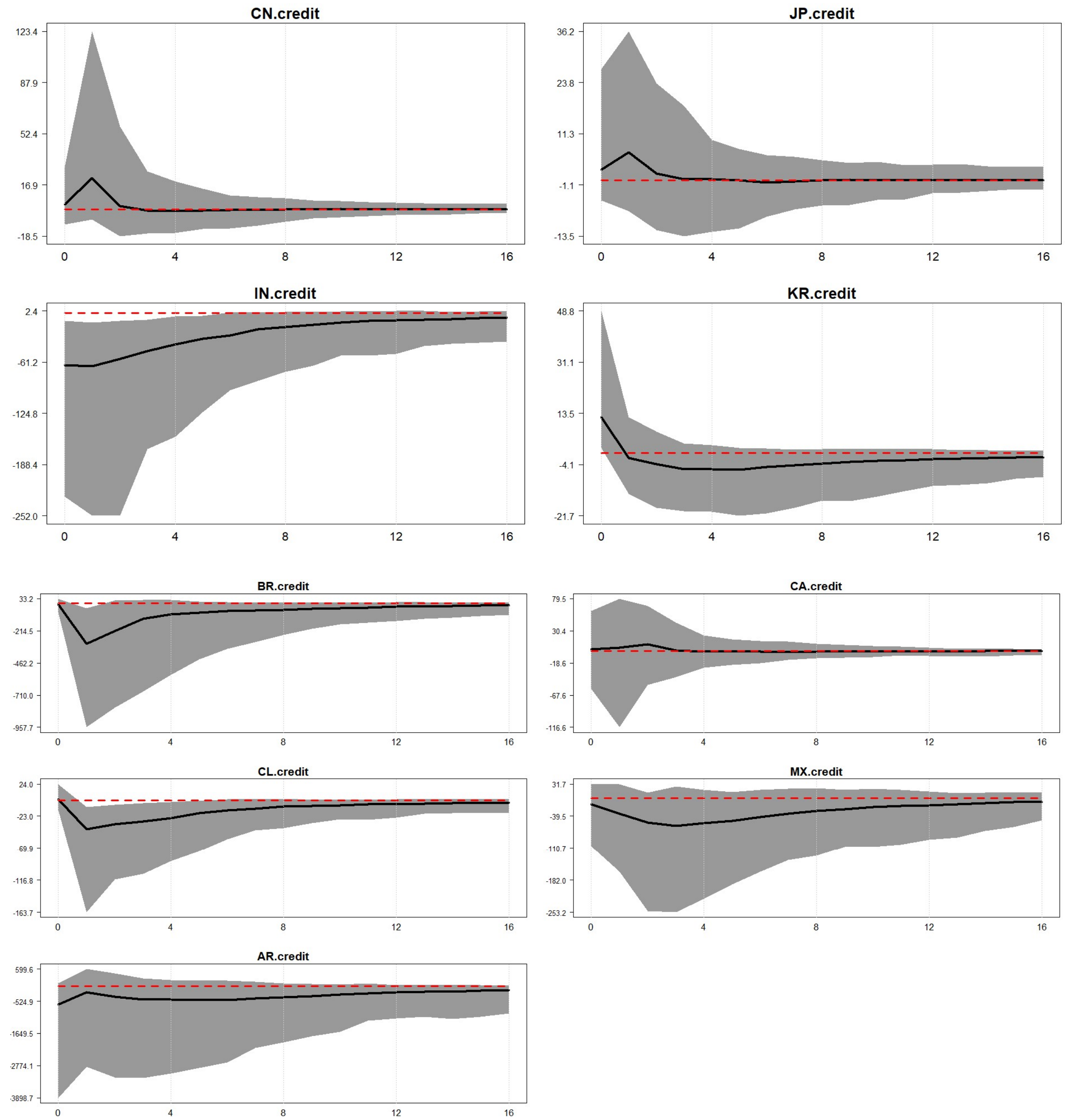
[19] This is badly dimensioned, knowing the rates were entered as 0.25*log(1+r/100). It can be re-dimensioned, however.

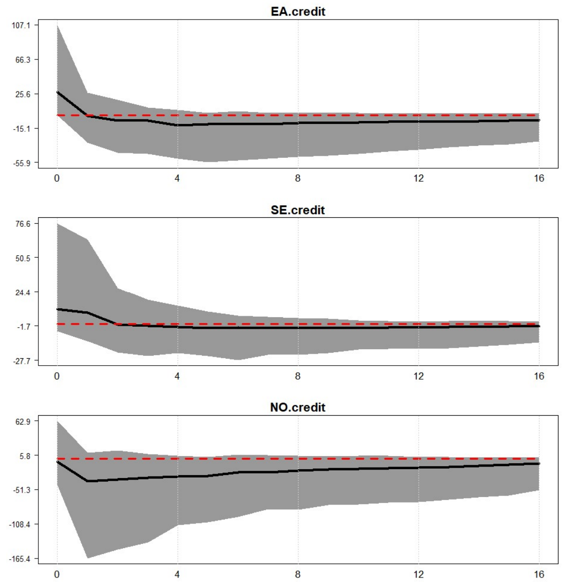


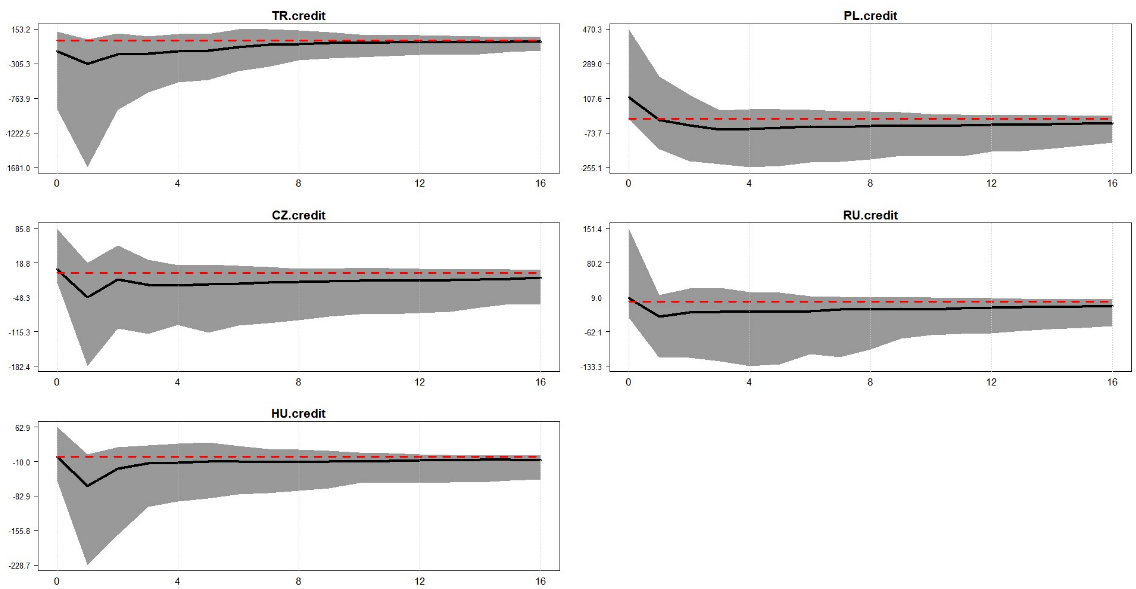
International responses to US monetary policy:

