Bayesian GVAR with *k*- Endogenous Dominants & Input-Output Weights:

Financial & Trade Channels in Crisis Transmission for BRICs[1]

ABSTRACT: In this work, we study the transmission of shocks (e.g. financial, monetary) between countries by developing a novel approach which relies on Bayesian techniques in order to estimate the GVAR model as a system of simultaneous equations, which we call Bayesian System GVAR (BSGVAR), while providing two procedures to select the dominant economies. Also, we use endogenously determined time varying weights with random coefficients. In this context, we utilize the proposed model to a selected panel of world economies that account for more than 90% of global production. Our work identifies and estimates the link between countries based on the global variables of trade and finance, which act as the transmission channels that have been documented in the literature as being most important. To this end, we investigate how the dominant economies of USA and EU17 will be affected by a potential slowdown in the BRICs. Consistent with international evidence, the empirical findings show that both monetary and financial variables, such as interest rates and total credit, have a significant impact on the transmission of shocks. According to our findings, the EU17 economy seems to be more vulnerable than the US economy to shocks from the BRICs.

1. INTRODUCTION

Despite the fact that we are still in the middle of a devastating global financial crisis, no adequate attention has been paid, so far, to the transmission of shocks(e.g. financial, monetary, etc) from the emerging and developing economies of the so-called BRICs to the US and EU economies, and *vice versa*. More precisely, what would the impact of a sudden shock in the BRICs be on other major economies of the world (e.g. US, EU), given that the BRICS account for about 20% of world GDP and 55% of the output of emerging and developing economies (World Economic Outlook, 2013)?

After all, it is widely accepted that over the past years, the economic and financial crisis has become increasingly globalized with important implications for: (a) the conduct of monetary and financial policies by central banks and (b) risk management by commercial banks and other relevant institutions. For instance, it is nowadays

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increasingly the case when setting interest rates, that central banking authorities need to take into consideration the complex interdependencies that exist between the output of the economy under investigation and the rest of the world's economies aggregate production (see, e.g., Pesaran et *al.* 2004).

In the meantime, in such a turbulent environment, the banking sector and especially commercial banks, continue to offer loans (even at a limited extent), and their main source of risk is credit risk, i.e. the uncertainty associated with borrowers' repayment of these loans. It is widely accepted that the quantity or percentage of non-performing loans is often associated with bank failures and financial crises in both developing and developed countries. Despite the fact that banks have developed sophisticated models for quantifying "ex ante" credit risk, empirical studies have shown that "ex post" credit risk, as reflected in the number of non-performing loans, is mainly affected by: (i) macroeconomic factors and (ii) financial factors.

Hence, the risk analyses of a bank's financial activities need to take into consideration domestic as well as international economic conditions of countries that directly or even indirectly influence the bank loan's portfolio, without neglecting the dominant role of certain economies, such as the USA or EU. Hence, in both cases, it would be extremely beneficial to work with global (macro-)econometric models, capable of generating scenario analyses, real-time simulations and forecasts related to countries in which they have considerable risk exposures based on a core set of macroeconomic and financial variables, including GDP and interest rates in a robust approach (see, *inter alia*, Pesaran et *al.* 2004).

To this end, the Global VAR approach (GVAR), developed originally by Pesaran et *al.* (2004), provides a quite flexible technique for assessing relationships between economic entities and constitutes a useful tool for analyzing the transmission of shocks (e.g. financial, monetary, etc)between economic regions. As we know, an advantage of the specific approach is that its results are data driven as opposed, for instance, to the heavy structures imposed on DCGE models.

In this work, we develop a novel approach, which relies on Bayesian techniques in order to estimate the GVAR as a system of simultaneous equations. In our work, the *main* differences with standard approaches are that: (a) our model parameters are treated as random variables with prior probabilities assigned to them and that (b) the different country VARX are estimated simultaneously as a system of equations and not separately for each country and then stacked together which is common practice as of yet.

Additionally, in the GVAR framework, it is widely accepted that the USA could be considered as being a dominant economy in the model. However, is the USA indeed dominant according to formal methods? Furthermore, is there any other dominant economy in the model? And if so, which one: EU or China? Furthermore, the determination of weights is, undoubtedly, an important issue that has not received sufficient attention in the literature, as of yet. In this paper, we do not consider the weights as given *a priori*. Instead, given a benchmark set of weights the model for the weights has endogenous time varying random coefficients.

The present paper contributes to the research conducted on modeling international transmission of fluctuations as follows: (a) it proposes system estimation for the GVAR with *K* dominants; (b) it provides two procedures in order to test for the existence of dominant entities; (c) it sets out a formal method for selecting the dominant entities; (d) it incorporates the transmission channels of global finance and trade; (e) it considers the weights as being endogenous with random coefficients based on the World Input – Output Table (WIOT); (f) it estimates how a sudden shock in the BRICs will affect EU17 and USA; (g) it incorporates economies that account for 90% of global production; (h) Last, and maybe most importantly, it develops a novel estimation method which relies on Bayesian techniques.

The remainder of the paper is structured as follows: Section 2 provides a brief overview of the literature; Section 3 provides the robust methodological framework upon which our model is structured; Section 4 provides the empirical analysis of the results; Section 5provides a brief discussion of the main results, while Section 6 concludes.

2. RELATED LITERATURE

As we know, there are numerous channels through which the transmissions of fluctuations can take place, such as common observed global shocks, global unobserved factors, or even specific national/sectoral shocks. See,*inter alia*, Stock and Watson (2005). And on the transmission of shocks between countries see, for instance, Artis et *al.* (1997), Bergman et *al.* (1998), Canova and Marrinan (1998), Kwark (1999), Clark and Shin (2000), Koseet*al.*(2002), Eickmeier (2007), Pesaran et *al.* (2004).

In this framework, the Global VAR approach (GVAR) provides a quite flexible technique for assessing relationships between economic variables and constitutes a useful tool for analyzing the transmission of economic shocks between economic regions. While factor augmented vector autoregressions (FAVAR) could be viewed as an alternative approach to GVAR (see e.g. Bernanke et *al.* 2005), the number of estimated factors used in FAVAR would be different for the different countries and it is not clear how they relate to each other globally (Dees et *al.* 2007). In a similar spirit, see Kapetanios and Pesaran (2007) who argue that GVAR estimators perform better than the corresponding ones based on principal components. Furthermore, Korobilis (2013a) proposed a FAVAR model with time-varying coefficients and stochastic volatility whose coefficients and error covariances change gradually over time or are subject to abrupt breaks. His model showed that both endogenous and exogenous shocks to the US economy resulted in the high inflation volatility during the 1970s and early 1980s.

