Globalization and International Business Cycle Dynamics – A Conditional GVAR Approach*

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Abstract

We examine the effects of increased international integration of both goods and financial markets on business cycle dynamics. To do so, we develop a new econometric framework for modelling cross-country spillovers in which the magnitude of these spillovers is an empirically determined function of the degree of a country's integration with international goods and financial markets. Our results suggest that the magnitude of cross-country spillovers for most country pairs has been increasing with strengthened goods and financial markets integration.

Keywords: Business Cycle Dynamics; International Goods and Financial Market Integration; Dynamic Panel Data Models; Global VAR Model.

JEL Classification: E32, F41, C33.

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1 Introduction

We examine the effects of increased international integration of both goods and financial markets on business cycle dynamics. In particular, we wish to provide evidence on whether strengthened trade and/or financial integration leads primarily to supply side specialization effects reducing exposure of a country to foreign shocks or whether demand side spillovers leading to strengthened synchronization of business cycle dynamics have been a quantitatively more important implication of trade and/or financial integration. To do so, we develop a new econometric framework for modelling cross-country spillovers in which the magnitude of these spillovers is an empirically determined function of the degree of a country's integration with international goods and financial markets. Our results suggest that the magnitude of cross-country spillovers for most country pairs has been increasing with strengthened goods and financial markets integration.

There has been strongly growing interest in the implications of increasing shares of a country's imports and exports relative to its GDP (which we label trade globalization) and of a country's inflows and outflows of financial capital relative to its GDP (which we label financial globalization) on its business cycle dynamics. For important contributions, see *inter alia* Kose, Prasad and Terrones (2003), Kose, Otrok and Whiteman (2003), Heathcote and Perri (2004), Imbs (2004, 2006), Canova, Ciccarelli and Ortega (2007), Inklaar, Jong-A-Pin and de Haan (2008), Yetman (2011), Artis and Okubo (2011).

As stressed by Kose, Prasad and Terrones (2003), economic theory is ambiguous in its predictions concerning the effects of trade and financial globalization on the spillovers of business cycle dynamics across countries. On the one hand, increased trade linkages could induce increased levels of specialization of production across countries, reducing business cycle synchronization. On the other hand, increased trade linkages could also lead to increased spillovers of demand shocks across countries, increasing business cycle synchronization. In similar fashion, increased financial linkages could on the one hand facilitate the process of increased specialization of production across countries, but on the other hand could also lead to increased synchronization of business cycles across countries through increased global exposure to shocks to asset returns in individual countries.

In terms of methodology, our approach comprises a vector autoregressive (VAR) approach to model the dynamics of real output, prices and the real exchange rate. In order to capture potential spillover effects between a sizeable number of countries as comprehensive as possible, we utilize the global VAR approach suggested by Pesaran, Schuermann and Weiner (2004). The additional impact of globalization measures as determinants of the dynamic properties of the variables is incorporated via conditioning the coefficients in the global VAR model on the trade and financial globalization variables. Here we generalize the approach suggested in Binder and Offermanns (2014). A similar technique in the context of a standard VAR model has also been employed by Georgiadis (2014).

This paper is organized as follows: Section 2 introduces the econometric model that we use to determine spillover effects between a sizeable number of countries. Section 3 presents the data set we use to empirically capture the trends of financial and trade globalization which is essential to international business cycle linkages. Section 4 specifies the empirical implementation and shows the results. Section 5 concludes.

2 Econometric Model

Investigating the m-dimensional vector $\boldsymbol{x}_{it}$ of variables across $i = 1, 2, ..., N$ countries and $t = 1, 2, ..., T$ time periods, the dynamics of these variables can be captured by a vector autoregressive (VAR) model of the form

$$\boldsymbol{G}(L)\boldsymbol{x}_t = \boldsymbol{\nu}_t \tag{1}$$

where L denotes the lag operator, $\boldsymbol{x}_t = (\boldsymbol{x}'_{1t}\ \boldsymbol{x}'_{2t}\ \dots\ \boldsymbol{x}'_{Nt})'$ denotes the variable of interest and $\boldsymbol{\nu}_t = (\boldsymbol{\nu}'_{1t}\ \boldsymbol{\nu}'_{2t}\ \dots\ \boldsymbol{\nu}'_{Nt})'$ represents shocks. This model can accommodate a rich structure of cross-country spillovers both through common factors in $\boldsymbol{\nu}_t$ and through the interrelations implied by $\boldsymbol{G}(L)$.

However, due to the enormous number of parameters to be estimated even for moderate sizes of N, a full parameterization of (1) is not feasible. Pesaran, Schuermann and Weiner (2004) propose a parsimonious way of re-specifying this model by modelling the relations between countries via their bilateral trade linkages (the global VAR (GVAR) approach). The key feature of this approach is to define so-called "foreign variables" $\boldsymbol{x}^*_{it}$ as

$$\boldsymbol{x}^*_{it} = \sum_{j=1}^{N} w_{ij}\boldsymbol{x}_{jt}, \quad \sum_{j=1}^{N} w_{ij} = 1, \quad w_{ii} = 0, \tag{2}$$

and at the estimation stage restrict spillovers to operate through these foreign variables only. Once such country-specific models have been estimated the global solution of these models implying restrictions on the lag polynomial $\boldsymbol{G}(L)$ in (1) can be obtained.

2.1 A Conditionally Pooled GVAR Model

Pesaran, Schuermann and Weiner (2004) propose to treat the coefficients in a GVAR model as varying in unrestricted fashion across countries. This is certainly a sensible modelling strategy when little is known regarding the sources of parameter heterogeneity. Here, our interest is in understanding how business cycle dynamics are affected by trade and financial globalization. We therefore re-specify the GVAR model such that its slope coefficients are homogeneous functions of a set of conditioning variables $\boldsymbol{z}_{it}$.[1]

We specify the following country-specific model:

$$\boldsymbol{x}_{it} = \sum_{s=1}^{q} \boldsymbol{A}_s(\boldsymbol{z}_{it})\boldsymbol{x}_{i,t-s} + \sum_{s=0}^{q^*} \boldsymbol{B}_s(\boldsymbol{z}_{it})\boldsymbol{x}^*_{i,t-s} + \sum_{s=0}^{r} \boldsymbol{C}_s(\boldsymbol{z}_{it})\boldsymbol{d}_{t-s} + \boldsymbol{\mu}_i + \boldsymbol{\varepsilon}_{it}, \tag{3}$$

where x_{it} is of dimension $(m \times 1)$ and $\boldsymbol{d}_t$ denotes observed global factors, common to all countries. After estimation, the coefficient matrices are augmented using matrices of zeros to obtain a representation at the order of p, which is defined as $p = \max\{q, q^*, r\}$.

Since we aim at obtaining the global solution of the model, we rewrite (3) as

$$\sum_{s=0}^{p} \tilde{\boldsymbol{A}}_s(\boldsymbol{z}_{it})\boldsymbol{x}_{i,t-s} + \sum_{s=0}^{p} \tilde{\boldsymbol{B}}_s(\boldsymbol{z}_{it})\boldsymbol{x}^*_{i,t-s} = \sum_{s=0}^{p} \boldsymbol{C}_s(\boldsymbol{z}_{it})\boldsymbol{d}_{t-s} + \boldsymbol{\mu}_i + \boldsymbol{\varepsilon}_{it}, \tag{4}$$

where $\tilde{\boldsymbol{A}}_s(\boldsymbol{z}_{it}) = -\boldsymbol{A}_s(\boldsymbol{z}_{it})$, $s = 1, 2, \ldots, p$, $\tilde{\boldsymbol{A}}_0(\boldsymbol{z}_{it}) = \boldsymbol{I}_m$, and $\tilde{\boldsymbol{B}}_s(\boldsymbol{z}_{it}) = -\boldsymbol{B}_s(\boldsymbol{z}_{it})$, $s = 0, 1, \ldots, p$.

Collecting the coefficients of $\boldsymbol{x}_{i,t-s}$ and $\boldsymbol{x}^*_{i,t-s}$ and defining $\boldsymbol{\nu}_{it}(\boldsymbol{z}_{it}) = \sum_{s=0}^{p} \boldsymbol{C}_s(\boldsymbol{z}_{it})\boldsymbol{d}_{t-s} + \boldsymbol{\mu}_i + \boldsymbol{\varepsilon}_{it}$, we have

$$\sum_{s=0}^{p} \boldsymbol{\Phi}_s(\boldsymbol{z}_{it}) \begin{pmatrix} \boldsymbol{x}_{i,t-s} \\ \boldsymbol{x}^*_{i,t-s} \end{pmatrix} = \boldsymbol{\nu}_{it}(\boldsymbol{z}_{it}), \tag{5}$$

where $\boldsymbol{\Phi}_s(\boldsymbol{z}_{it}) = [\tilde{\boldsymbol{A}}_s(\boldsymbol{z}_{it})\ \tilde{\boldsymbol{B}}_s(\boldsymbol{z}_{it})]$ for $s = 0, 1, ..., p$.

In the next step, we stack the coefficient matrices by constructing

$$\boldsymbol{\Theta}(\boldsymbol{Z}_t) = \begin{pmatrix} \boldsymbol{\Theta}(\boldsymbol{z}_{1t}) & 0 & ... & 0 \\ 0 & \boldsymbol{\Theta}(\boldsymbol{z}_{2t}) & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & ... & \boldsymbol{\Theta}(\boldsymbol{z}_{Nt}) \end{pmatrix}_{Nm \times 2Nm(p+1)}, \tag{6}$$

where $\boldsymbol{\Theta}(\boldsymbol{z}_{it}) = [\boldsymbol{\Phi}_0(\boldsymbol{z}_{it})\ \boldsymbol{\Phi}_1(\boldsymbol{z}_{it})\ \ldots\ \boldsymbol{\Phi}_p(\boldsymbol{z}_{it})]$.

Finally, we obtain the $(Nm \times Nm(p+1))$ matrix $\boldsymbol{G}(\boldsymbol{Z}_t, \boldsymbol{W}_t) = \boldsymbol{\Theta}(\boldsymbol{Z}_t)\, \boldsymbol{W}_t$ which has the structure

$$\boldsymbol{G}(\boldsymbol{Z}_t, \boldsymbol{W}_t) = [\boldsymbol{G}_0(\boldsymbol{Z}_t, \boldsymbol{W}_t)\ \boldsymbol{G}_1(\boldsymbol{Z}_t, \boldsymbol{W}_t)\ \ldots\ \boldsymbol{G}_p(\boldsymbol{Z}_t, \boldsymbol{W}_t)], \tag{7}$$

with each $\boldsymbol{G}_s(\boldsymbol{Z}_t, \boldsymbol{W}_t)$, $s = 0, 1, \ldots, p$, having dimension $(Nm \times Nm)$.

[1] The conditioning variables $\boldsymbol{z}_{it}$ will be constructed on the basis of measures of goods and financial market integration that are pre-determined in time period t. See Section 3 for further details.