Credit responses

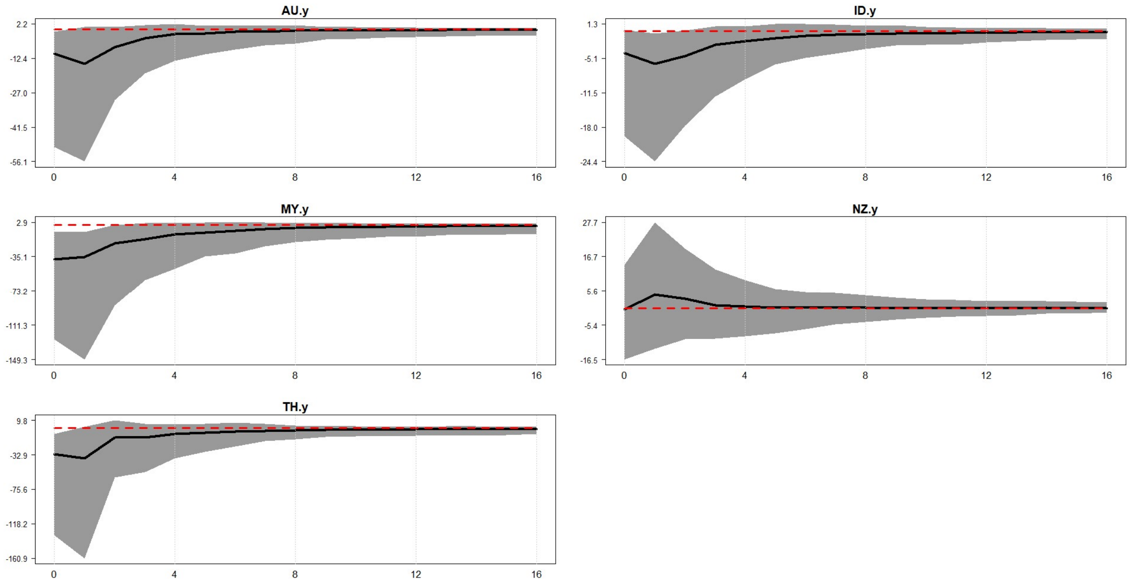


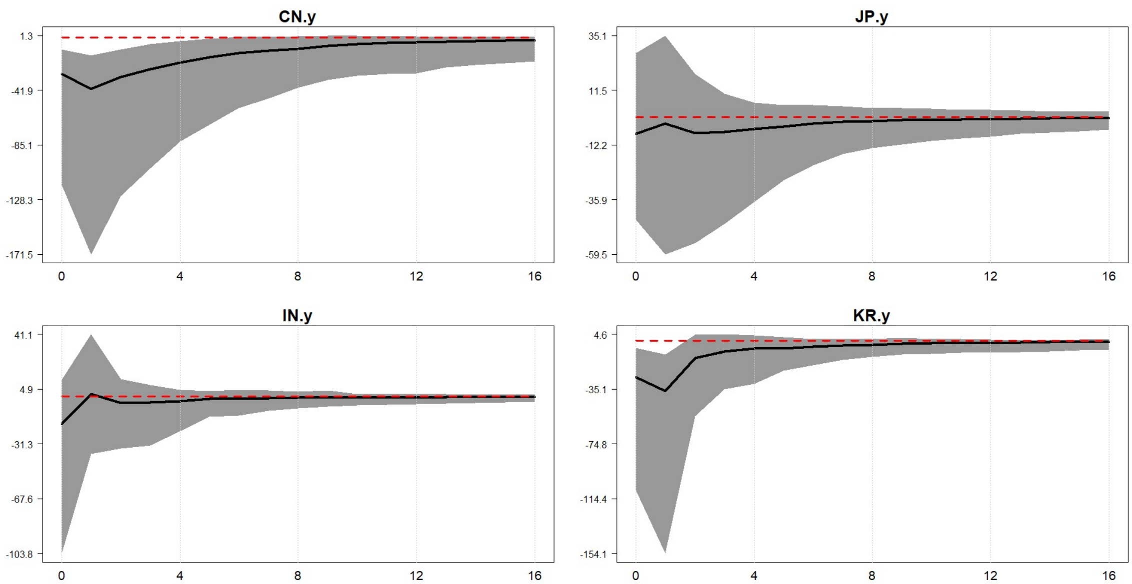

CN.credit
123.4
87.9
52.4
16.9
-18.5
JP.credit
36.2
23.8
11.3
-1.1
-13.5
IN.credit
2.4
-61.2
-124.8
-188.4
-252.0
KR.credit
48.8
31.1
13.5
-4.1
-21.7
BR.credit
33.2
-214.5
-462.2
-710.0
-957.7
CA.credit
79.5
30.4
-18.6
-67.6
-116.6
CL.credit
24.0
-23.0
69.9
-116.8
-163.7
MX.credit
31.7
-39.5
110.7
-182.0
-253.2
AR.credit
599.6
-524.9
-1649.5
-2774.1
-3898.7
0
4
8
12
16