The present work would have been practically impossible without previous contributions in the field of GVAR which was first introduced by Pesaran et *al.* (2004) and developed through several high caliber theoretical and empirical contributions. For instance, Pesaran and Smith (2006) showed that the VARX* models could be derived as solutions to a DSGE model. Next, Dées et *al.* (2007b) presented tests for controlling for the long-run restrictions within a GVAR context. Furthermore, Chudik and Pesaran (2011) derived the conditions under which the GVAR approach is applicable in a large system of endogenously determined variables.

The GVAR model was applied to a variety of settings and respective research questions, such as the international linkages of the euro area (Dées et *al.* 2005, 2007a), a credit risk analysis (Pesaran et *al.* 2006), the construction of measures of steady-state of the global economy (Dées et *al.* 2009), an analysis of the UK's and Sweden's decision not to join EMU (Pesaran et *al.* 2007), the application of the GVAR approach to the issue of international trade and global imbalances in Greenwood-Nimmo et *al.* (2010), Bussière et *al.* (2013). and the transmission of the so-called debt crisis from EU to US (Konstantakis and Michaelides, 2014). Furthermore, until recently, each country was treated in a "small economy" framework (Schmitt-Grohe and Uribe, 2003). There the idea was that all foreign economies are typically approximated by one representative economy constructed as a weighted average of foreign economies, while the rest of the countries' aggregate variables are generally treated as exogenous to the home economy. However, Chudik and Straub (2011) demonstrated recently that such an approach is justified only if no country is dominant. In a similar vein, recently Chudik and Smith (2013), following Chudik and Pesaran (2011), derived a GVAR approach as an approximation to an Infinite-Dimensional VAR (IVAR) model corresponding to the world featuring one dominant economy, i.e. the USA.In a seminal paper, Dees et *al.* (2014), created a multi-country rational expectations model in a GVAR framework, in attempt to explore the measurement of steady state in a new-Keynesian context.

Of course, since the beginning of the US subprime crisis in 2007, the economies of BRICs have attracted the growing attention of economists around the world in an attempt to assess their role in the global recession. In this context, Eichengreen et *al.*(2012a) and Eichengreen et *al.* (2012b) showed that the BRIC economies in particular. and the emerging markets in general. were unable to steer clear of the U.S financial crisis.Aloui et *al.* (2011) study the co-movements between the BRIC stock markets and the U.S. during the period of the global financial crisis. They find that dependency on the U.S. is higher and more persistent for Brazil–Russia than for China–India, a view that goes hand in hand with the findings of Bianconi et *al.* (2013). Additionally,Zouhair et *al.* (2014)investigated the co-movements of financial markets between the BRIC economies and the US, during the subprime crisis. According to their findings, BRIC's are dependent on the US economy, giving credit to the dominant role of US. Very recently, using a FAVAR model, Ratti and Vespignani (2015) showed that liquidity shocks in the BRIC economies result in a permanent rise of the commodity prices in the G3 economies, highlighting thus the importance of the BRIC economies for the global market.

In what follows, an overview of procedures and methodology to be implemented in this study is presented.

3. METHODOLOGY[2]

System GVAR Model

3.1 The Global VAR Model

The proposed Bayesian approach for estimating the GVAR has numerous advantages related to overcoming the over-fitting problem associated with the traditional VAR approaches, but also to its increased flexibility. Probably, the main advantage of our approach is the possibility of mixing different pieces of information (sample information, prior information, etc) in order to construct a model that accounts for the stochastic character of the variables that leads to a better approximation of reality.

Analytically, the main reason for using a Bayesian approach is that it facilitates representing and taking fuller account of the uncertainties related to model and parameter values. In contrast, most decision analyses based on maximum likelihood (or least squares) estimation involve fixing the values of parameters that may, in actuality, have an important bearing on the final outcome of the analysis and for which there is considerable uncertainty. One of the major benefits of the Bayesian approach is the ability to incorporate prior information. Also, MCMC, along with other numerical

[2] For a detailed exposition, see the Technical Appendix presenting all the methods of this paper.

methods, makes computations tractable for virtually all parametric models. See among others Carlin and Lewis (2000), Robert (2001) and Wasserman (2004).

Following Zellner and Huang (1962, p. 241) the GVAR can be written, compactly, in the form of multivariate regression:

$$Y = Z\beta + \varepsilon, \quad \varepsilon_t \sim N\left(0, \Sigma \otimes I_n\right) \qquad \textbf{[1]}$$

Where *n* is the number of elements in y_{it}, which expresses the endogenous variables, i.e. a (*mx1*) vector of m variables for country i and date $t = 1,\ldots,T$ (Korobilis 2013, pp. 206, 213, 215, 225).

In this work, we consider the following VARX model for each country $i = 1,\ldots,N$ and date $t = 1,\ldots,T$:

$$\underset{(1\times m)}{y'_{it}} = \underset{(1xm)}{a_{io}} + \sum_{l=1}^{L_1} y'_{i,t-l} \underset{(m\times m)}{A_{il}} + \sum_{l=0}^{L_2} y^{*'}_{i,t-l} \underset{(m\times m)}{B_{il}} + \sum_{l=0}^{L_3} \underset{(1\times k)}{x'_{t-l}} \underset{(k\times m)}{C_{il}} + u'_{it} \qquad \textbf{[2]}$$

where a_{i0} denotes a (*1xm*) vector of *m* intercepts, $\underset{(1\times m)}{y'_{i,t}} = \left[y_{i,t_1}, \ldots, y_{i,t_m} \right]$ denotes the transposed of a (*mx1*) vector y_{i,t_m} of m variables for country i expressing the so-called endogenous variables; $\underset{(1\times m)}{y^{*'}_{i,t}} = \left[y^*_{i,t_1}, \ldots, y^*_{i,t_m} \right]$ denotes the transposed of a (*mx1*) vector $y^*_{i,t}$, of m foreign-specific variables, and $x'_t = \left[x_{t_1}, \ldots, x_{t_k} \right]$ denotes the transposed of a (*kx1*) vector of *k* global variables that are exogenous to every VARX model. In general, the *m* and *k* may be allowed to vary between countries i, that is m_i and k_i for each country $i = 1,\ldots,N$.

For the foreign-specific variables we have: $y_{it}^{*\prime} = \sum_{c=1}^{N} w_{ic} y'_{ct} = w'_i \underset{(N\times m)}{Y_t}$, where w_i represents the vector of weights of country i with every country $c \neq i,\ \mathrm{c} = 1,\ldots, N-1$, with $w_{ii} = 0$, $\sum_{c\neq i} w_{ic} = 1$.