The matrix of weights $\boldsymbol{W}_t$ is defined as

$$\boldsymbol{W}_t = \begin{pmatrix} \boldsymbol{\mathcal{W}}_{1t} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\mathcal{W}}_{1,t-1} & \dots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \boldsymbol{\mathcal{W}}_{1,t-p} \\ \boldsymbol{\mathcal{W}}_{2t} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\mathcal{W}}_{2,t-1} & \dots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \boldsymbol{\mathcal{W}}_{2,t-p} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{\mathcal{W}}_{Nt} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\mathcal{W}}_{N,t-1} & \dots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \boldsymbol{\mathcal{W}}_{N,t-p} \end{pmatrix}_{2Nm(p+1)\times Nm(p+1)},$$

where

$$\boldsymbol{\mathcal{W}}_{it} = \begin{pmatrix} \boldsymbol{J}_{i1}^{(m)} & \boldsymbol{J}_{i2}^{(m)} & \dots & \boldsymbol{J}_{iN}^{(m)} \\ \boldsymbol{W}_{i1,t}^{(m)} & \boldsymbol{W}_{i2,t}^{(m)} & \dots & \boldsymbol{W}_{iN,t}^{(m)} \end{pmatrix}_{2m\times Nm},$$

with

$$\boldsymbol{J}_{ij}^{(m)} = \begin{cases} \boldsymbol{I}_m & \text{for } i = j \\ \mathbf{0}_m & \text{for } i \neq j \end{cases},$$

and

$$\boldsymbol{W}_{ij,t}^{(m)} = \begin{cases} \mathbf{0}_m & \text{for } i = j \\ w_{ij,t}\boldsymbol{I}_m & \text{for } i \neq j \end{cases}.$$

2.2 Implementation of Bivariate Conditioning

For the implementation of the conditional homogeneity of the model coefficients as a function of $\boldsymbol{z}_{it}$, we follow the approach in Binder and Offermanns (2014) and extend it to the bivariate case. In particular, we assume the polynomial in the bivariate conditioning variable $\boldsymbol{z}_{it} = (z_{1,it}\ z_{2,it})'$ to be constituted by the tensor product of two univariate Chebyshev polynomials of order τ each and define

$$\boldsymbol{\mathcal{C}}_{\tau\tau}(\boldsymbol{z}_{it}) = \begin{pmatrix} c_0(z_{1,it})c_0(z_{2,it}) & c_0(z_{1,it})c_1(z_{2,it}) & \dots & c_0(z_{1,it})c_\tau(z_{2,it}) \\ c_1(z_{1,it})c_0(z_{2,it}) & c_1(z_{1,it})c_1(z_{2,it}) & \dots & c_1(z_{1,it})c_\tau(z_{2,it}) \\ \vdots & \vdots & \ddots & \vdots \\ c_\tau(z_{1,it})c_0(z_{2,it}) & c_\tau(z_{1,it})c_1(z_{2,it}) & \dots & c_\tau(z_{1,it})c_\tau(z_{2,it}) \end{pmatrix}_{(\tau+1)\times(\tau+1)}, \tag{8}$$

with $c_{s+1}(z_{it}) = 2z_{it}c_s(z_{it}) - c_{s-1}(z_{it})$, $s = 1, 2, ..., \tau$, $c_0(z_{it}) = 1$ and $c_1(z_{it}) = z_{it}$.

The conditioning works as follows: Let $\boldsymbol{\Gamma}(\boldsymbol{z}_{it})$ be an $(m \times n)$ dimensional coefficient matrix, and let $\gamma_{k\ell}(\boldsymbol{z}_{it})$, $k = 1, 2, ..., m$, $\ell = 1, 2, ..., n$, denote the element at position (k, ℓ) of this matrix. Then we specify this element as

$$\gamma_{k\ell}(\boldsymbol{z}_{it}) = \sum_{q=0}^{\tau}\sum_{r=0}^{\tau} h_{qr}^{(\gamma_{k\ell})} c_q(z_{1,it})c_r(z_{2,it}) = \boldsymbol{h}^{(\gamma_{k\ell})'} \operatorname{vec}[\boldsymbol{\mathcal{C}}_{\tau\tau}(\boldsymbol{z}_{it})], \tag{9}$$

with

$$\boldsymbol{h}^{(\gamma_{k\ell})} = \left(h_{00}^{(\gamma_{k\ell})}\ h_{10}^{(\gamma_{k\ell})}\ \dots\ h_{\tau 0}^{(\gamma_{k\ell})}\ h_{01}^{(\gamma_{k\ell})}\ h_{11}^{(\gamma_{k\ell})}\ \dots\ h_{\tau 1}^{(\gamma_{k\ell})}\ \dots\ h_{0\tau}^{(\gamma_{k\ell})}\ h_{1\tau}^{(\gamma_{k\ell})}\ \dots\ h_{\tau\tau}^{(\gamma_{k\ell})}\right)',$$

such that $\boldsymbol{\Gamma}(\boldsymbol{z}_{it})$ becomes

$$\boldsymbol{\Gamma}(\boldsymbol{z}_{it}) = \boldsymbol{H}^{(\boldsymbol{\Gamma})}\{\boldsymbol{I}_n \otimes \operatorname{vec}[\boldsymbol{\mathcal{C}}_{\tau\tau}(\boldsymbol{z}_{it})]\}, \tag{10}$$

where

$$\boldsymbol{H}^{(\boldsymbol{\Gamma})} = \begin{pmatrix} \boldsymbol{h}^{(\gamma_{1,1})'} & \boldsymbol{h}^{(\gamma_{1,2})'} & \dots & \boldsymbol{h}^{(\gamma_{1,n})'} \\ \boldsymbol{h}^{(\gamma_{2,1})'} & \boldsymbol{h}^{(\gamma_{2,2})'} & \dots & \boldsymbol{h}^{(\gamma_{2,n})'} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{h}^{(\gamma_{m,1})'} & \boldsymbol{h}^{(\gamma_{m,2})'} & \dots & \boldsymbol{h}^{(\gamma_{m,n})'} \end{pmatrix}_{m\times n(\tau+1)^2}. \tag{11}$$

2.3 Estimation Method

The key feature of the model with conditioning is to obtain a representation where some form of pooling across countries is feasible, to be able to exploit the cross-sectional dimension of the data despite country-specific dynamics. Hence, the estimation step itself is carried out using a fixed-effect panel VAR specification.[2] We write (3) in compact form as a VARX model

$$\boldsymbol{x}_{it} = \boldsymbol{\Psi}(\boldsymbol{z}_{it})\boldsymbol{v}_{it} + \boldsymbol{\mu}_i + \boldsymbol{\varepsilon}_{it}, \tag{12}$$

[2]The term *(fixed-effect) panel VAR model* is used in different forms in the literature. In what follows, we will employ this term to describe a VAR model which has (conditionally) homogeneous slope coefficients, but idiosyncratic intercepts (more generally: idiosyncratic deterministics) and idiosyncratic variances, as well as a sufficiently large time dimension which allows individual-specific estimation of all these parameters.

where

$$\boldsymbol{\Psi}(\boldsymbol{z}_{it}) = [\boldsymbol{A}_1(\boldsymbol{z}_{it})\ \boldsymbol{A}_2(\boldsymbol{z}_{it})\ ...\ \boldsymbol{A}_q(\boldsymbol{z}_{it})\ \boldsymbol{B}_0(\boldsymbol{z}_{it})\ \boldsymbol{B}_1(\boldsymbol{z}_{it})\ \boldsymbol{B}_{q^*}(\boldsymbol{z}_{it})\ \boldsymbol{C}_0(\boldsymbol{z}_{it})\ \boldsymbol{C}_1(\boldsymbol{z}_{it})\ ...\ \boldsymbol{C}_r(\boldsymbol{z}_{it})],$$

with dimension $(m \times \kappa)$, $\kappa = mq + m(q^* + 1) + k(r + 1)$,

$$\boldsymbol{v}_{it} = (\boldsymbol{x}'_{i,t-1}\ \boldsymbol{x}'_{i,t-2}\ ...\ \boldsymbol{x}'_{i,t-q}\ \boldsymbol{x}^{*\prime}_{it}\ \boldsymbol{x}^{*\prime}_{i,t-1}\ ...\ \boldsymbol{x}^{*\prime}_{i,t-q^*}\ \boldsymbol{d}'_t\ \boldsymbol{d}'_{t-1}\ ...\ \boldsymbol{d}'_{t-r})',$$

with dimension $(\kappa \times 1)$ and

$$V(\boldsymbol{\varepsilon}_{it}) = \boldsymbol{\Sigma}_i \quad \forall\ t = 1, 2, ..., T_i. \tag{13}$$

Following (11), we can re-write model (12) as

$$\begin{aligned} \boldsymbol{x}_{it} &= \boldsymbol{H}^{(\boldsymbol{\Psi})}\{\boldsymbol{I}_\kappa \otimes \mathrm{vec}[\boldsymbol{\mathcal{C}}_{\tau\tau}(\boldsymbol{z}_{it})]\}\boldsymbol{v}_{it} + \boldsymbol{\mu}_i + \boldsymbol{\varepsilon}_{it} & (14)\\ &= \boldsymbol{H}^{(\boldsymbol{\Psi})}\,\mathrm{vec}\{\mathrm{vec}[\boldsymbol{\mathcal{C}}_{\tau\tau}(\boldsymbol{z}_{it})]\boldsymbol{v}'_{it}\} + \boldsymbol{\mu}_i + \boldsymbol{\varepsilon}_{it}. & (15)\end{aligned}$$

To simplify notation, we define $\boldsymbol{\Xi} = \boldsymbol{H}^{(\boldsymbol{\Psi})\prime}$ and $\boldsymbol{u}_{it} = \mathrm{vec}\{\mathrm{vec}[\boldsymbol{\mathcal{C}}_{\tau\tau}(\boldsymbol{z}_{it})]\boldsymbol{v}'_{it}\}$. After (transposing and) stacking the model across t we obtain

$$\boldsymbol{X}_i = \boldsymbol{U}_i\boldsymbol{\Xi} + \boldsymbol{\iota}_{T_i}\boldsymbol{\mu}'_i + \boldsymbol{\varepsilon}_i, \tag{16}$$

with $\boldsymbol{X}_i = (\boldsymbol{x}_{i1}\ \boldsymbol{x}_{i2}\ \ldots\ \boldsymbol{x}_{iT})'$, $\boldsymbol{U}_i = (\boldsymbol{u}_{i1}\ \boldsymbol{u}_{i2}\ \ldots\ \boldsymbol{u}_{iT})'$, $\boldsymbol{\varepsilon}_i = (\boldsymbol{\varepsilon}_{i1}\ \boldsymbol{\varepsilon}_{i2}\ \ldots\ \boldsymbol{\varepsilon}_{iT})'$ and $\boldsymbol{\iota}_{T_i}$ denoting a $(T_i \times 1)$ vector of ones. We account for the heterogeneous intercepts by defining the orthogonal projection matrix

$$\boldsymbol{M}_{\mathbf{1},T_i} = \boldsymbol{I}_{T_i} - \boldsymbol{\iota}_{T_i}(\boldsymbol{\iota}'_{T_i}\boldsymbol{\iota}_{T_i})^{-1}\boldsymbol{\iota}'_{T_i}, \tag{17}$$

and left-multiplying it to (16)

$$\boldsymbol{M}_{\mathbf{1},T_i}\boldsymbol{X}_i = \boldsymbol{X}_{\mathbf{1},i} = \boldsymbol{M}_{\mathbf{1},T_i}\boldsymbol{U}_i\boldsymbol{\Xi} + \boldsymbol{\varepsilon}_i. \tag{18}$$