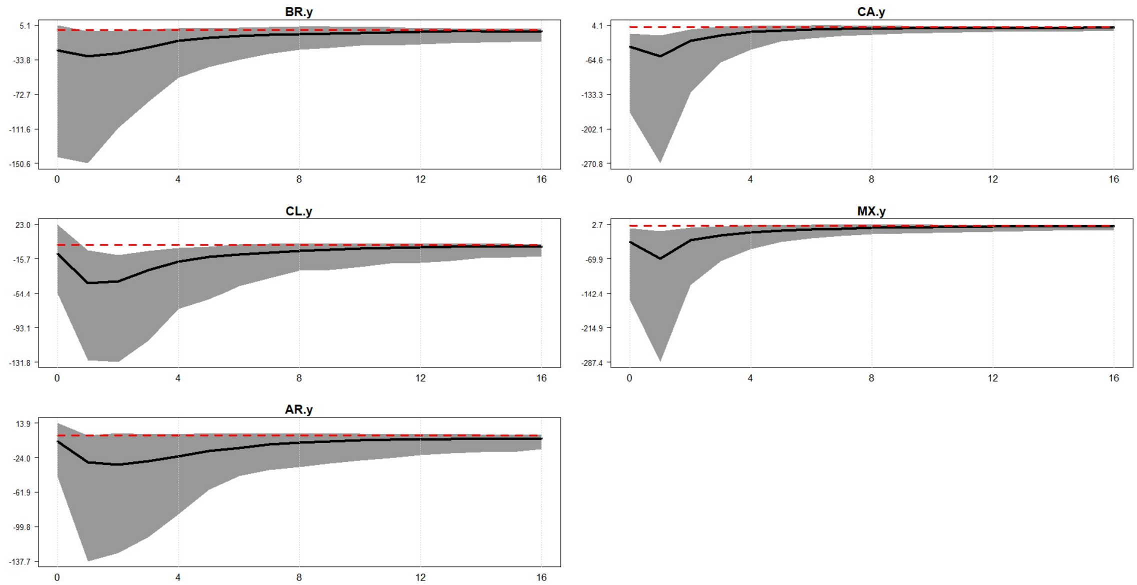


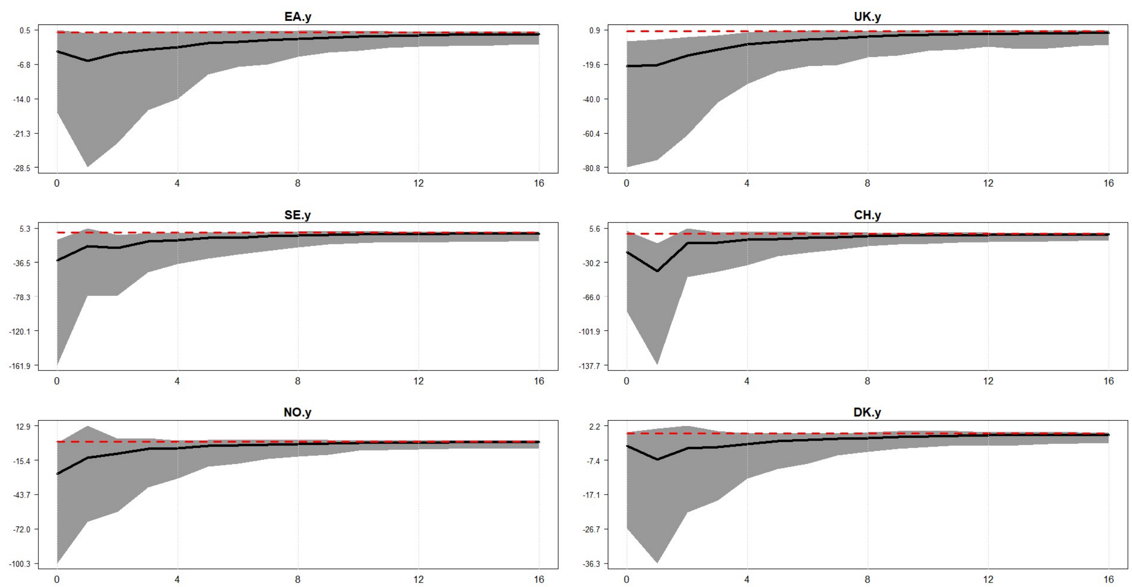


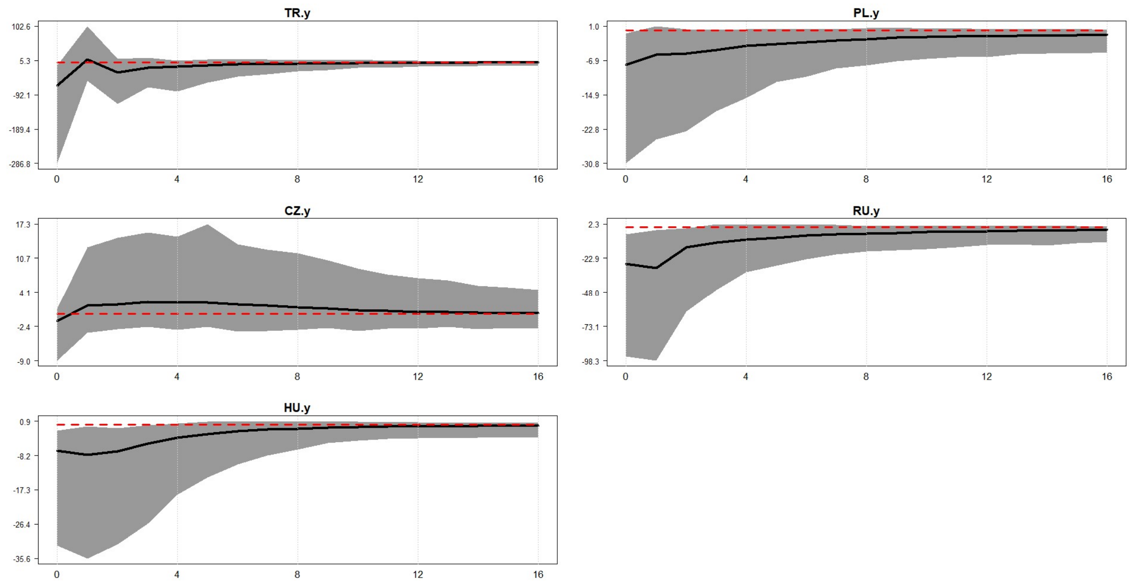
Output responses


AU.y
ID.y
MY.y
NZ.y
TH.y


CN.y
JP.y
IN.y
KR.y

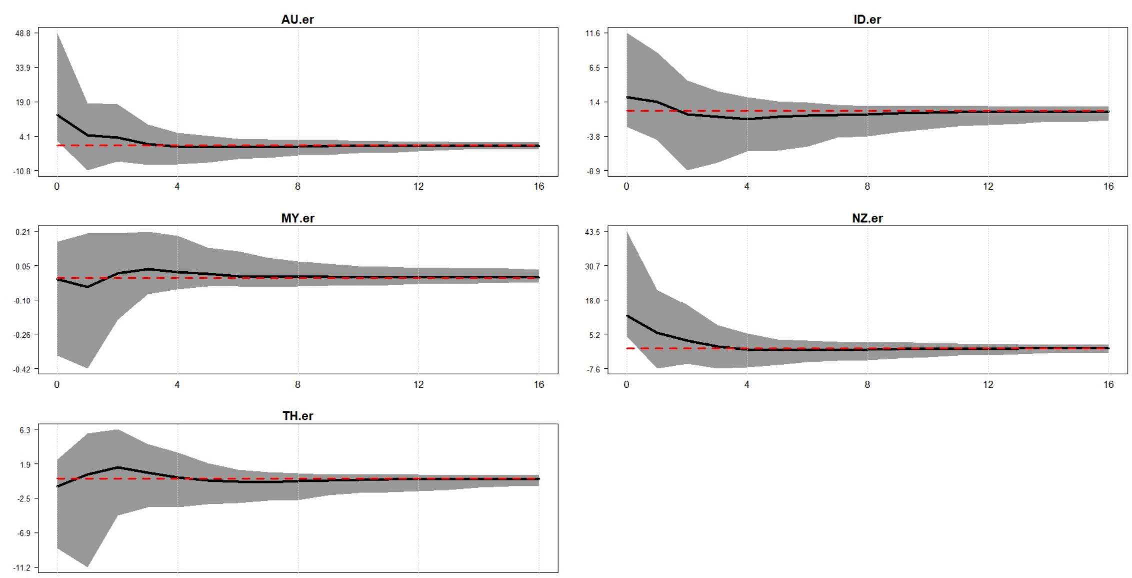

BR.y
5.1
-33.8
-72.7
-111.6
-150.6
CA.y
4.1
-64.6
-133.3
-202.1
-270.8
CL.y
23.0
-15.7
-54.4
-93.1
-131.8
MX.y
2.7
-69.9
-142.4
-214.9
-287.4
AR.y
13.9
-24.0
-61.9
-99.8
-137.7
0
4
8
12
16