As we have seen, the determination of weights is, undoubtedly, an important issue that has not received sufficient attention in the literature, as of yet. In this paper, we do not consider the weights as given *a priori*. Instead, given a benchmark set of weights $\overline{w}_{ic,t}$ which are possibly time-invariant, we assume the following process:

$$w_{ic,t} = \rho_{ic} w_{ic,t-1} + \alpha_{ic} \overline{w}_{ic,t} + \varepsilon_{it}$$

where $\overline{w}_{ic,t}$ represents the ratio of trade flows to the total for country i. Therefore, we assume that the weights are persistent (through the coefficients ρ) and they also depend on a set of benchmark weights. Notably, the model for weights has random coefficients ρ_{ic} and α_{ic}.

In our disposal we have a set $\overline{w}_{ic}$ of weights that "most likely" reflect the interdependencies. These are commonly available and they would have been used as final weights as suggested by previous research. The "steady state" from the equation above implies:

$$\rho_{ic} + \alpha_{ic} = 1$$

Supposing that the "steady state" is close to the commonly available set of weights, so that we can calibrate proper priors, we have the semi-informative prior:

$$\rho_{ic} + \alpha_{ic} \sim N\left(1, \varpi^2\right)$$

Given ρ_{ic} the equation above provides a semi-informative prior for the coefficients γ_{ic}. It is perhaps easier to consider given priors for the γ_{ic} s and derive the prior for ρ_{ic} through

$$\rho_{ic} = 1 - \frac{\alpha_{ic} + \gamma_{ic}{}' \overline{z}_{ic}}{\overline{w}_{ic}}$$

$\varpi = 0.1$. Moreover we assume $\varepsilon_{it} \sim N\left(0, \sigma_{\varepsilon}^2\right)$ and $\frac{0.1}{\sigma_{\varepsilon}^2} \sim \chi^2\left(1\right)$ which are proper but "non-informative". The prior is of course, a member of the inverse-*gamma* family of distributions.

Now, by stacking together the VARXs we obtain: $\underset{(N\times m)}{Y_t^*} = \underset{(N\times N)}{W_t}\, Y_t$, where W represents the $N \times N$ matrix of weights, Y_t^* is an $N \times m$ matrix whose rows represent the m foreign – specific variables for the row country, for a given observation.

In the traditional GVAR approach, the individual country VARX models are estimated and the endogenous variables of the global economy are stacked together and solved. However, this is not expected to approximate reality with any given accuracy since the different models interact simultaneously through their global variables that are incorporated in each VARX model for all countries i=1,..,N. After all, the dominant countries and the possible global variables act as common regressors.

The main advantage of system estimation versus the equation-by-equation estimation lies on the utilization of the 'full information' that the data provide. In general, in the presence of full identification, estimation of a system of equations yields unbiased and efficient estimators, as opposed to the equation-by-equation estimation that fully ignores any interdependence between the error terms due to common regressors. Thus, our model can be applied when there may be several equations, which appear to be unrelated; however, they may be related by the fact that: (a) some coefficients are the same or assumed to be zero; (b) the disturbances are correlated across equations; and/or (c) a subset of right hand side variables are the same. This third condition is of particular interest because it allows each of the dependent variables to have a different design matrix with some of the predictor variables being the same.

To this end, the present more general approach, instead of estimating one VARX for each region separately, which is *then* stacked together with the others to obtain the Global VAR, we estimate the Global VAR *directly as a system of simultaneous equations*, which we call System GVAR (SBGVAR).

In this work, the endogenous variables y_{it} denote a 9×1 vector of macroeconomic variables belonging to each country *i*, $i = 1, \ldots, 9$, consisting of Gross Domestic Product (GDP) and Interest rate (Ir), and are regressed: on an intercept a_{i0}, on their lags up to the order L_1, the contemporaneous and lagged up to the order L_2 foreign variables $y^*_{i,t}$, and some contemporaneous and lagged up to the order L_3 common global factors x_t. The error term u'_{it} is assumed to be normally distributed with mean zero and the variance-covariance matrix Σ_i.

The foreign variables $y^*_{i,t}$ represent a weighted average of the other country's variables, whose weights have been discussed previously. Following common practice, the "commonly available weights" –that we discussed earlier to define processes for the weights- are typically equal to the trade shares (as % of total trade) of each country to the other. Thus, the VARX model for each country using the notation presented earlier is as follows:

$$y'_{it} = a_i + \Phi_i(L, L_1)y'_{it} + \Lambda_i(L, L_2)y*'_{it} + \Psi_i(L, L_3)x_t + u_{it}\,\textbf{[3]}$$

For $i = 1,\ldots,9$ and T=1,...,t; where $\Phi_i(L, L_1)$, $\Psi_i(L, L_2)$and $\Lambda_i(L, L_3)$ are the matrixes of the lag polynomial of the associated coefficients of the country-specific, of the foreign, and of the global variables, respectively. In this work, matrix $W_i$is a 9x9dimensional matrix of weights.

Following Chudik and Smith (2013), who are based on Chudik and Pesaran (2011), we treat (at least) one economy as being "dominant". Technically speaking (Chudik and Smith 2013, p. 14), the main implication for our empirical model, in the presence of a dominant economy, is that the VARX model for each country i=2,..9 needs to incorporate $y_{1,t} = \{GDP_{1,t}, Ir_{1,t}\}$ as its endogenous variables. Specifically: $w_{1,i} = 1$,∀i=2,...,9 meaning that the variables referring to the dominant economy are un-weighted and endogenous to each country's i=2,…9 VARX model.

Meanwhile, the model for the dominant economy is a separate model where the variables $y_{1,t}$ are treated endogenously with the foreign variables $y^*_{1,t}$. Lastly, u_{it} is a vector of idiosyncratic, serially uncorrelated country-specific shocks with $u_{it} \sim N(0, \Sigma)$, so that the VARX models are not independent, and there is another potential transmission mechanism. As discussed earlier, we estimate the SGVAR directly as a system of equations.

We examine the dynamic characteristic of the SBGVAR model through the so-called Generalized Impulse Response Functions (GIRFs) following Koop et *al.* (1996) and Pesaran and Shin (1998). Analytically, a positive standard error unit shock is examined on every variable in the universe of our model aiming at determining the extent to which each economy, responds to a shock. A basic advantage of this approach is that the GIRFs are invariant to the ordering of the equations.

The (Generalized) Impulse Response Function (GIRF) can be expressed as follows:

$$I_{j\,(n)} = \sigma_{jj}{}^{-1/2} + B_n \Sigma e_j \forall n = 1, 2, \ldots \textbf{[4]}$$

where: $I_{j\,(n)}$is the Impulse Response Function *n* periods after a positive standard error unit shock; σ_{jj} is the *j*th row and *j*th column element of the variance–covariance matrix Σ of the lower Cholesky decomposition matrix of the error term which is assumed to be normally distributed; B is the coefficients' matrix when inversely expressing the VAR model as an equivalent MA process and e_j is the column vector of a unity matrix. See Koop et *al.* (1996) and Pesaran and Shin (1998). Simulation from their posterior distribution is straightforward.