The next step is to vectorize the model

$$\begin{aligned} \mathrm{vec}(\boldsymbol{X}_{\mathbf{1},i}) = \tilde{\boldsymbol{x}}_{\mathbf{1},i} &= \mathrm{vec}[\boldsymbol{U}_{\mathbf{1},i}\boldsymbol{\Xi}] + \mathrm{vec}(\boldsymbol{\varepsilon}_i) & (19)\\ &= (\boldsymbol{I}_m \otimes \boldsymbol{U}_{\mathbf{1},i})\,\mathrm{vec}(\boldsymbol{\Xi}) + \tilde{\boldsymbol{\varepsilon}}_i, & (20)\end{aligned}$$

with obvious notation and stack it across i to arrive at the final panel form

$$\tilde{\boldsymbol{x}}_{\mathbf{1}} = \tilde{\boldsymbol{U}}_{\mathbf{1}}\,\mathrm{vec}(\boldsymbol{\Xi}) + \tilde{\boldsymbol{\varepsilon}}, \tag{21}$$

where $\tilde{\boldsymbol{x}}_{\mathbf{1}} = (\tilde{\boldsymbol{x}}'_{\mathbf{1},1}\ \tilde{\boldsymbol{x}}'_{\mathbf{1},2}\ \ldots\ \tilde{\boldsymbol{x}}'_{\mathbf{1},N})'$ and $\tilde{\boldsymbol{U}}_{\mathbf{1}} = (\tilde{\boldsymbol{U}}'_{\mathbf{1},1}\ \tilde{\boldsymbol{U}}'_{\mathbf{1},2}\ \ldots\ \tilde{\boldsymbol{U}}'_{\mathbf{1},N})'$ with $\tilde{\boldsymbol{U}}_{\mathbf{1},i} = \boldsymbol{I}_m \otimes \boldsymbol{U}_{\mathbf{1},i}$. $\boldsymbol{\Xi}$ can now be estimated with generalized least squares (GLS) as

$$\mathrm{vec}(\hat{\boldsymbol{\Xi}}) = [\tilde{\boldsymbol{U}}'_{\mathbf{1}}\hat{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{U}}_{\mathbf{1}}]^{-1}\tilde{\boldsymbol{U}}'_{\mathbf{1}}\hat{\boldsymbol{\Omega}}^{-1}\tilde{\boldsymbol{x}}_{\mathbf{1}}, \tag{22}$$

where, due to the block-diagonal structure of the covariance matrix $\boldsymbol{\Omega}$,

$$\hat{\boldsymbol{\Omega}}^{-1} = \text{blockdiag}(\hat{\boldsymbol{\Sigma}}_1^{-1} \otimes \boldsymbol{I}_{T_1}, \hat{\boldsymbol{\Sigma}}_2^{-1} \otimes \boldsymbol{I}_{T_2}, \ldots, \hat{\boldsymbol{\Sigma}}_N^{-1} \otimes \boldsymbol{I}_{T_N}). \tag{23}$$

The idiosyncratic variances can be obtained by estimating (18) with OLS for each cross-section unit i,

$$\hat{\boldsymbol{\Sigma}}_i = \frac{1}{T_i - \kappa(\tau+1)^2 - 1} \hat{\boldsymbol{\varepsilon}}_i' \hat{\boldsymbol{\varepsilon}}_i, \tag{24}$$

However, for $\tau > 0$, the number of parameters per equation can quickly become large relative to the number of observations available for each country such that a modified approach to estimating $\boldsymbol{\Sigma}_i$ is necessary. Hence we proceed in the following way: First, we compute residuals $\hat{\boldsymbol{\varepsilon}}_i$ from country-specific OLS estimation of (16) without conditioning, that is, for $\boldsymbol{u}_{it}$ defined using vec$[\boldsymbol{\mathcal{C}}_{00}(\boldsymbol{z}_{it})]$. Second, we regress $\hat{\boldsymbol{\varepsilon}}_{it}^2$ on vec$[\boldsymbol{\mathcal{C}}_{\tau\tau}(\boldsymbol{z}_{it})]$ to capture the influence of variation in the conditioning variables on estimation uncertainty and compute $\hat{\boldsymbol{\Sigma}}_i$ by evaluating this auxiliary regression at the sample average values of the conditioning variables for each country.

2.4 Global Solution

Once the GVAR model has been estimated, we need to solve out the country-specific equations to express for each country the set of variables in $\boldsymbol{x}_{it}$ as a function of lagged values of $\boldsymbol{x}_{it}$ as well as current and lagged values of $\boldsymbol{x}_{jt}$, $j = 1, 2, ..., N$, $j \neq i$. The resultant global solution is of the form of (1), but with numerous within- and cross-equation restrictions.

3 Data

At this stage our model comprises three variables in $\boldsymbol{x}_{it}$: real GDP in domestic currency as the variable of interest, the consumer price index (CPI) and the real effective exchange rate. The main source for these variables is the International Financial Statistics (IFS) database maintained by the IMF which provides quarterly data for the period since 1970 the earliest up to 2005.

Data for both nominal and real GDP are provided in units of domestic currency and are seasonally adjusted for some of the countries (most of the industrial countries and a few others). Hence, we adjust the non-adjusted series for seasonality as well, using the Census X-12 algorithm of the National Bureau of Economic Research. German GDP (both real and nominal) shows a level shift in 1991:Q1; we remove this level shift on the basis of estimation of an ARIMA(1,1,1)[3] model (in logs) with a dummy variable which equals one in this quarter

[3]The magnitude of the estimated parameter is robust to alternative choices of the lag order of the ARIMA model.

and zero otherwise. The series for the GDP deflator are obtained by dividing nominal GDP by real GDP. CPI data is also adjusted for seasonality and replaced by the GDP deflator whenever the series is completely unavailable. Effective exchange rates as well as foreign prices are computed using bilateral trade weights from the Direction of Trade Statistics (DOTS) database of the IMF.

Before estimation, we filter the three variables entering $\boldsymbol{x}_{it}$ (logarithm of real GDP, logarithm of CPI and logarithm of the real effective exchange rate) using the bandpass filter of Christiano and Fitzgerald (2003), to extract their components over typical business cycle frequencies between 2 and 32 quarters. As a consequence, these variables do not exhibit any deterministic trending behavior either such that we include an intercept as the only deterministic component of the model.

For the conditioning variables, we obtain annual data for trade flows and financial transactions from the BOPS and for nominal GDP from the IFS. Gross trade flows are obtained from the Balance of Payments Statistics (BOPS) database, which is incorporated in the IFS, and are reported in U.S. Dollars. We define "trade flows" as the sum of transactions in goods and services, that is, gross trade outflows (GTO) as exports of goods plus exports of services, and gross trade inflows (GTI) as the sum of imports of goods plus imports of services. We perform seasonal adjustment on the GTO and GTI series using the same procedure as for GDP. In a (very) few cases, gaps of up to four quarters between two long periods of observations for gross trade outflows or inflows are closed using related observations on exports and imports, respectively, from the IFS, and employing the interpolating procedure by Chow and Lin (1971).

Gross financial outflows (GFO) are defined as the sum of transactions in financial assets, and gross financial inflows (GFI) are defined as the sum of transactions in financial liabilities according the components of the *financial account* of the Balance of Payments, i.e. we have

$$GFO = DIA + PIA + OIA + FDA,$$

and

$$GFI = DIL + PIL + OIL + FDL,$$

where $DIA(L)$ denote direct investment assets (liabilities), $PIA(L)$ denote portfolio investment assets (liabilities), $OIA(L)$ denote other investment assets (liabilities) and $FDA(L)$ denote financial derivative assets (liabilities). Given the scarcity of observations for the latter, we do not require this component to be available to compute a gross flow figure.[4] BOPS data are available in U.S. Dollars, whereas nominal GDP is available from the IFS in domestic currency only and is converted to U.S. Dollar figures using annual bilateral exchange

[4] Although transactions in financial derivative assets and liabilities have become sizable in recent years, this approach does not seem to induce structural breaks into the time series.

rates from the same source (period average data).

Prior to constructing ratios between gross trade (financial) flows and nominal GDP as our variables entering $\boldsymbol{z}_{it}$, we perform a Beveridge-Nelson decomposition on each of the three series, to eliminate the permanent component and keep only the stationary and deterministic ("cyclical") parts. The decomposition is based on the estimation of an ARIMA(p,1,0) model for the (logged) original series and the construction of the cyclical component according to Newbold (1990). Finally, the resultant ratios are transformed to quarterly frequency, the cyclical component of this ratio is smoothed by extracting its nonlinear trend component via the Hodrick-Prescott filter, and the smoothed component is lagged one time period.[5]

Concerning the case of Belgium for which separate BOPS data are not available prior to the late 1990s, we construct all series for the monetary union between Belgium and Luxembourg and then obtain the data for Belgium by scaling the final gross flow figures with its GDP relative to the union's GDP.

Following the GVAR literature (Pesaran, Schuermann and Weiner, 2004; Dees, di Mauro, Pesaran and Smith, 2007), we construct the weights w_{ij} as bilateral trade weights measuring the share of exports and imports between country i and j in total exports and imports for country i, obtained from the DOTS database. The trade weights we use are averages of the trade weights over the time period 1970 to 2005.[6]

4 Empirical Implementation and Results

The general econometric specification presented in Section 2, which involves a sizeable number of parameters to be estimated, is implemented focusing on conditionally homogeneous effects of the three variables on the business cycle measure, i.e. in the equation for (filtered) output. The two conditioning variables, gross trade flows as a ratio to GDP and gross financial flows as a ratio to GDP, enter the respective equation via bivariate Chebyshev polynomials of order $\tau = 1$. The (filtered) price and real effective exchange rate variables are both assumed to be weakly exogenous for the impulse response analysis and separate time-series processes for these are estimated using unconditional country-specific models. The lag order is selected using the Akaike Information Criterion based on a maximum lag order of four.

The estimation sample includes a set of 23 countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Israel, Italy, Japan, Korea, Mexico, Netherlands, Norway, Philippines, Portugal, Spain, Sweden, Switzerland, UK and USA)

[5]Note that the cyclical component already is I(0) through the Beveridge-Nelson decomposition. The Hodrick-Prescott filter here only serves as a means to smooth the cyclical component.

[6]Unfortunately, information on bilateral capital flows is too sparse to construct capital flow weights for the financial variables.

with quarterly observations from 1970 the earliest until the second quarter of 2005. Our panel is unbalanced as the starting period differs across countries (for detailed information, see Table 1).