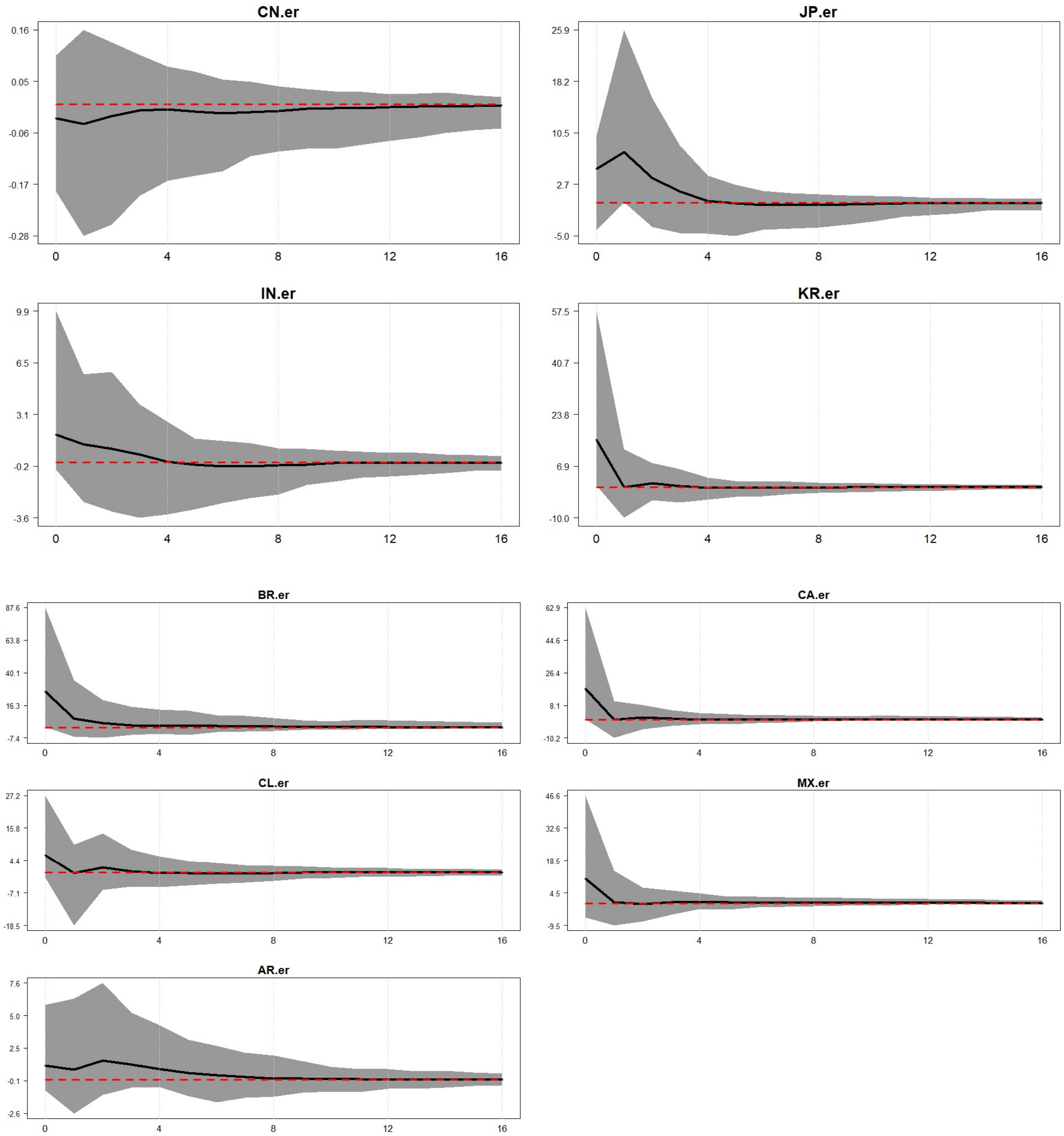

EA.y
0.5
-6.8
-14.0
-21.3
-28.5
UK.y
0.9
-19.6
-40.0
-60.4
-80.8
SE.y
5.3
-36.5
-78.3
-120.1
-161.9
CH.y
5.6
-30.2
-66.0
-101.9
-137.7
NO.y
12.9
-15.4
-43.7
-72.0
-100.3
DK.y
2.2
-7.4
-17.1
-26.7
-36.3
0
4
8
12
16

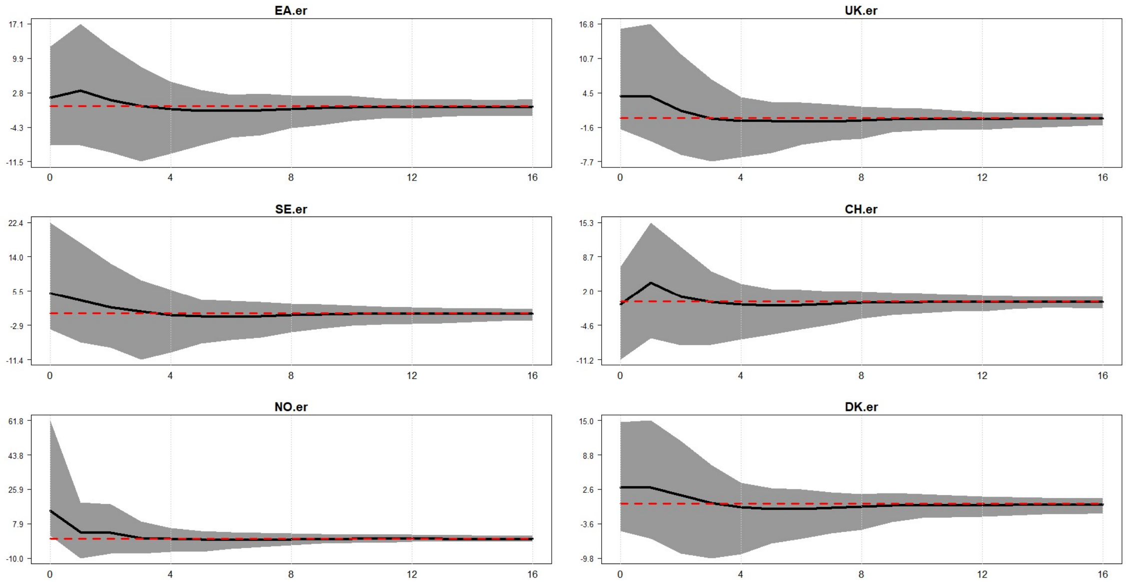


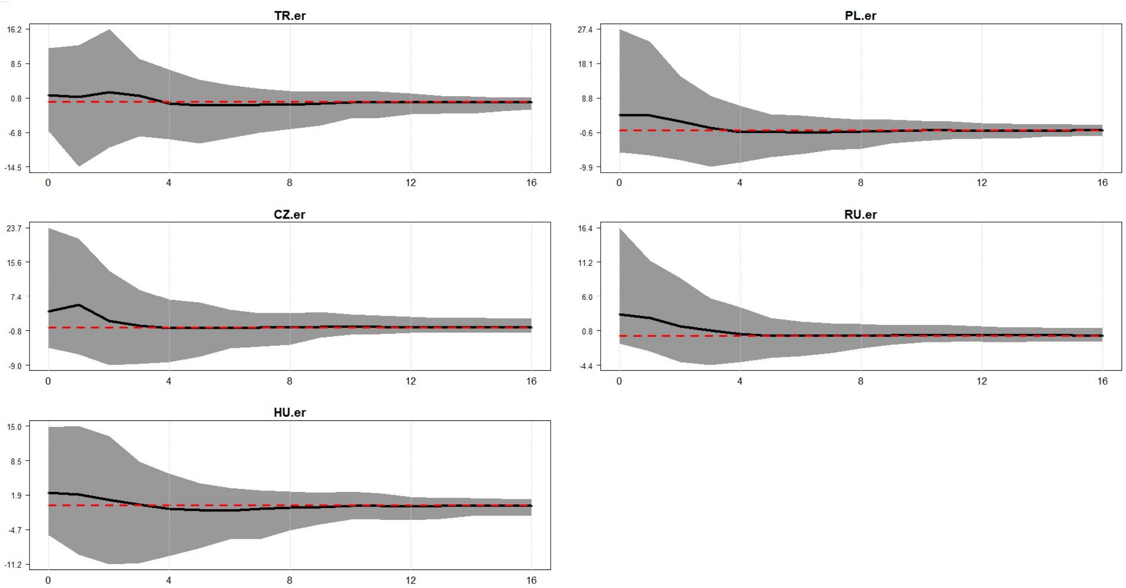
Exchange rate responses:

They all depreciate as expected.