3.2 Priors

Recently, Koop (2013), motivated by the recent interest in the use of Bayesian VARs for forecasting, found that Bayesian VARs forecast better than factor methods and provided an extensive comparison of the strengths and weaknesses of various approaches, focusing on cases where the number of dependent variables is large. He showed the importance of using forecast metrics based on the entire predictive density, instead of relying solely on point forecasts.

Also, Korobilis (2013b) developed methods for automatic selection of variables in Bayesian VARs using the Gibbs sampler and provided computationally efficient algorithms for stochastic variable selection in generic linear and nonlinear models, as well as models of large dimensions. He concluded that data-based restrictions of VAR coefficients help improve upon their unrestricted counterparts in forecasting, and in many cases they compare favorably to shrinkage estimators.

In this context, given that the VARs contain a large number of parameters, principled priors have to be introduced on the parameters, especially in relatively small data sets. Here, we deviate from standard practice in certain ways. First, Wishart priors on Σ are convenient as they facilitate analytical integration of this matrix out of the joint posterior. We take the view that Σ is likely to be diagonal, after having expressed all variables in standard units. There are several advantages in using a diagonal specification for Σ, the most important of which probably being that a diagonal Σimplies that the vector derived is the same as the vector computed equation by equation.

The posterior distribution has density whose kernel is:

$$p(\beta,\Sigma \mid Y,Z) \propto L(\beta,\Sigma;Y,Z)\, p(\beta,\Sigma) \quad \textbf{[5]}$$

Due to the priors we place on Σ, it is not possible to integrate it out explicitly from the posterior (see Korobilis 2013, pp. 225-226; Zellner, 1971, p. 243, eq. 8.86).

This is achieved by repametrizing $\Sigma = C'C$ and adopting priors on the free elements of the lower triangular matrix C. Second, suppose $\mathcal{L}(\mu,\varphi^2)$ denotes the Laplace distribution with location μ and scale parameter φ^2. The Laplace distribution is used extensively in the LASSO literature on Bayesian priors (Yuan and Lin 2005). For the elements of C we have priors such that $c_i \sim \mathcal{L}(1,\sigma_c^2)$ if c_i contributes to the formation of diagonal elements of Σ and $c_i \sim \mathcal{L}\left(0, \varphi_o \sigma_c^2\right)$ otherwise, where $\sigma_c^2 = 1$ and φ_o is a free parameter. The density of the Laplace distribution is:

$$p(x \mid \mu, \varphi) = \frac{1}{2\varphi^2} \exp\left(-\frac{|x-\mu|}{\varphi}\right) \quad \textbf{[6]}$$

Without loss of generality, we can assume that $\alpha = \beta = O$. For the elements of Γ_1 we adopt a Minnesota-type prior in which the diagonal elements follow $\mathcal{L}\left(0.9, \varphi_1^2\right)$ distributions, the off diagonal elements follow $\mathcal{L}(0, \phi_2^2)$ distributions. The elements of matrices Γ_l $(l \geq 2)$ follow $\mathcal{L}\left(0, \varphi_3^2\right)$ distributions. The same priors are adopted for A_l and the elements of B are centered around $\mathcal{L}\left(0, \varphi_3^2\right)$ priors. We follow the same practice for Δ_1 and Δ_l (for $l \geq 2$): The diagonal elements follow $\mathcal{L}\left(0.1, \varphi_4^2\right)$ distributions, and the off diagonal elements follow $\mathcal{L}(0, \phi_5^2)$ distributions.

As the number of lags (L_1, L_2, L_3) are unknown and define different models, they are treated as "parameters" following Poisson priors concentrated around $\mathcal{P}\left(\lambda_j\right)$, $j = 1, 2, 3$ where $\lambda_j > 0$ denotes the Poisson parameter set to $\lambda_j = 1$ in all cases.

Of course, an alternative would be to follow Bayesian model selection using Bernoulli indicators as, for example, in Koop (2013) and Korobilis (2013b). However, the computational elaboration showed that our approach performed similarly and led to the selection of the same models with a standard Jeffreys' prior on Σ. The computational results are available upon request.

3.3 Specification of priors and posterior analysis

The specification of priors relies on empirical Bayes methods. Eight (8) quarters of the data are left out as a hold-out sample. M parameters of the φ-type are randomly chosen over the interval $(0.001, 1)$. For the specification of trade weights, parameters $\bar{\alpha}, \sigma_{\alpha}, \varpi, \alpha_{ic}, \rho_{ic}, \gamma_{ic}$ are drawn randomly from their priors. Given the full specification of the priors, M models with given priors are estimated using posterior MCMC analysis organized around the Metropolis-Hastings algorithm (1970). The posterior can be written in the form: $p(\theta | Y) = L(\theta; Y)\, p(\theta)$, where $L(\theta; Y)$ is the normal likelihood and $p(\theta)$ is the prior.

Using standard notation, the likelihood function is the following:

$$L(\beta, \Sigma; y, Z) \propto |\Sigma|^{-T/2} \exp\left\{-\tfrac{1}{2}(Y - Z\beta)' \left(\Sigma^{-1} \otimes I_n\right)(Y - Z\beta)\right\} \quad \textbf{[7]}$$

Finally, the forecasting performance of the models is examined in the hold-out sample and the model with the smallest mean-squared-forecast-error is selected. Our implementation of the Metropolis-Hastings algorithm relies on: (i) a component-wise update from the conditional posterior distribution of each parameter in C, (ii) a multivariate normal proposal for all other parameters[3] using 10,000+B draws the first B of which are discarded to mitigate the impact of start-up effects. B is chosen according to Geweke's (1992) convergence diagnostics.

The number of lags (L_1, L_2, L_3) is chosen randomly from the prior, which is not very different from conditioning on values of these lags and performing posterior analysis for the given values. The proposal for each MCMC update of the parameters is a

[3]All other parameters are regression-like parameters in the VAR. The multivariate normal proposal was crafted using least squares quantities and its scaled covariance matrix, where the scaling constant is adapted during the transient phase. This resulted, typically, in very fast convergence whereas updating each component individually (even after allowing for adjustment of the intervals) was slower and produced higher autocorrelations. For a description of the Metropolis-Hastings algorithm see Geweke (1999).

uniform distribution in an interval of the form $[a,b]$, which is updated during the transient phase to achieve acceptance rates between 20% and 30%. In our application, M=10,000 models are examined in total. Typically the value of *B* ranged between 2,500 and 5,000, depending on the model[4].