Our analysis of the dynamic effects of both domestic shocks and spillovers from shocks in a foreign country is based on generalized impulse response functions (Pesaran and Shin, 1998), which enable capturing contemporaneous covariation between all shocks. The rows in Figures 1 to 9 show the responses of output to shocks in each of the three variables, where the first column depicts the average response during the contemporaneous and the first four quarters, and the second column depicts the average response during quarters five to eight. All impulse response functions are obtained using a two-dimensional grid of values for domestic conditioning variables, while the values for the other countries' conditioning variables are varied according to their sample correlation with the domestic (i.e., the responding) country.

In order to limit the large amount of information from all possible cross-country relations, in Figures 1 to 6 we confine ourselves to reporting on the average effects of shocks in the U.S., Germany and Japan on output in these countries. Taking the broad picture, the first-year horizon usually features positive effects of all variables on output, while negative effects more often occur over the second-year horizon.

The results suggest that for most of the reported country pairs, the spillovers from one country to another are stronger with increasing globalization in both, the trade and the financial dimension (i.e., comparing low values with high values for both variables). We usually observe stronger effects for the case where the impact on average is positive, but often also when it is negative.

Documenting increased spillovers, however, is only a part of the story. Comparison with Figures 7 to 9 shows that in most cases, the strengthening or weakening effect of globalization is in accordance with the domestic response of output to the shock under regard: As an example, German output responds increasingly positively (negatively) to a shock in U.S. output during the first (second) year (see Figures 1.a and 1.b). The reaction of U.S. output to this shock is qualitatively similar, and moreover, we also observe qualitative similarity to the increasingly positive (decreasingly negative) response of German output to U.S. inflation during the first (second) year.

In sum, there is strong evidence that business cycle dynamics are increasingly synchronized with stronger globalization in both, the trade and the financial dimension. On the other hand, the effects of globalization in only one of the two dimensions are more ambiguous. Depending on the level of, say, financial flows, trade globalization can have a strengthening or weakening effect on the output response to a foreign shock. There may be several reasons for this result: it may in part be due to our (still simple) specification of this effect as being marginally linear.[7] However, it also hints to the strong role of idiosyncratic factors affecting the shape of the impulse response functions for each country pair. Moreover, we have to take account of the fact that for most countries in our sample, globalization in both, the trade and the financial dimension was the dominant trend during the last three or four decades, leaving only a few observations with independent variation in the single dimensions.

5 Conclusion

We examined the effects of increased international integration of both goods and financial markets on business cycle dynamics. In particular, we provided evidence on the strengthened effect of trade and financial integration on exposure to foreign shocks. Even in the (fewer) cases where this exposure was reduced following increased international integration, this reaction was qualitatively similar to the domestic country's reaction to the shock under regard. Hence, our results suggest increasing international synchronization of business cycles, probably implying a dominance of demand side spillovers over supply-side specialization effects. Marginal effects of either trade or financial globalization are fairly heterogeneous and point to a strong role of idiosyncratic factors in business cycle determination.

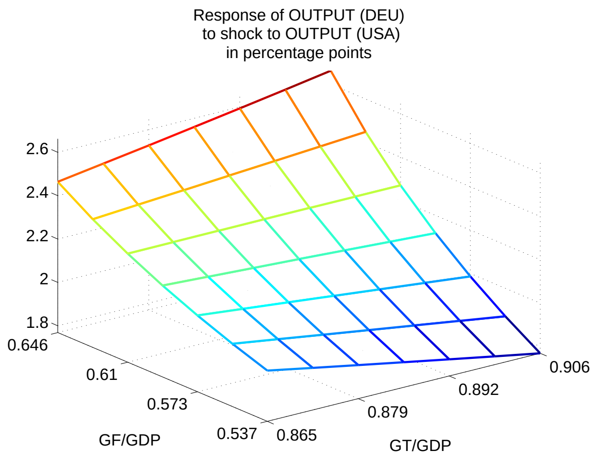
[7] Note that increasing the order of the two-dimensional polynomial requires a prohibitively large number of observations.

Appendix

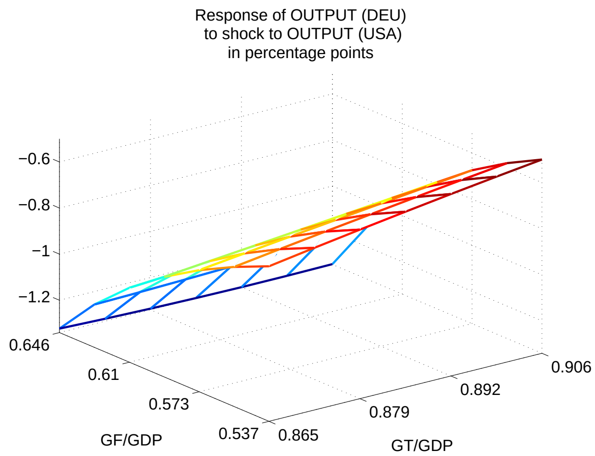
Table 1: Sample Size of Included Countries

Country	Sample Start	Sample End
Australia	1970 Q 1	2005 Q 2
Austria	1976 Q 1	2005 Q 2
Belgium	1980 Q 1	2005 Q 2
Canada	1970 Q 1	2005 Q 2
Denmark	1984 Q 2	2005 Q 2
Finland	1977 Q 2	2005 Q 2
France	1978 Q 1	2005 Q 2
Germany	1974 Q 2	2005 Q 2
Hong Kong	1980 Q 4	2005 Q 2
Israel	1980 Q 1	2005 Q 2
Italy	1980 Q 1	2005 Q 2
Japan	1980 Q 2	2005 Q 2
Korea	1979 Q 2	2005 Q 2
Mexico	1983 Q 2	2005 Q 2
Netherlands	1977 Q 1	2005 Q 2
Norway	1977 Q 2	2005 Q 2
Philippines	1981 Q 1	2005 Q 2
Portugal	1979 Q 2	2005 Q 2
Spain	1977 Q 2	2005 Q 2
Sweden	1974 Q 2	2005 Q 2
Switzerland	1985 Q 2	2005 Q 2
UK	1973 Q 2	2005 Q 2
USA	1972 Q 2	2005 Q 2

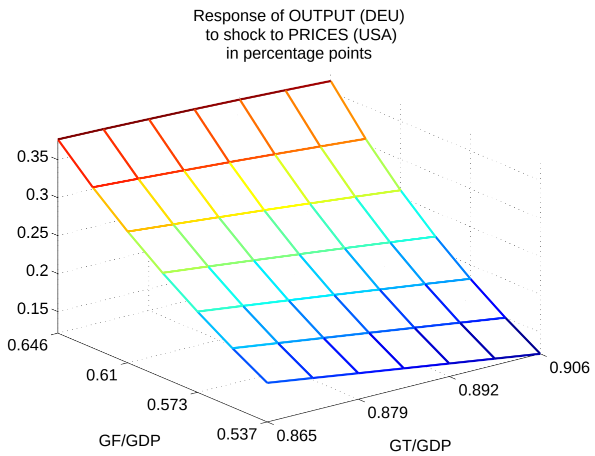
Figure 1: Average Generalized Impulse Responses of Germany to U.S. Shocks



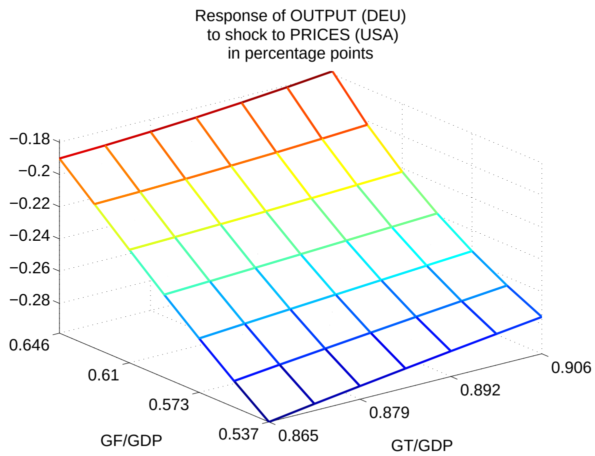
(a) Horizon 0–4 Quarters



(b) Horizon 5–8 Quarters



(c) Horizon 0–4 Quarters



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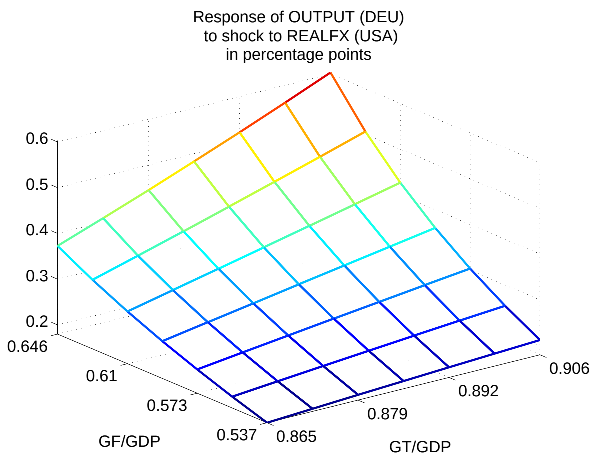

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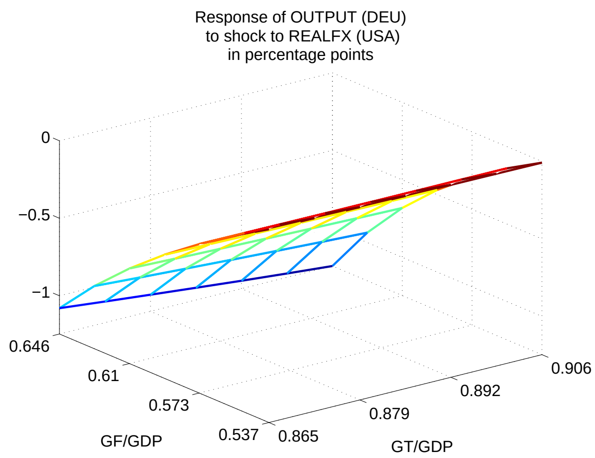
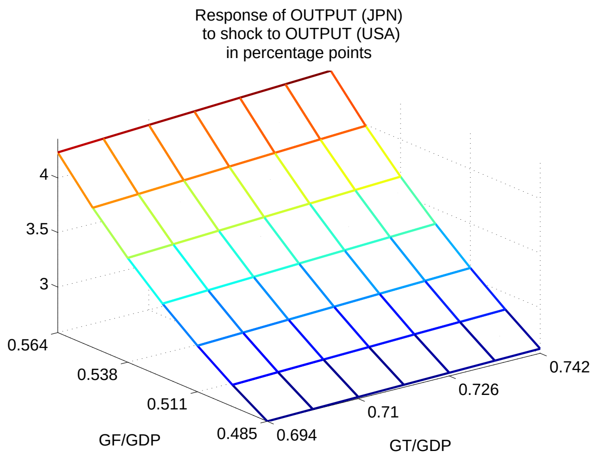


(f) Horizon 5–8 Quarters

Notes: Generalized impulse response functions evaluated over the specified grid of values for the depicted conditioning variable(s) in the response country, varying the values for the conditioning variables of all other countries according to the sample correlation between the corresponding conditioning variable in the respective country and in the response country.