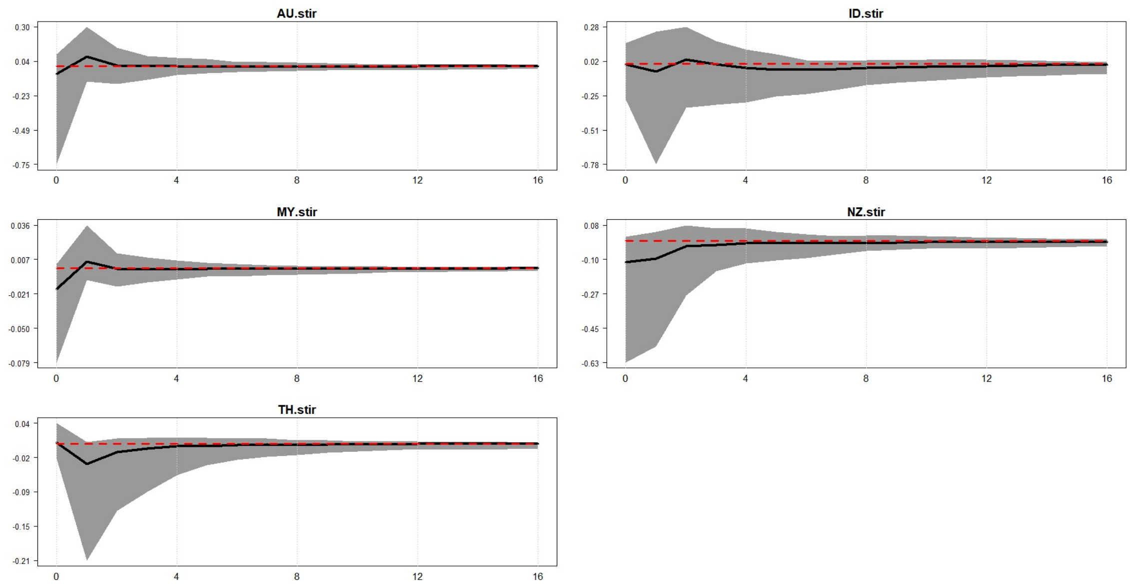


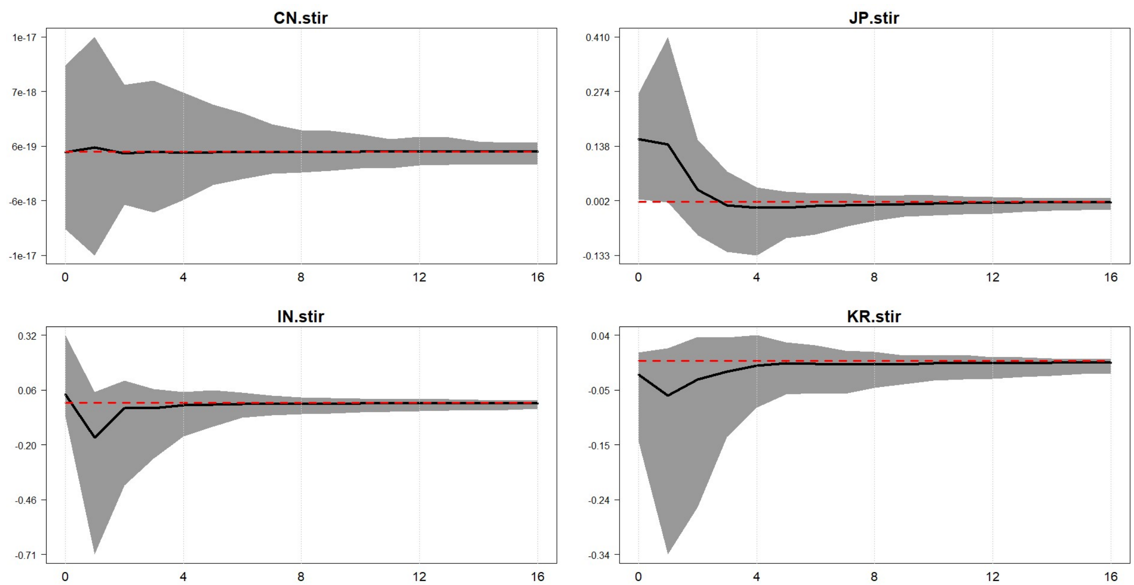

CN.er
0.16
0.05
-0.06
-0.17
-0.28
0 4 8 12 16
JP.er
25.9
18.2
10.5
2.7
-5.0
0 4 8 12 16
IN.er
9.9
6.5
3.1
-0.2
-3.6
0 4 8 12 16
KR.er
57.5
40.7
23.8
6.9
-10.0
0 4 8 12 16
BR.er
87.6
63.8
40.1
16.3
-7.4
0 4 8 12 16
CA.er
62.9
44.6
26.4
8.1
-10.2
0 4 8 12 16
CL.er
27.2
15.8
4.4
-7.1
-18.5
0 4 8 12 16
MX.er
46.6
32.6
18.6
4.5
-9.5
0 4 8 12 16
AR.er
7.6
5.0
2.5
-0.1
-2.6
0 4 8 12 16