For the nine (9) models that performed best, we have computed Generalized Impulse Response Functions (GIRFs)[5]. The *final* GIRFs were computed using model averaging where the weights are computed from the marginal likelihood of each model. The marginal likelihood is computed, for each model, using the candidate's formula with a normal approximation to the exact posterior of the parameters following DiCiccio et *al.*(1997). This procedure is fast and easy to apply, which is important in this context where repeated MCMC simulations have to be considered. Standard errors of the GIRFs are computed in routinely using the posterior draws for the parameters[6] and the subsequent computation of GIRFs for each draw, after thinning every other 10th draw to mitigate inherent autocorrelation induced by MCMC.

3.5 The Weight Matrix

As we have seen, the so-called foreign variables represent a weighted average of the other countries' variables. Following common practice, the "commonly available weights" – that we discussed earlier to define processes for the weights- are equal to the trade

[4] MCMC procedures performed very well and convergence was fast; in fact, the auto-correlograms of the draws show that they are insignificant after the 10th lag.
[5] The method avoids the inherent drawback of Cholesky decomposition in which impulse responses may depend on the particular ordering of the variables that has been adopted. For the methodology see Koop, Pesaran and Potter (1996).
[6]We use a Newey-West HAC estimator with 10 lags applied to the draws for GIRFs.

shares. In other words, in the core of the GVAR methodology at the international level is the so-called trade weight matrix(e.g. the seminal work by Pesaran et *al.* 2004 and the related literature [Section 2, above]).

The weight matrix is about estimating the flow of output (goods and services) produced in one economy/country/region that is transmitted to every other economy/country/region in the universe of our model. However, the trade shares, which are typically used as proxies for the GVAR weights, only depict the *direct* trade relationships among countries as part of net exports, neglecting the *indirect* production connections which are due, for instance, to the intermediate inputs produced in various countries. Hence, relying solely on direct trade relationships, which neglect- for instance - intermediate flows would, clearly, be inadequate if not misleading.

To overcome this shortcoming of the model, we use the World Input Output Tables (WIOT)[7] - which are publically available online - to serve as the tools to construct the GVAR weight matrix and. To this end, we propose and derive a simple, fast and efficient, yet practical, framework for constructing the weight matrix based on the technical coefficients matrix.

Apparently, the proposed framework has considerable advantages. With respect to the traditional GVAR approach, the weight matrix constructed in this work- which is derived based on Leontief's Input Output matrix -, is perfectly capable of accurately expressing the total, i.e. *direct and indirect* linkages between the various economies in the model. Hence, the modeling of the world economy is complete since there are no missing relationships and/or interconnection channels due to the fact that all economies are explicitly and accurately included in the GVAR model (Timmer et *al.*, 2015).

[7]For details on WIOT and the so-called World Input Output Database (WIOD), see Timmer et *al.* (2015).

For a technical exposition of the proposed technique on how to calculate the weights, which is simple, fast and efficient, see Technical Appendix 2.

The derived net intra-sectoral flow weight matrix W is directly analogous to the typical weight matrix of the GVAR model and, in addition, accounts for the *direct and indirect* interconnections of the countries in the model and channels of transmission.

3.6 Selecting the Dominant Economies

Now, crucial in the calculation of the weight matrix W is matrix Q (see Appendix B), which has the following form:

$$Q \equiv \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nn} \end{pmatrix}$$

where each element of Q is given by the expression: $x_{ij} \equiv a_{ij}X_j$ **[8]**

and the x_{ij} element of matrix Q expresses the product of economy i that is used from economy j, X_j is the total output of the j-th economy and a_{ij} is interpreted as the quantity of output from economy i required to produce one unit of output in economy j.

In simple words, the row elements express the quantities of goods and services, in value terms, supplied by one economy to itself and all others. Similarly, column elements express quantities obtained by an economy from itself and all others. In general, matrix Q expresses an inter-country flow matrix.

Bródy (1997) showed that the behavior of systems describing economic interdependencies depends on the ratio of the modulus of the subdominant eigenvalues to the dominant one, such that a ratio close to zero implies negligible power of this economy. Let λ(pf) = λ(1) denote the dominant eigenvalue of *Q* and the normalized eigenvalues: $\rho(\mathrm{i}) \equiv |\lambda(i)/\lambda(pf)|$, i=2,3..., are the *non*-dominant normalized eigenvalues. The number of dominant economies is i^* such that $\rho(i^*)>0.4$, $i^*= 1,2,3...$, since values <0.40 are practically negligible (Mariolis and Tsoulfidis, 2014).

Now, since the j-th line of *Q* shows the value of goods and services that the j-th economy supplies to itself and all others, the largest line sum corresponds to the economies that produce and, in the same time, supply the largest output to the rest of the economies. Mathematically:

$$\left\{\sum_{j=1}^{N} y_{i^*j}, j = 1, \dots, N\right\} = max_j\left\{\sum_{j=1}^{N} y_{ij}, j = 1, \dots, N/\rho(\mathrm{i}) > 0.4\right\} \mathbf{[9]}$$

Hence, the largest line sum corresponds to the dominant economy, the second largest to the second-dominant economy, etc.

3.7A Bayes factor approach to test for a dominant economy

Apart from the previous approach, which is non-stochastic, we can estimate different GVAR schemes based on different assumptions about the dominant economy. For each model we can estimate its marginal likelihood using the approach of Chib (1995), which requires an additional Gibbs sampling simulation. However, since posterior conditional distributions are available in closed form this task is not particularly difficult. Since marginal likelihoods can be computed, model comparison can be performed relatively easily using the Bayes factor in favor of EU17 and US being dominant against any other pair of economies. The Bayes factor can be evaluated easily as the difference of log marginal likelihoods. For any likelihood $L(Y/\theta)$ and prior density $p(\theta)$ the marginal likelihood is given by the basic marginal likelihood identity:

$$M(Y)=\frac{L(\mathrm{Y}/\theta)\,p(\theta)}{p(\theta/Y)}\ \textbf{[10]}$$

where $p(\theta|Y)$ is the value of the posterior at any high posterior probability mass θ.