Figure 2: Average Generalized Impulse Responses of Japan to U.S. Shocks



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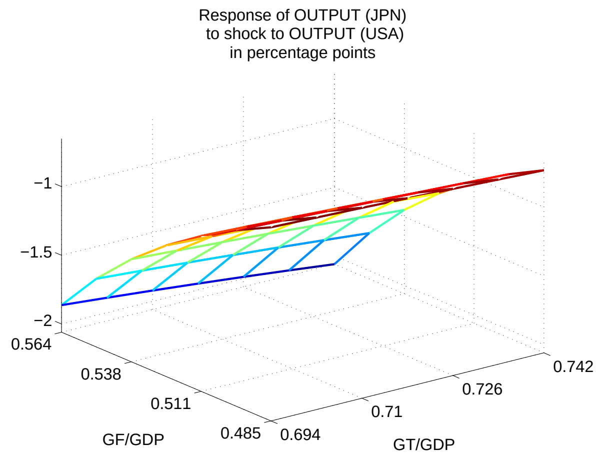

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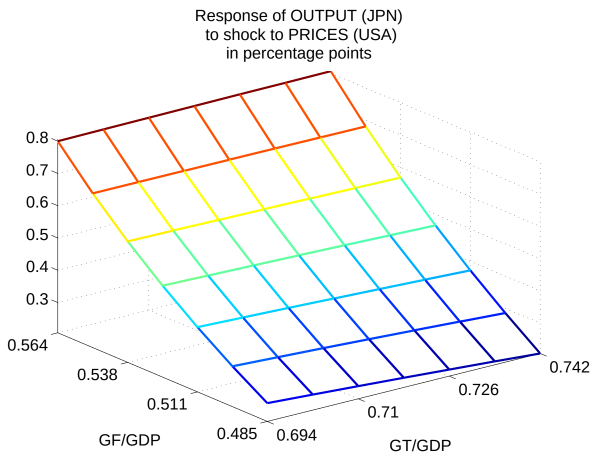

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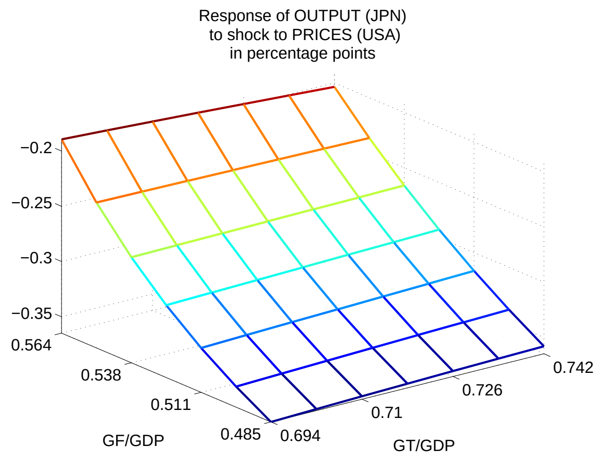

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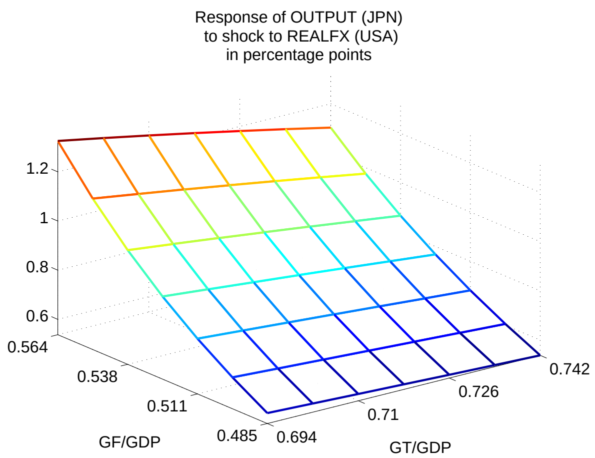

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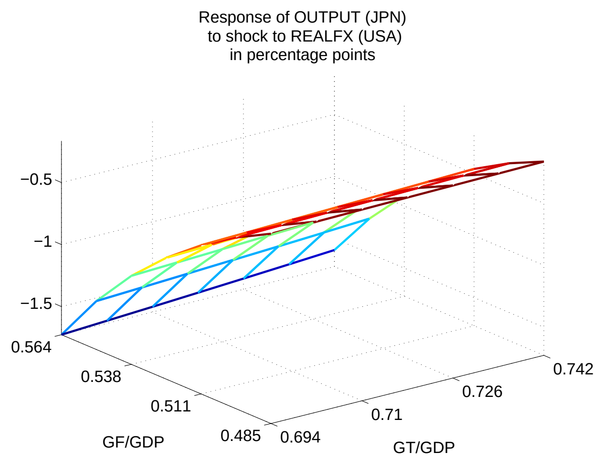
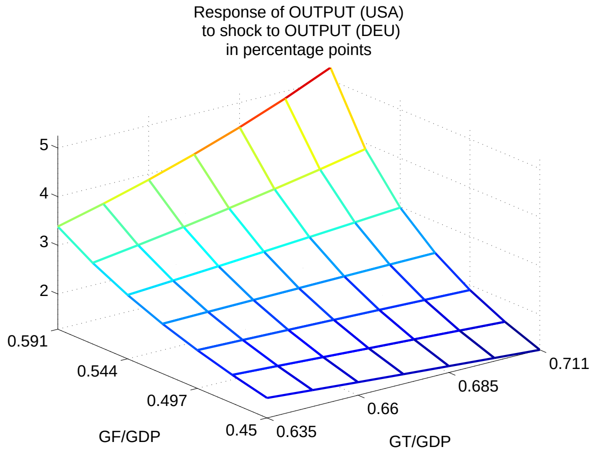


(f) Horizon 5–8 Quarters

Notes: Generalized impulse response functions evaluated over the specified grid of values for the depicted conditioning variable(s) in the response country, varying the values for the conditioning variables of all other countries according to the sample correlation between the corresponding conditioning variable in the respective country and in the response country.

Figure 3: Average Generalized Impulse Responses of the U.S. to German Shocks



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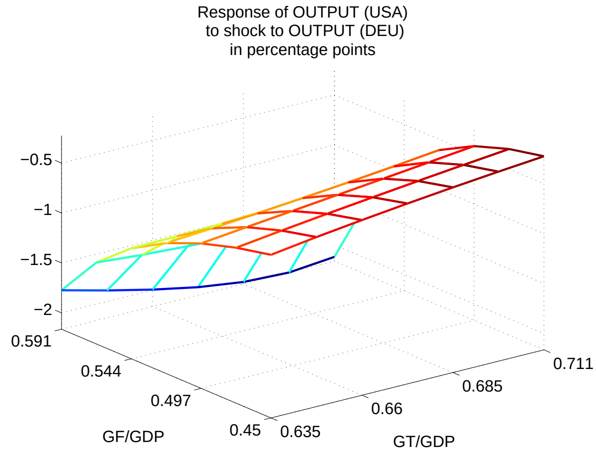

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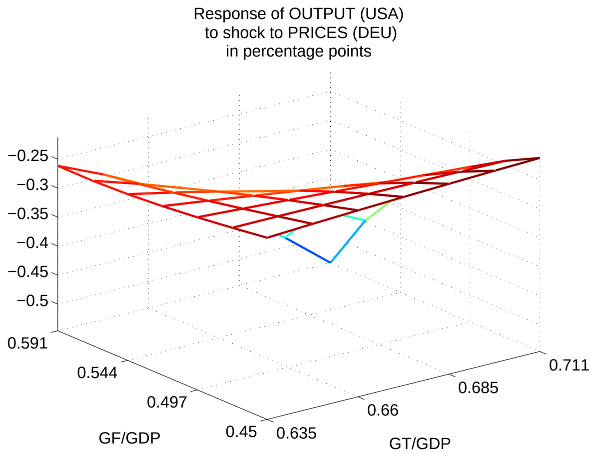

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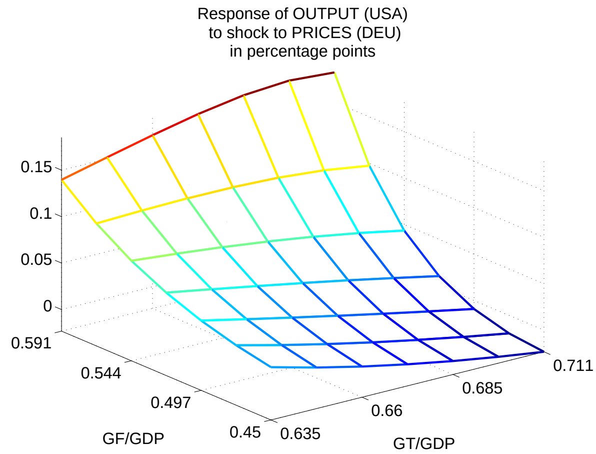

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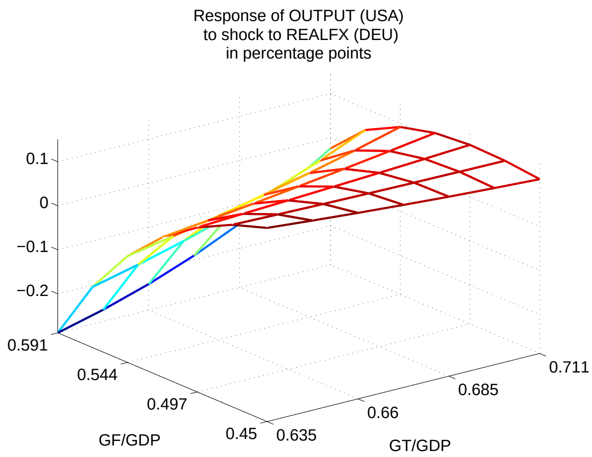