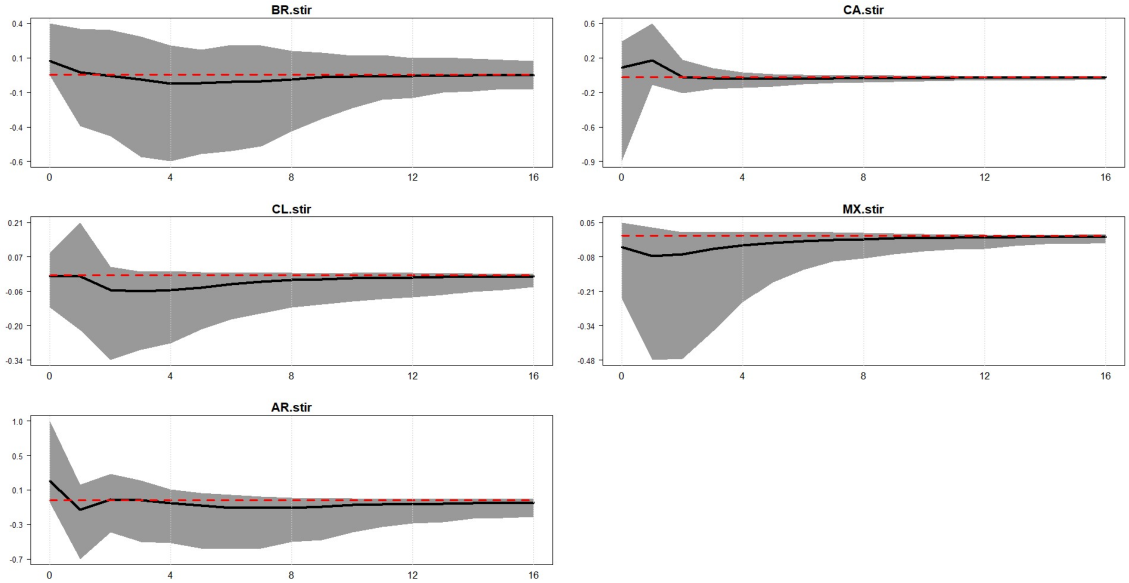


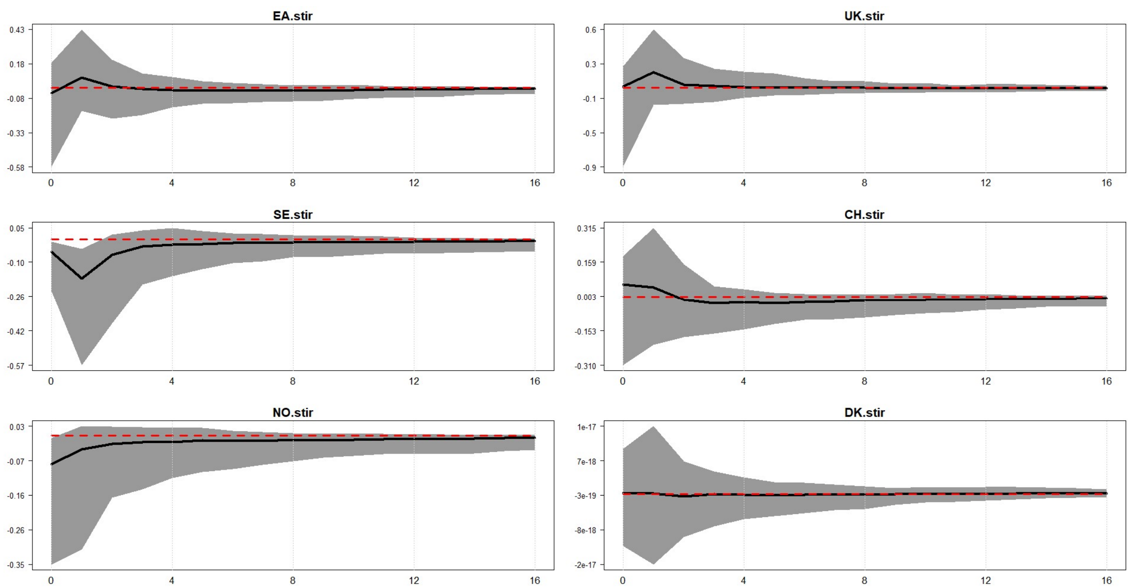


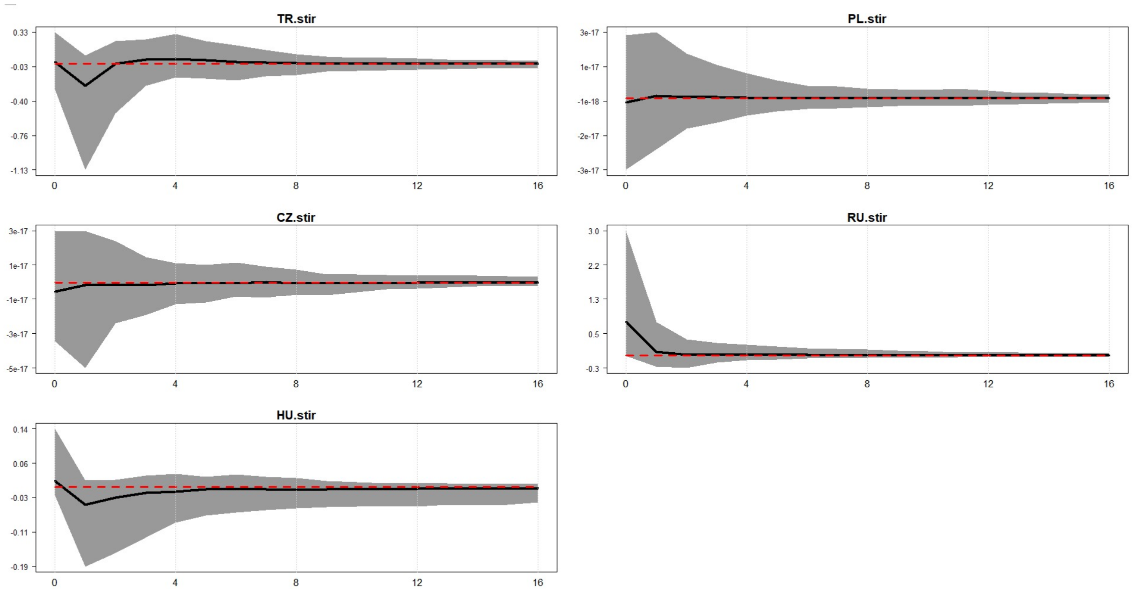
Interest rate


AU.stir
0.30
0.04
-0.23
-0.49
-0.75
ID.stir
0.28
0.02
-0.25
-0.51
-0.78
MY.stir
0.036
0.007
-0.021
-0.050
-0.079
NZ.stir
0.08
-0.10
-0.27
-0.45
-0.63
TH.stir
0.04
-0.02
-0.09
-0.15
-0.21
0
4
8
12
16


CN.stir
1e-17
7e-18
6e-19
-6e-18
-1e-17
JP.stir
0.410
0.274
0.138
0.002
-0.133
IN.stir
0.32
0.06
-0.20
-0.46
-0.71
KR.stir
0.04
-0.05
-0.15
-0.24
-0.34
0
4
8
12
16


BR.stir
0.4
0.1
-0.1
-0.4
-0.6
CA.stir
0.6
0.2
-0.2
-0.6
-0.9
CL.stir
0.21
0.07
-0.06
-0.20
-0.34
MX.stir
0.05
-0.08
-0.21
-0.34
-0.48
AR.stir
1.0
0.5
0.1
-0.3
-0.7
0
4
8
12
16

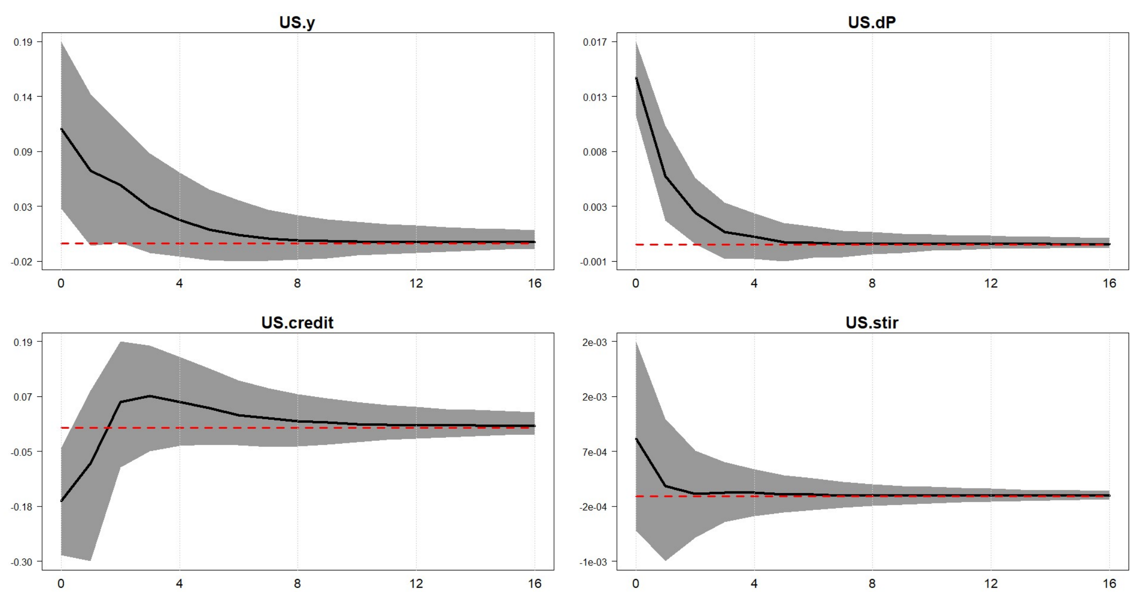

EA.stir
0.43
0.18
-0.08
-0.33
-0.58
UK.stir
0.6
0.3
-0.1
-0.5
-0.9
SE.stir
0.05
-0.10
-0.26
-0.42
-0.57
CH.stir
0.315
0.159
0.003
-0.153
-0.310
NO.stir
0.03
-0.07
-0.16
-0.26
-0.35
DK.stir
1e-17
7e-18
-3e-19
-8e-18
-2e-17
0
4
8
12
16



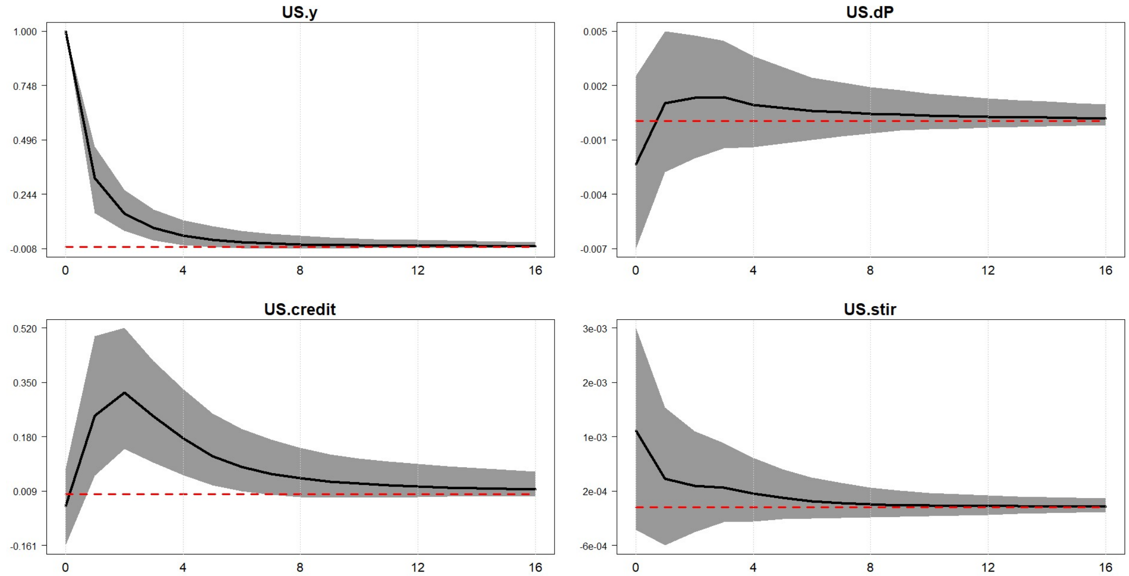
IRFs from *Cholesky* ordering:

Domestic responses of the USA:

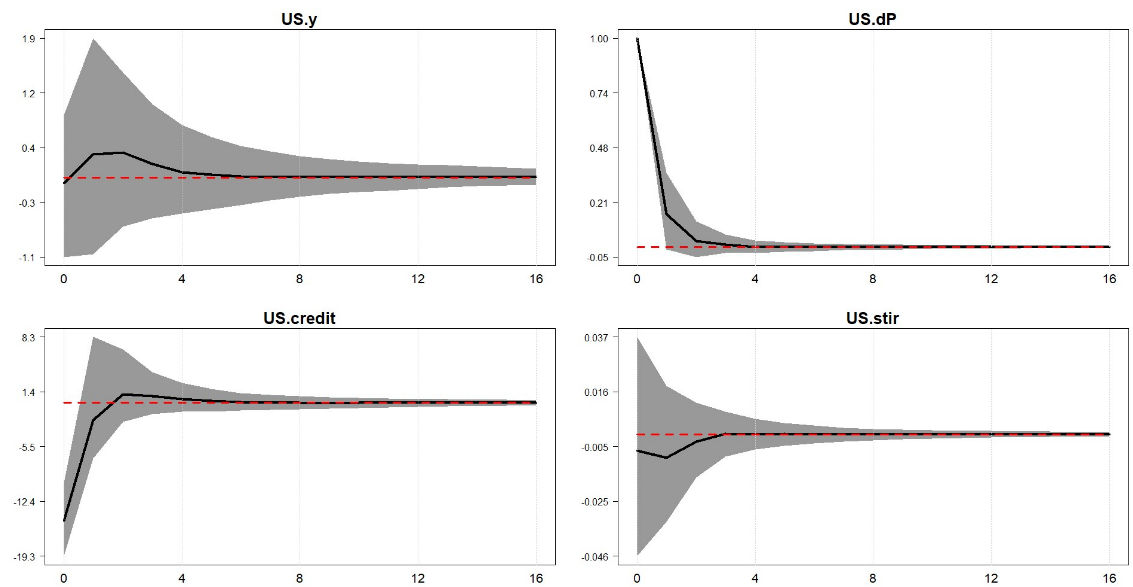
Shock on oil:



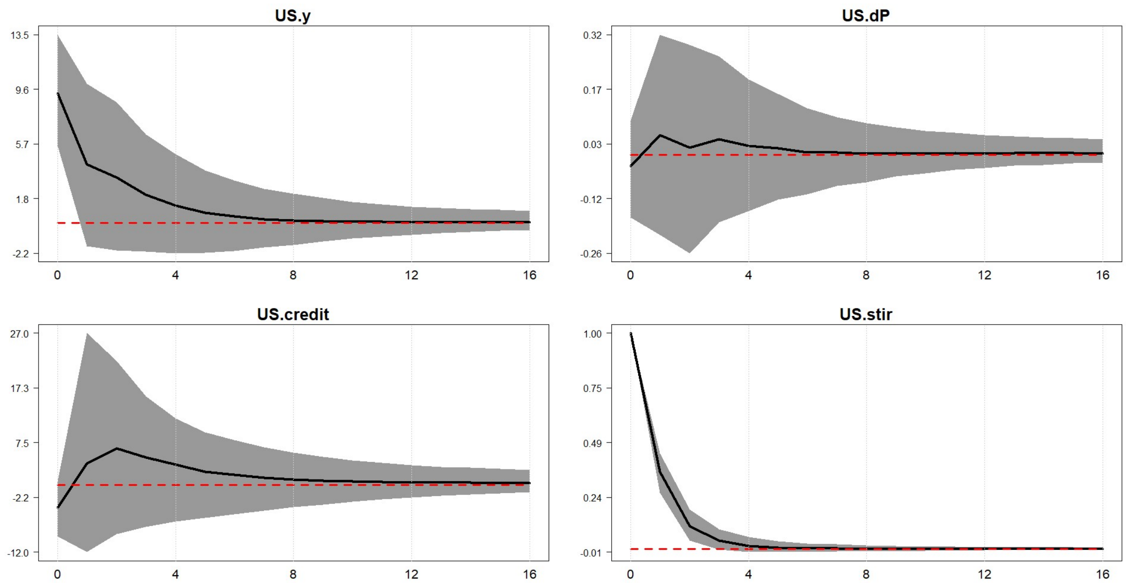
Shock on output:



Shock on inflation:

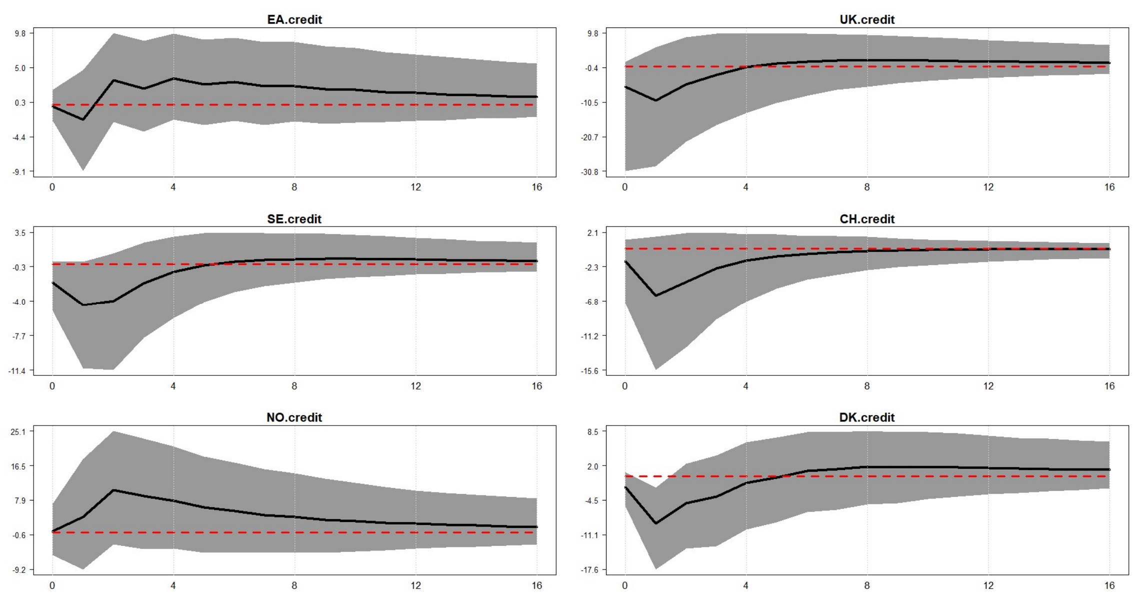


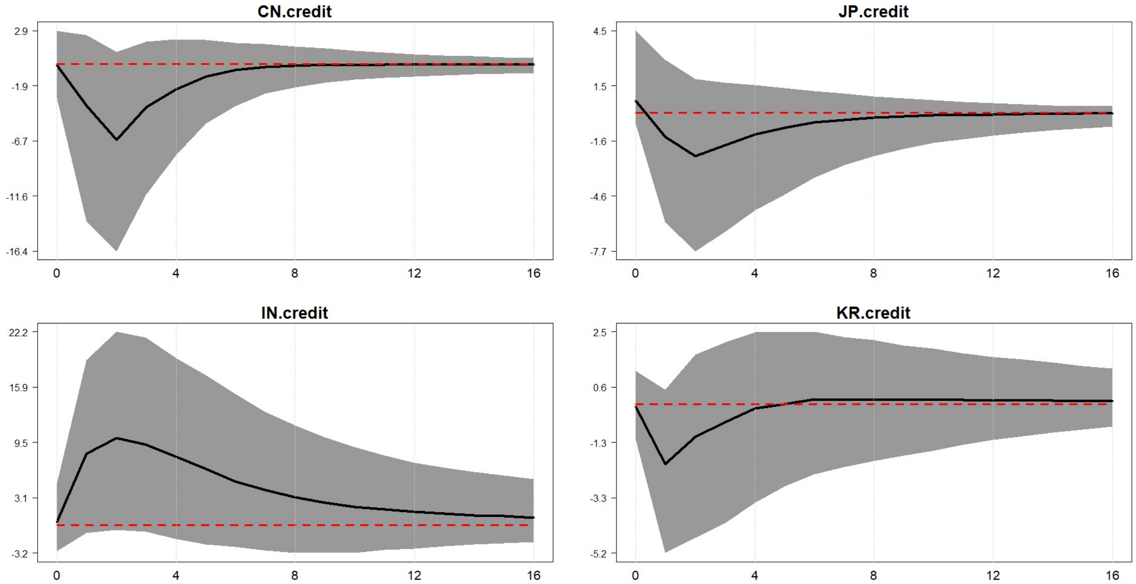
Shock on the shadow rate:

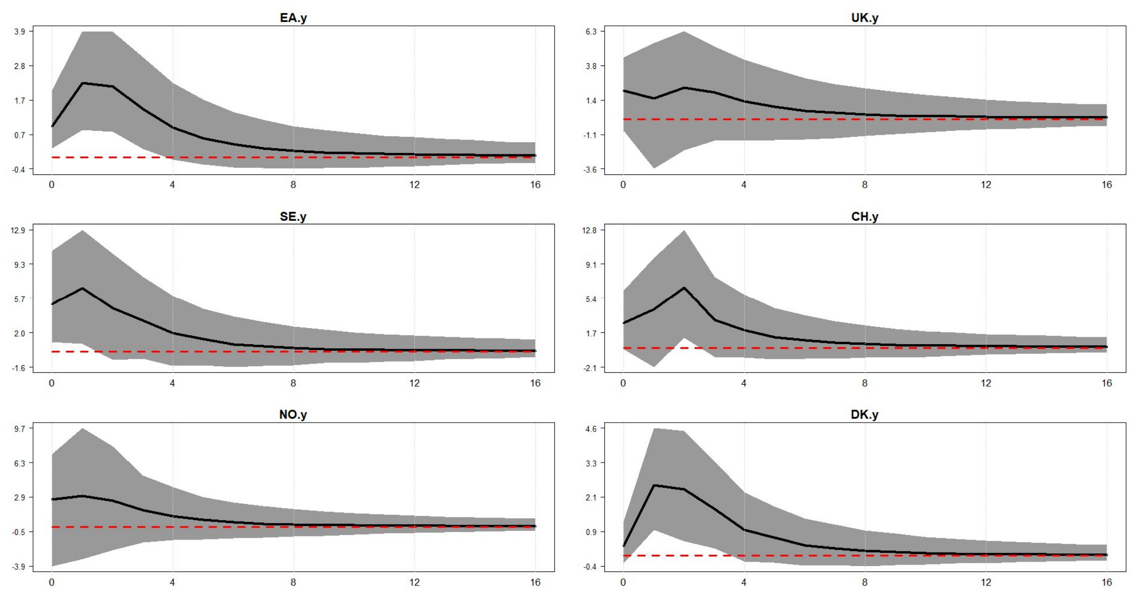


International responses to US monetary policy:

We only report Europe and East/South Asia, for credit and output. The responses of credit are acceptable. However, output increases after a monetary contraction.




CN.credit
JP.credit
IN.credit
KR.credit
2.9
-1.9
-6.7
-11.6
-16.4
4.5
1.5
-1.6
-4.6
-7.7
22.2
15.9
9.5
3.1
-3.2
2.5
0.6
-1.3
-3.3
-5.2
0
4
8
12
16


EA.y
UK.y
SE.y
CH.y
NO.y
DK.y
3.9
2.8
1.7
0.7
-0.4
6.3
3.8
1.4
-1.1
-3.6
12.9
9.3
5.7
2.0
-1.6
12.8
9.1
5.4
1.7
-2.1
9.7
6.3
2.9
-0.5
-3.9
4.6
3.3
2.1
0.9
-0.4
0
4
8
12
16

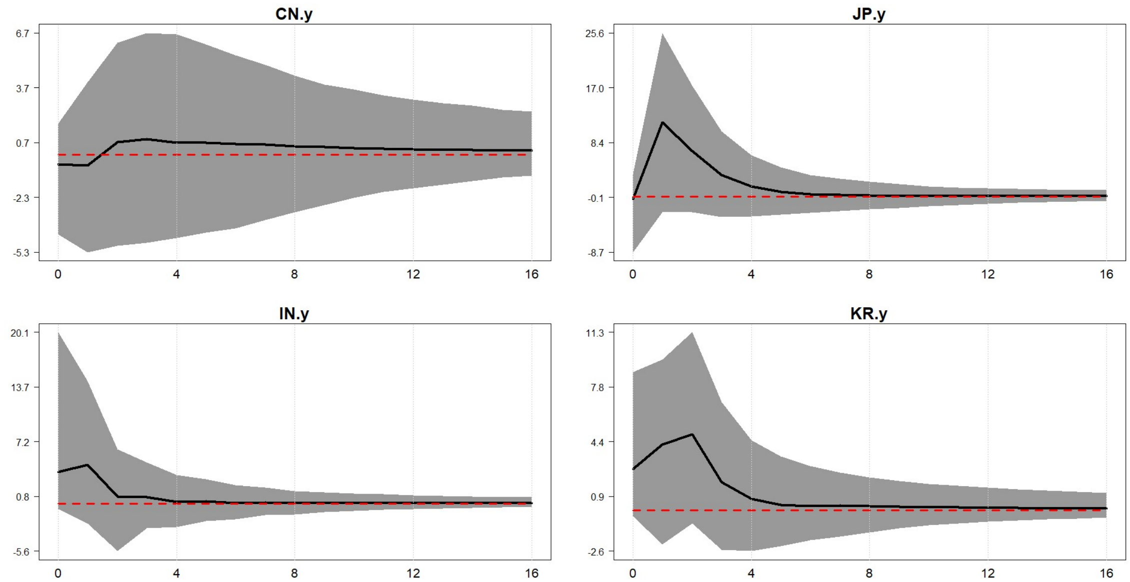


Table 5: regression of the output spillover (4Q avg.) over manufacturing share of GDP, iMaPP, interactions of the two, and capital controls.

```
Call:
lm(formula = Y ~ KA + iMaPP + Manuf + Pru_Man)

Residuals:
    Min      1Q  Median      3Q     Max 
-21.465  -7.265   1.433  10.042  13.848 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -12.584148  16.505525  -0.762    0.456
KA           -4.898010  10.312653  -0.475    0.641
iMaPP        -0.133441   0.610669  -0.219    0.830
Manuf         0.307122   0.857076   0.358    0.725
Pru_Man      -0.007055   0.024659  -0.286    0.778

Residual standard error: 12.18 on 17 degrees of freedom
Multiple R-squared:  0.1683,	Adjusted R-squared:  -0.02733 
F-statistic: 0.8603 on 4 and 17 DF,  p-value: 0.5073
```

Table 6: regression of the output spillover (4Q avg.) over market capitalization in % of GDP, iMaPP, interactions of the two, and capital controls.

```
Call:
lm(formula = Y ~ KA + iMaPP + Market_cap + Pru_Mark)

Residuals:
    Min      1Q  Median      3Q     Max 
-25.736  -2.846   2.177   6.945  11.256 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  8.966560  12.469438   0.719    0.482
KA          -5.083440   8.044564  -0.632    0.536
iMaPP       -0.578693   0.506728  -1.142    0.269
Market_cap  -0.198772   0.168575  -1.179    0.255
Pru_Mark     0.003733   0.007502   0.498    0.625

Residual standard error: 10.59 on 17 degrees of freedom
Multiple R-squared:  0.3716,	Adjusted R-squared:  0.2238 
F-statistic: 2.514 on 4 and 17 DF,  p-value: 0.08012
```