Then, for a given $\overline{\theta}$, the posterior ordinate can be estimated exploiting the information in the collection of complete conditional densities. Computation of the numerator is trivial, while the denominator can be computed using Chib's (1995) approach. Suppose we have the decomposition $\theta=[\theta'_1,\theta_2']'$ and let z denote latent data so as to allow for data augmentation in posterior simulation. Then the Gibbs sampler is defined through the complete conditional densities:

$$\mathrm{p}(\theta_1\,|\,\mathrm{Y},\theta_2,\mathrm{z});\;\; \mathrm{p}(\theta_2\,|\,\mathrm{Y},\theta_1,\mathrm{z});\;\; \mathrm{p}(\mathrm{z}|\mathrm{Y},\theta)\ \textbf{[11]}$$

Suppose that $\overline{\theta}=(\overline{\theta_1},\overline{\theta_2})$ is the selected point. The objective is to estimate the posterior density $p(\overline{\theta}|Y)$ which is given by the expression:

$$p(\overline{\theta}|Y)=p(\overline{\theta_1}\,|\,\mathrm{Y})\,\mathrm{p}(\overline{\theta_2}\,|\,\mathrm{Y},\overline{\theta_1})\ \textbf{[12]}$$

where : $p(\overline{\theta_1}\,|\,\mathrm{Y})=\int p(\overline{\theta_1}\,|\,\mathrm{Y},\overline{\theta_2},\mathrm{z})\,\mathrm{p}(\overline{\theta_2},z\,|\,Y)\,d\theta_2 dz$ and

$\mathrm{p}(\overline{\theta_2}\,|\,\mathrm{Y},\overline{\theta_1})=\int p(\overline{\theta}_2\,|\,\mathrm{Y},\overline{\theta_1},\mathrm{z})\,\mathrm{p}(\mathrm{z}\,|\,\mathrm{Y},\overline{\theta_1})dz$

Then, the first ordinate, $p(\overline{\theta_1} \mid \mathrm{Y})$, could be easily computed taking the ergodic average of the full conditional density with the posterior draws of (θ_2, z) leading to the estimate:

$$\widehat{p}(\overline{\theta_1} \mid \mathrm{Y}) = G^{-1}\sum_{g=1}^{G} p(\overline{\theta_1} \mid \mathrm{Y}, \theta_2^{(\mathrm{g})}, \mathrm{z}) \quad \textbf{[13]}$$

Now, notice that the draws of z, from the Gibbs sampler are from the distribution $[z \mid Y]$, and in this context, the complete conditional density on θ_2 could not be directly averaged. In order to deal with this problem we continue sampling for an additional G iterations with the complete conditional densities: $\{\mathrm{p}(\theta_2 \mid \mathrm{Y}, \overline{\theta_1}, \mathrm{z});\ \mathrm{p}(\mathrm{z}|\mathrm{Y}, \overline{\theta}_1, \theta_2)\}$ where in each of these densities we set $\theta_1 = \overline{\theta_1}$. Then from MCMC theory we have that the draws $\{\mathrm{z}^{(j)}\}$ from this run follow the density $p(z \mid Y, \overline{\theta}_1)$ as required. Consequently we obtain the estimate:

$$\widehat{p}(\overline{\theta_2} \mid \mathrm{Y}) = G^{-1}\sum_{j=1}^{G} p(\overline{\theta_2} \mid \mathrm{Y}, \overline{\theta_1}, \mathrm{z}^{(j)}) \quad \textbf{[14]}$$

Apparently, under regularity conditions, both estimates are simulation consistent, as a consequence of the ergodic theorem (Tierney, 1994).

Now, in order to compute the Bayes factor for any two models *k* and l i.e. $m(y/M_k)/m(y/M_l)$ the calculation described earlier is repeated for all models, and the following estimate is used:

$$\widehat{B_{kl}} = \exp\left\{ln\widehat{m}\left(\frac{y}{M_k}\right) - ln\widehat{m}\left(\frac{y}{M_l}\right)\right\} \textbf{[15]}$$

An estimate of the posterior odds of any two models is given by multiplying the estimated Bayes factor by the prior odds (see Chib, 1995).

4. EMPIRICAL RESULTS

4.1 Data and Variables

The data are quarterly and cover the period 1992(Q1)-2014(Q3), fully capturing the ongoing recession. For all the economies that enter the SBGVAR model i.e. USA, EU17, Brazil, Russia, India, China, Japan, Australia, Canada we used data on: their exchange rates to the US dollar, GDP deflator, GDP in current prices and Interest rates. All data come from the OECD database. The implicit assumption is that the variables of global finance and global trade act as transmission channels of the crisis. Hence, regarding the global variables, we use the aggregate values of (i) Worldwide Total Credit and also (ii)Worldwide Total Trade, both in millions of US dollars, which were obtained in constant 2005 prices from the World Data Bank. The trade weights are calculated as discussed earlier, based on the World Input Output Table (WIOT) which is publically available online (www.wiod.org).Additionally, in each VARX model we included relevant dummy variables that account for the global financial crisis of 2007-2009 as well as for local and regional crises that some countries experienced during the period investigated like, e.g.,the Russian crisis of 1998, the "lost decade" of the Japanese economy, the currency crisis in Brazil etc.

Next, using the GDP deflator of each economy's, i=1,..,9, GDP_i we calculated the GDP in constant 2005 prices usingthe formula:

$$GDP_{2005_i} = \frac{GDP_i\ current\ prices}{GDP_i\ deflator}$$

Then, we made use of the exchange rate of each economy (except for the US),to transformGDP_{2005_i}, into US dollars, using the formula:

$$GDP_{i,2005\ in\ \$} = GDP_{2005_i} * exchange\ rate_i$$

4.2 Selecting the Dominant Economies

In order to apply the methodology described earlier we calculate matrix Qand its eigenvalue distribution. Table 1, presents the eigenvalues of matrix Q,and Table 2presents the respective normalized eigenvalues.

Table1: Eigenvaluesof Q	
Eigenvalue	λ_i
1	5348322
2	-3850037
3	-1731834
4	949640.6
5	-403756
6	-218763
7	-90612.9
8	15034.48
9	-1515.08

Table 2: Normalized Eigenvalues of Q	
Eigenvalue	ρ_i
1	1.000
2	0.720
3	0.324
4	0.178
5	0.075
6	0.041
7	0.017
8	0.003
9	0.000

The results in Table 2 clearly indicate the existence of two (2) dominant economies for which: $\rho(i^*) > 0.4$ ($\rho_1 = 1, \rho_2 = 0.72$).

Following the methodology set out earlier,the dominant economies are those of USA and EU17(Table 3), which correspond to the largest line sum and thus, have the largest exchangeable quantities among the economies that enter the GVAR model. Notice that together the two economies account for more than 30% of global output (CIA, 2013).

Table 3: Line Sums of matrix Q

Country	Line Sums of Q
USA	10015884
EU17	10370978
JAP	3035229
CAN	1600717
AUS	968903.2
BRA	1182714
IND	2918545
CHI	5361855
RUS	1099599

In order to test for the dominance of the pair USA - EU17 in the universe of our model we conduct Bayes Factor Analysis as described in earlier. In this context, we present the results in Table 4 using the baseline prior.

Table 4: Bayes factors in favor of USA-EU17 being dominant

Against	
US and China	539.12±13.89
EU17 and China	291.26±2.48

Note: ± denotes two times the standard deviation from 10,000 alternative priors.