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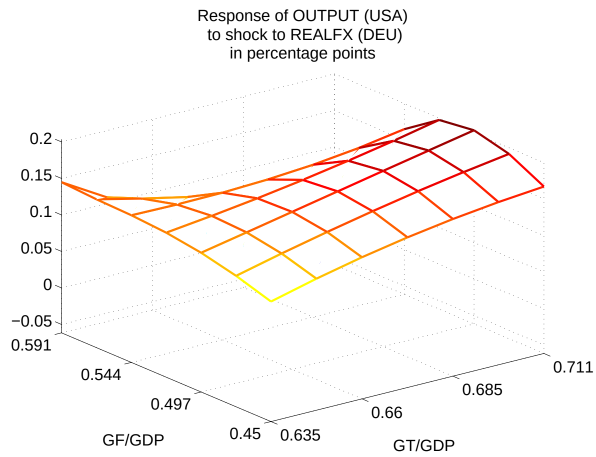
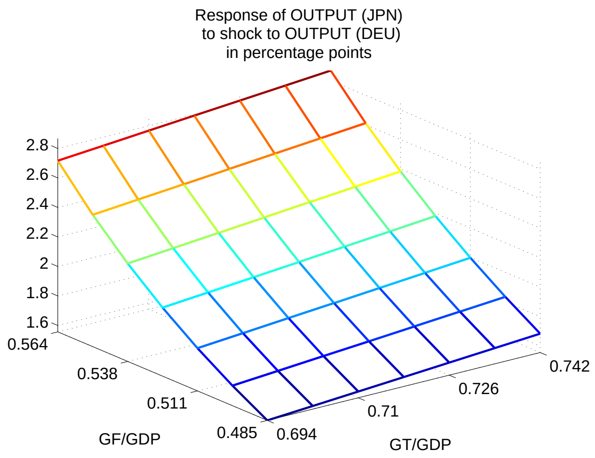


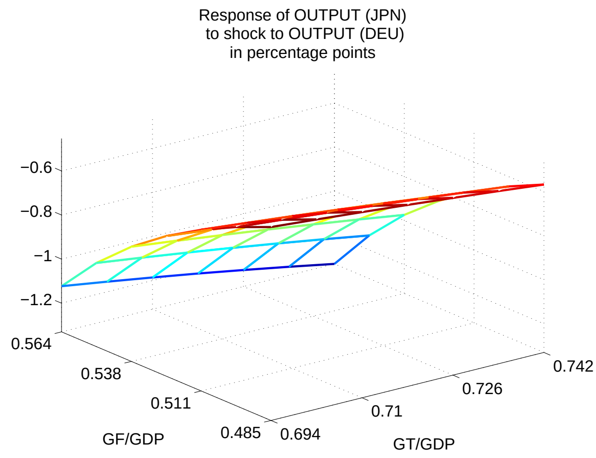
(f) Horizon 5–8 Quarters

Notes: Generalized impulse response functions evaluated over the specified grid of values for the depicted conditioning variable(s) in the response country, varying the values for the conditioning variables of all other countries according to the sample correlation between the corresponding conditioning variable in the respective country and in the response country.

Figure 4: Average Generalized Impulse Responses of Japan to German Shocks



(a) Horizon 0–4 Quarters



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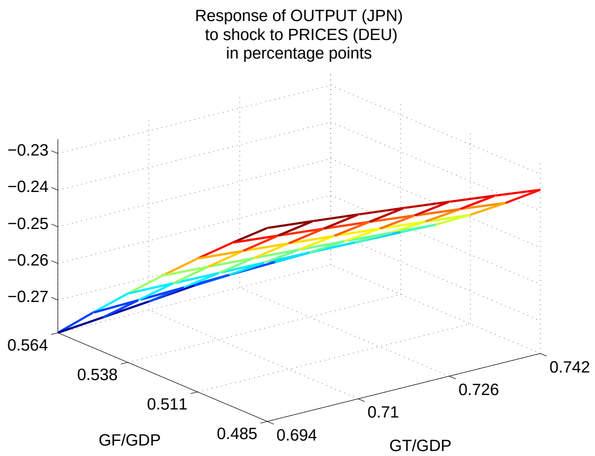

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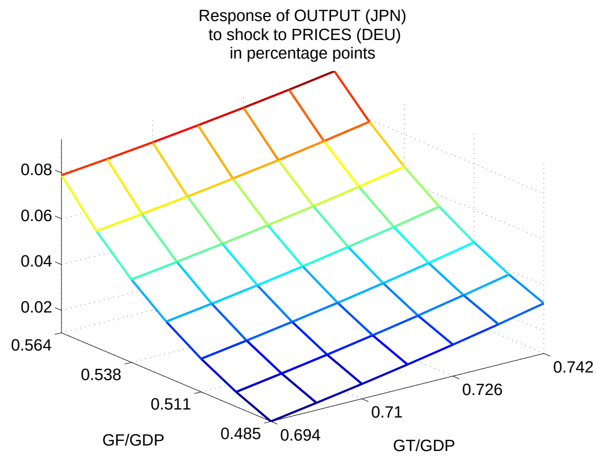

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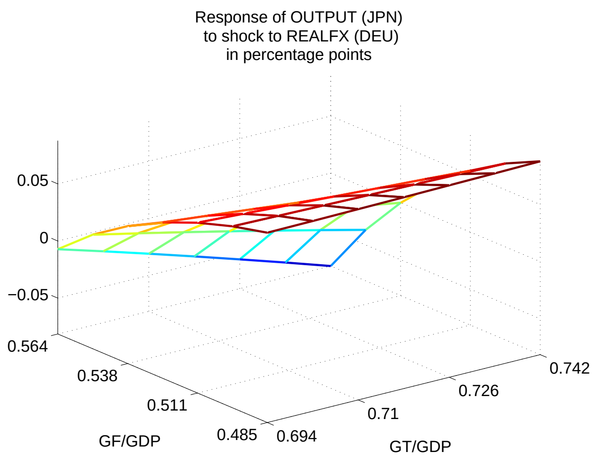

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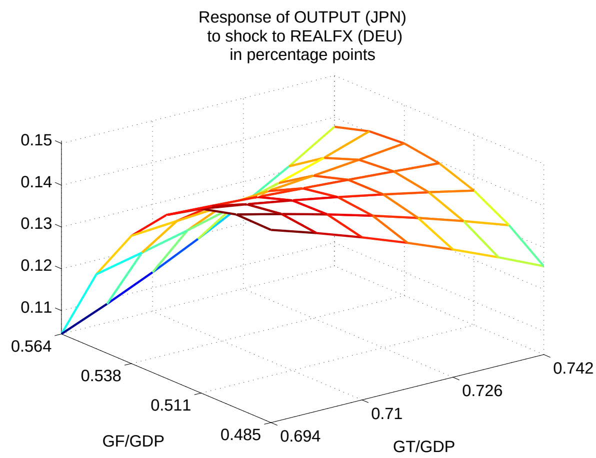
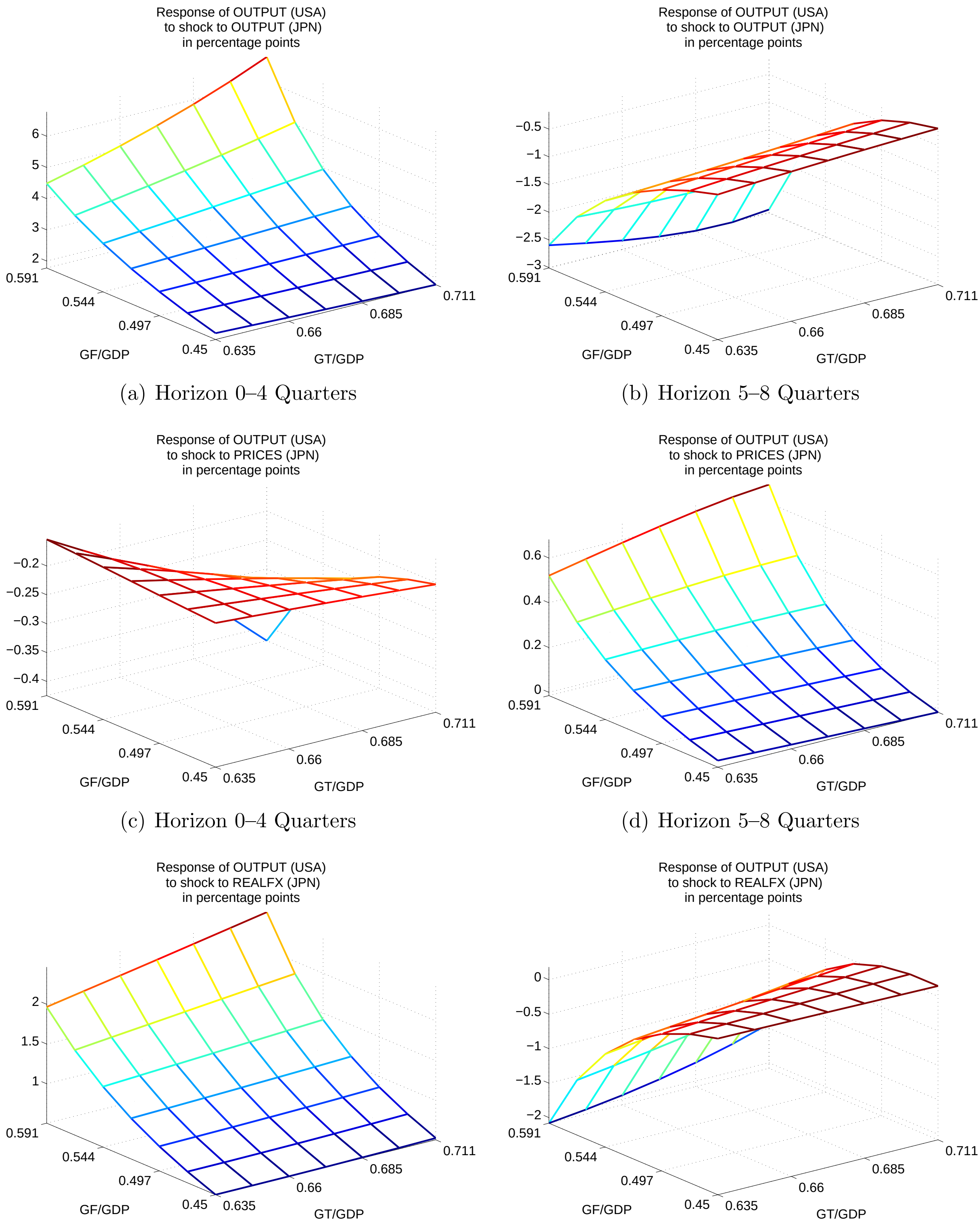


(f) Horizon 5–8 Quarters

Notes: Generalized impulse response functions evaluated over the specified grid of values for the depicted conditioning variable(s) in the response country, varying the values for the conditioning variables of all other countries according to the sample correlation between the corresponding conditioning variable in the respective country and in the response country.

Figure 5: Average Generalized Impulse Responses of the U.S. to Japanese Shocks



(a) Horizon 0–4 Quarters

(b) Horizon 5–8 Quarters

(c) Horizon 0–4 Quarters

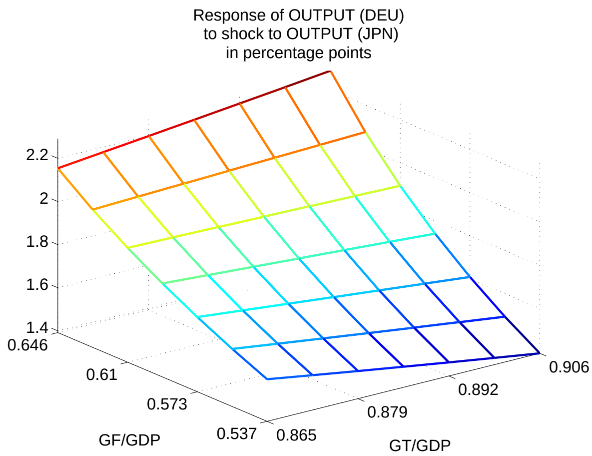
(d) Horizon 5–8 Quarters

(e) Horizon 0–4 Quarters

(f) Horizon 5–8 Quarters

Notes: Generalized impulse response functions evaluated over the specified grid of values for the depicted conditioning variable(s) in the response country, varying the values for the conditioning variables of all other countries according to the sample correlation between the corresponding conditioning variable in the respective country and in the response country.