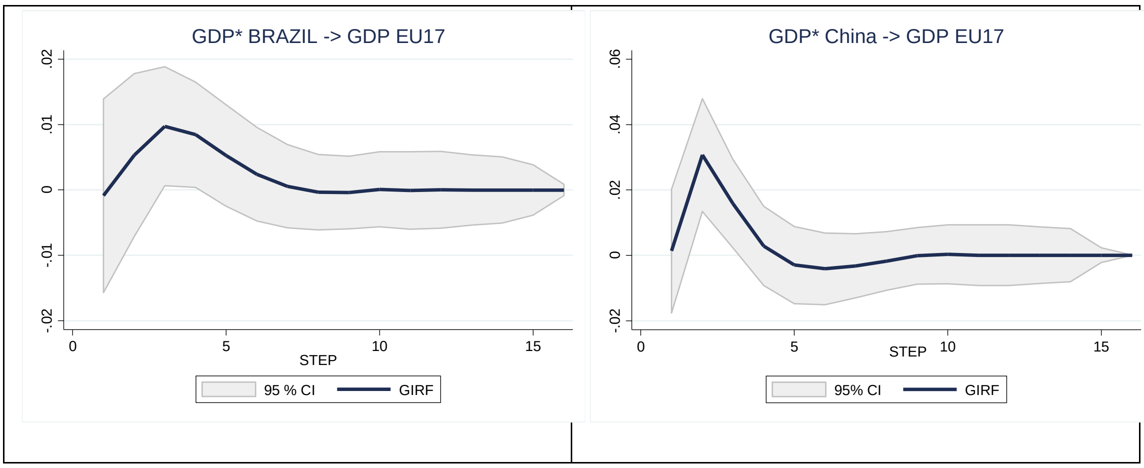
From the Bayes factors in favor of US - EU17 being the dominant economies compared to US - China as well as EU17 - China, it becomes evident that the hypothesis receives great support from the data.

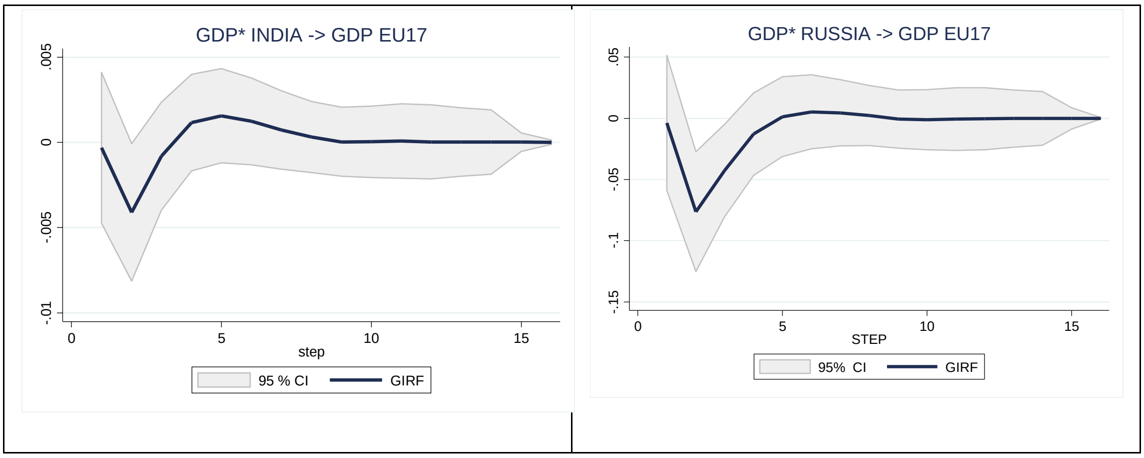
4.3 Generalized Impulse Response Functions

Based on the methodology described in the previous section we estimate the SBGVAR model and compute the GIRFs, following Pesaran and Shin (1998). Each GIRF shows the dynamic response of the GDP of each economy to shocks in the rest of the economies' GDP and Interest rates, for a period of up to 4 years.

For the sake of economy, we focus on the impact of a shock in the GDP of BRICs on the GDP of the dominant economies, i.e. EU17 (Figure 1) and US (Figure 2).All Figures present the posterior mean estimates of the GIRFs and the respective 95% confidence bands, regarding the response of the dominant economies i.e. US and EU17 to an impact on the GDPs of BRIC economies. In what follows, we will base our detailed analysis of GIRFs on the confidence intervals, i.e. a statistically significant deviation from the initial equilibrium position of each GIRF is identified when zero does not belong to the respective confidence band.