Figure 6: Average Generalized Impulse Responses of Germany to Japanese Shocks



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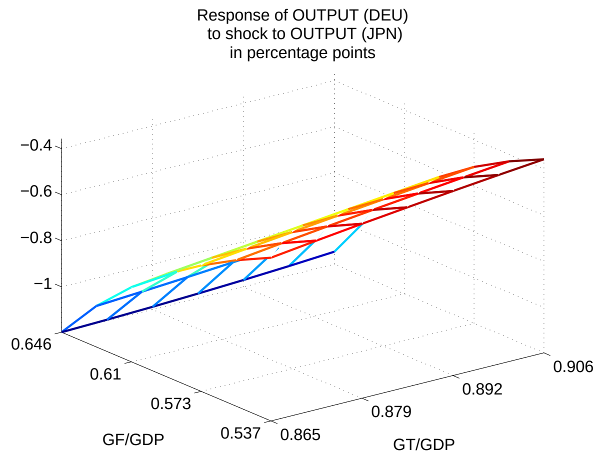

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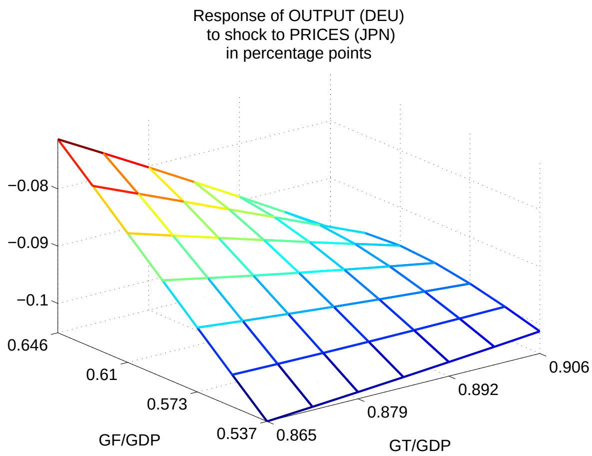

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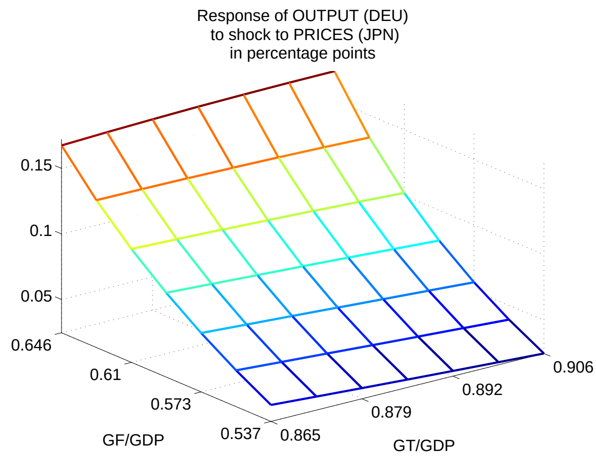
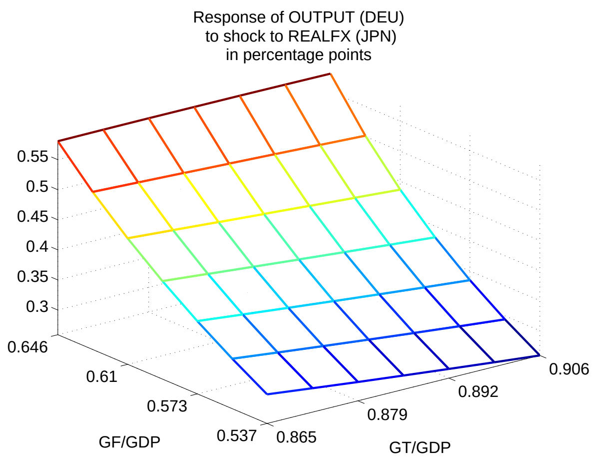
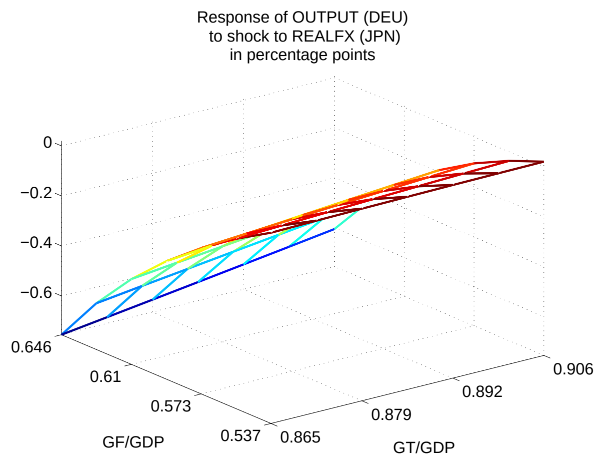


(d) Horizon 5–8 Quarters



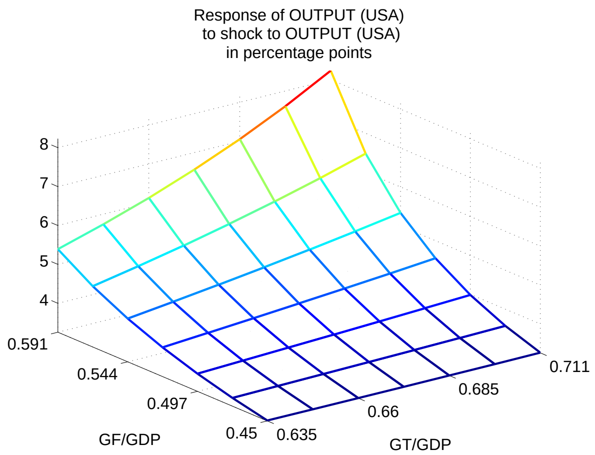
(e) Horizon 0–4 Quarters



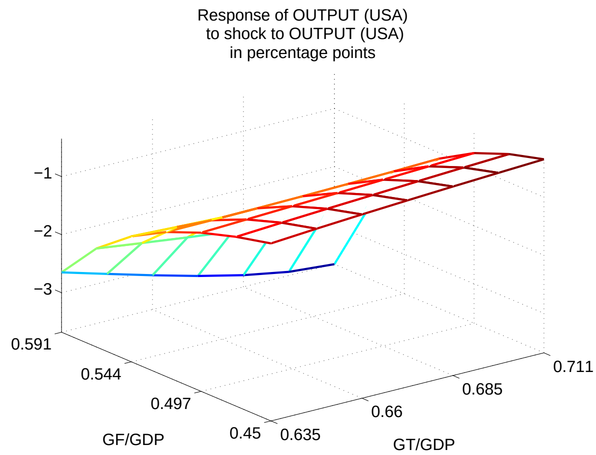
(f) Horizon 5–8 Quarters

Notes: Generalized impulse response functions evaluated over the specified grid of values for the depicted conditioning variable(s) in the response country, varying the values for the conditioning variables of all other countries according to the sample correlation between the corresponding conditioning variable in the respective country and in the response country.

Figure 7: Average Generalized Impulse Responses of the U.S. to U.S. Shocks



(a) Horizon 0–4 Quarters



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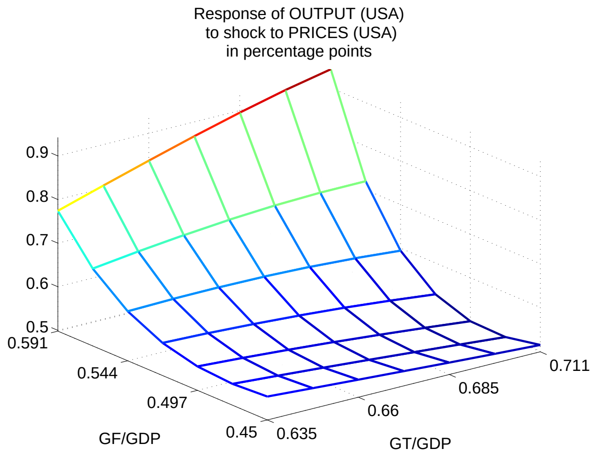

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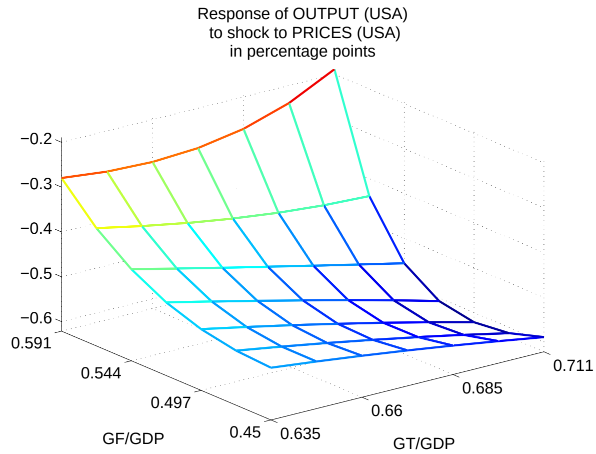
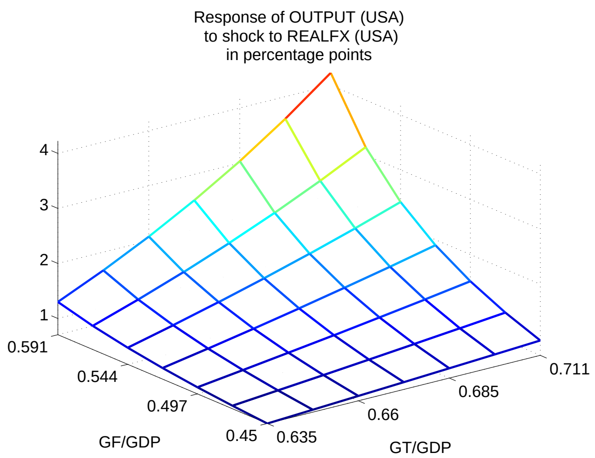
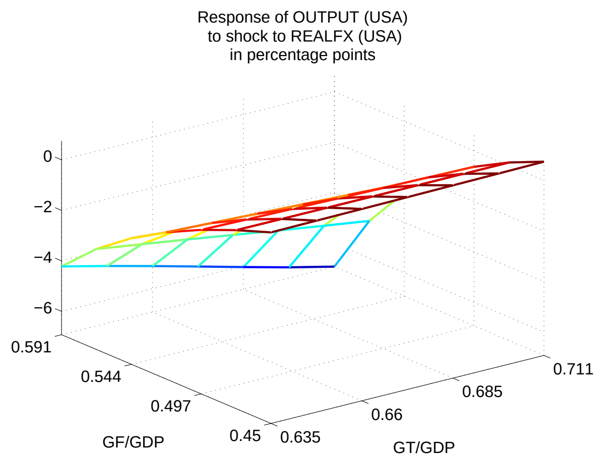


(d) Horizon 5–8 Quarters



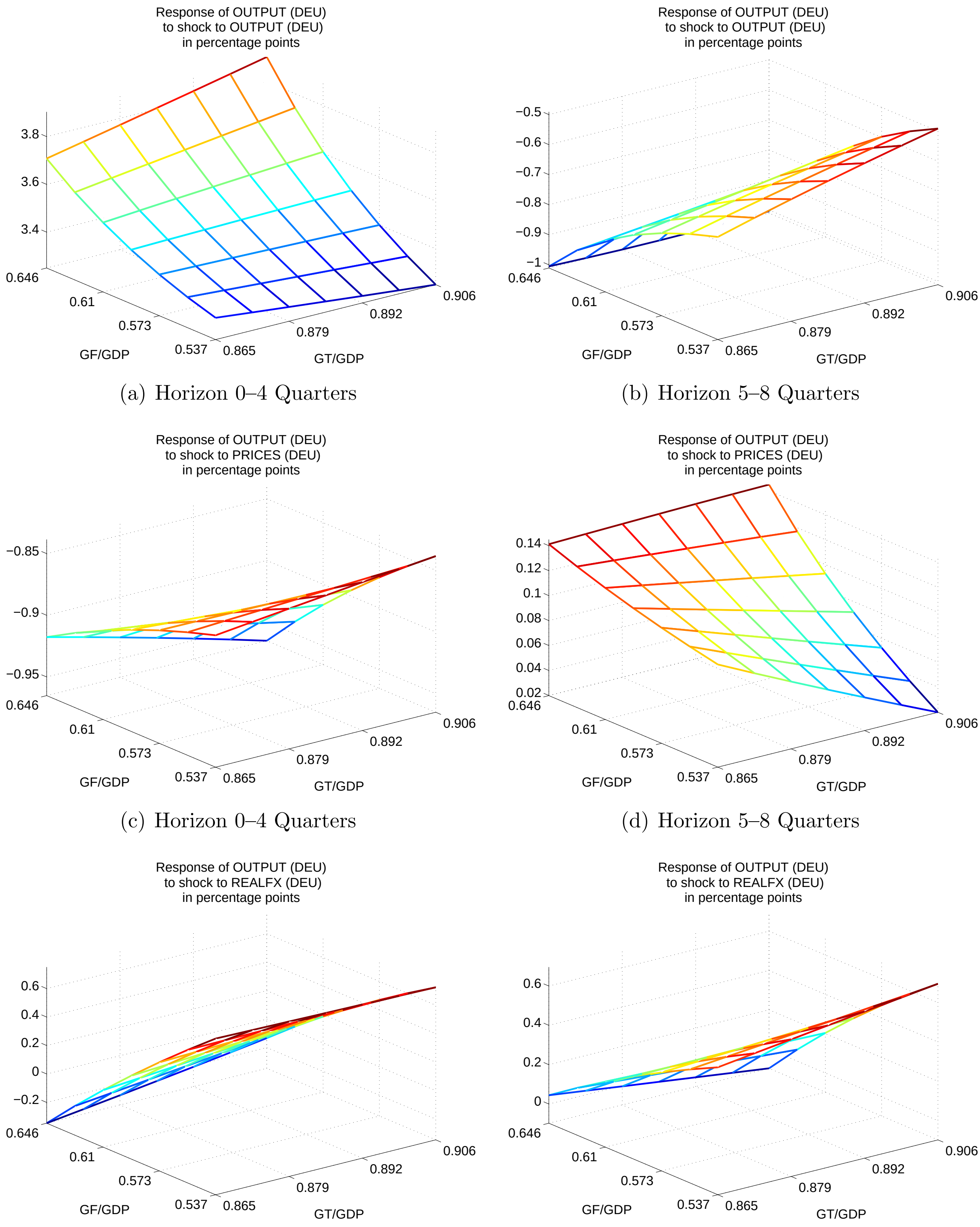
(e) Horizon 0–4 Quarters



(f) Horizon 5–8 Quarters

Notes: Generalized impulse response functions evaluated over the specified grid of values for the depicted conditioning variable(s) in the response country, varying the values for the conditioning variables of all other countries according to the sample correlation between the corresponding conditioning variable in the respective country and in the response country.

Figure 8: Average Generalized Impulse Responses of Germany to German Shocks



(a) Horizon 0–4 Quarters

(b) Horizon 5–8 Quarters

(c) Horizon 0–4 Quarters

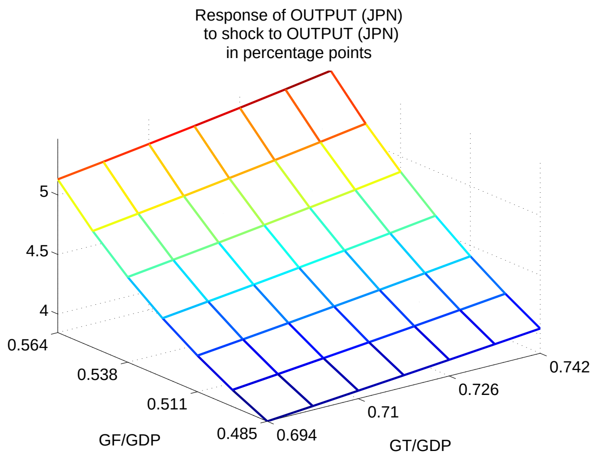
(d) Horizon 5–8 Quarters

(e) Horizon 0–4 Quarters

(f) Horizon 5–8 Quarters

Notes: Generalized impulse response functions evaluated over the specified grid of values for the depicted conditioning variable(s) in the response country, varying the values for the conditioning variables of all other countries according to the sample correlation between the corresponding conditioning variable in the respective country and in the response country.

Figure 9: Average Generalized Impulse Responses of Japan to Japanese Shocks



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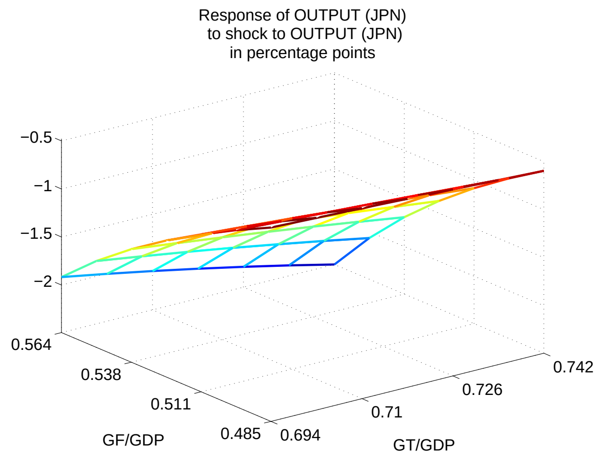

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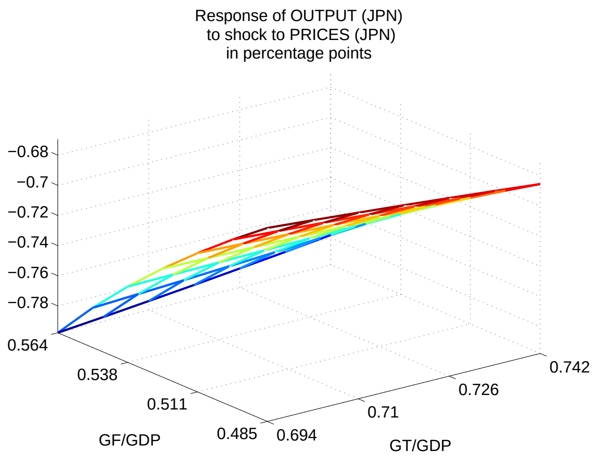

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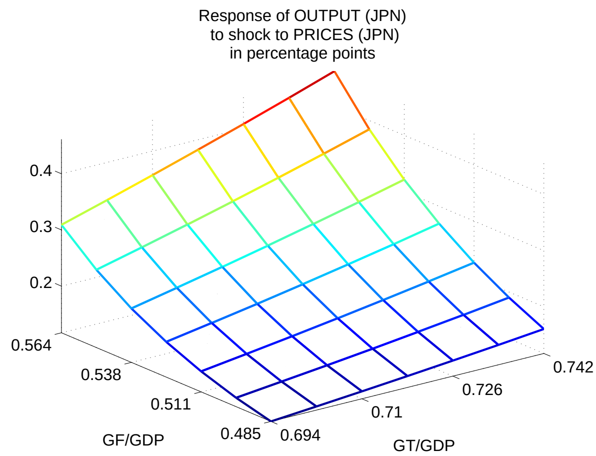
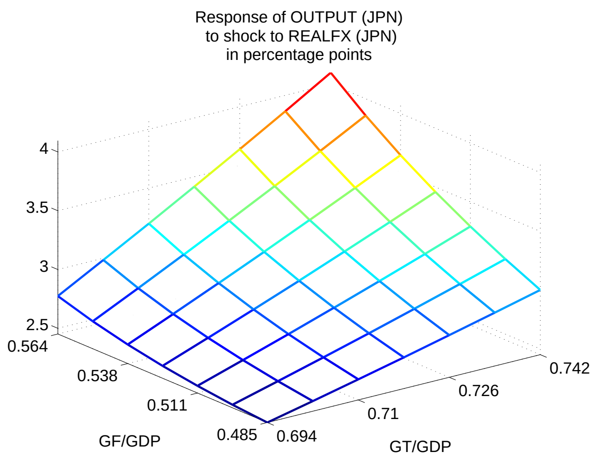


(d) Horizon 5–8 Quarters



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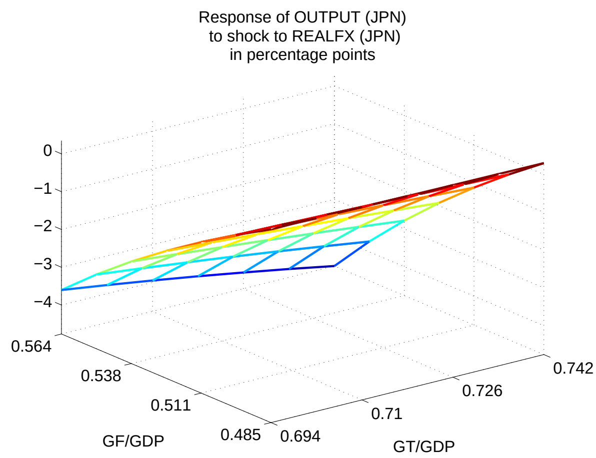

(f) Horizon 5–8 Quarters

Notes: Generalized impulse response functions evaluated over the specified grid of values for the depicted conditioning variable(s) in the response country, varying the values for the conditioning variables of all other countries according to the sample correlation between the corresponding conditioning variable in the respective country and in the response country.

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