Figure 1: Response of GDP EU 17 to BRICs GDP

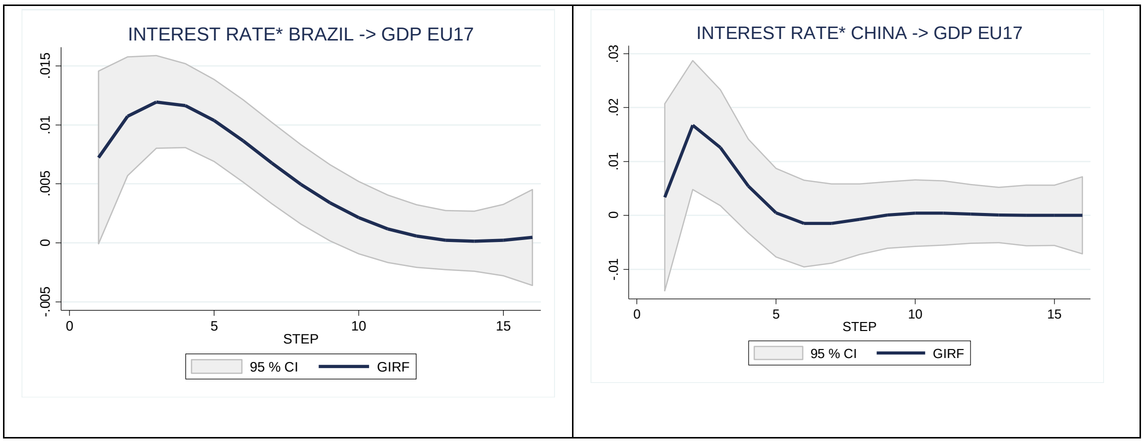


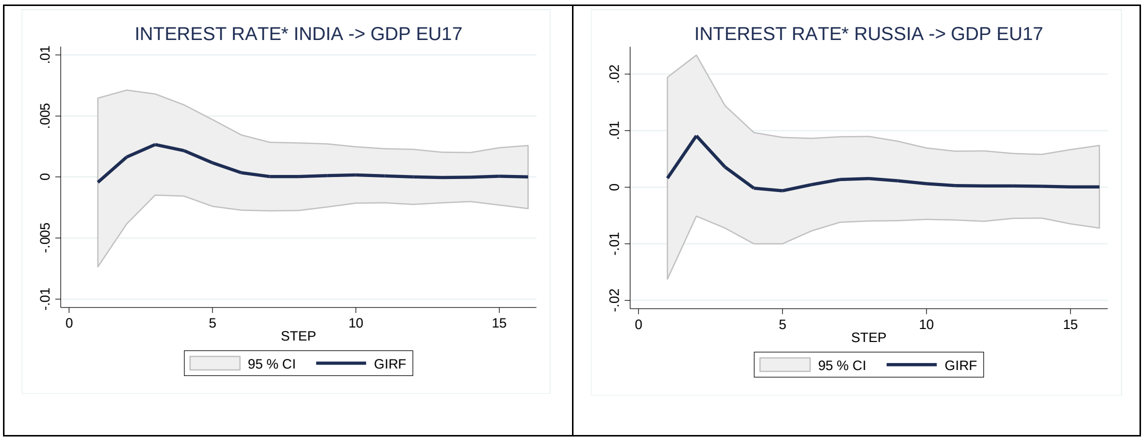


The results depicted inFigure 1 suggest that a unit shock in the GDP's of both China and Russia, respectively, has a statistically significant impact on the GDP of EU17, while neither a shock in the Brazilian GDP nor a shock in the GDP of India seem to have a significant impact on EU17's GDP.

Next, we turn to the impact of a unit shock to the BRIC's interest rate on the EU17 GDP (Figure 2).

Figure 2: Response of GDP EU17 to BRICs interest rate





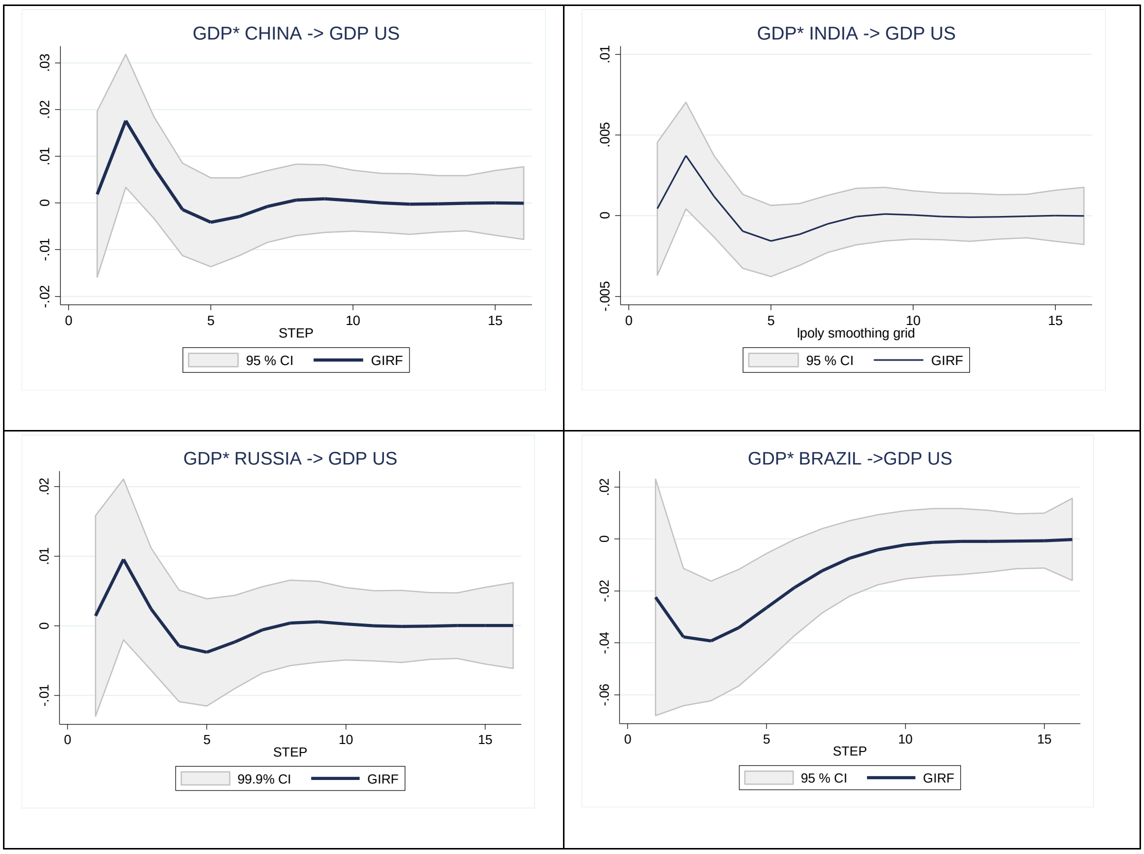
The results suggest that a unit shock on both, the Brazilian and the Chinese Interest Rate, has a statistically significant impact on the GDP of EU17, while the EU17 GDP seems to be unaffected by a shock in either the Indian or the Russian GDP. The key statistics and the maximum deviations of each GIRF are summarized in Table 5.

Table 5: Descriptive statistics, maximum deviation and Stat. Significance (EU17)

GIRF	Mean	Standard Deviation	Min	Max	InitialEquilibriumPosition	Maximum deviation fromequilibrium
GDP*CHINA ->GDP EU17	0.003	0.100	0.000	0.040	0.000	0.040
GDP*INDIA ->GDP EU17	-0.001	0.002	-0.006	0.003	0.000	-0.006
GDP*BRAZIL->GDP EU17	0.002	0.005	-0.001	0.020	0.000	0.020
GDP*RUSSIA ->GDP EU17	-0.008	0.025	-0.103	0.000	0.000	-0.103
INTEREST RATE* BRAZIL ->GDP EU17	0.005	0.007	0.000	0.022	0.000	0.022
INTEREST RATE* CHINA -> GDP EU17	0.002	0.007	0.000	0.029	0.000	0.029
INTEREST RATE* INDIA ->GDP EU17	0.000	0.002	-0.001	0.006	0.000	0.006
INTEREST RATE* RUSSIA ->GDP EU17	0.001	0.005	-0.008	0.017	0.000	0.017

As far as the US economy is concerned, Figure 3 shows how the US GDP is affected by a unit shock in the GDP of the BRIC's.

Figure 3: Response of GDP US to BRICs GDP



According to the results, only the Chinese GDP seems to have a statistically significant impact on the US GDP, while the impact of the rest of the BRIC economies is negligible.

Next, Figure 4 presents the impact of a unit shock in the BRIC's interest rate on the US GDP. The results clearly indicate that the US GDP remains statistically significantly unaffected by any deviation in the BRIC's interest rate.

Figure 4: Response of GDP US to BRICs Interest Rate

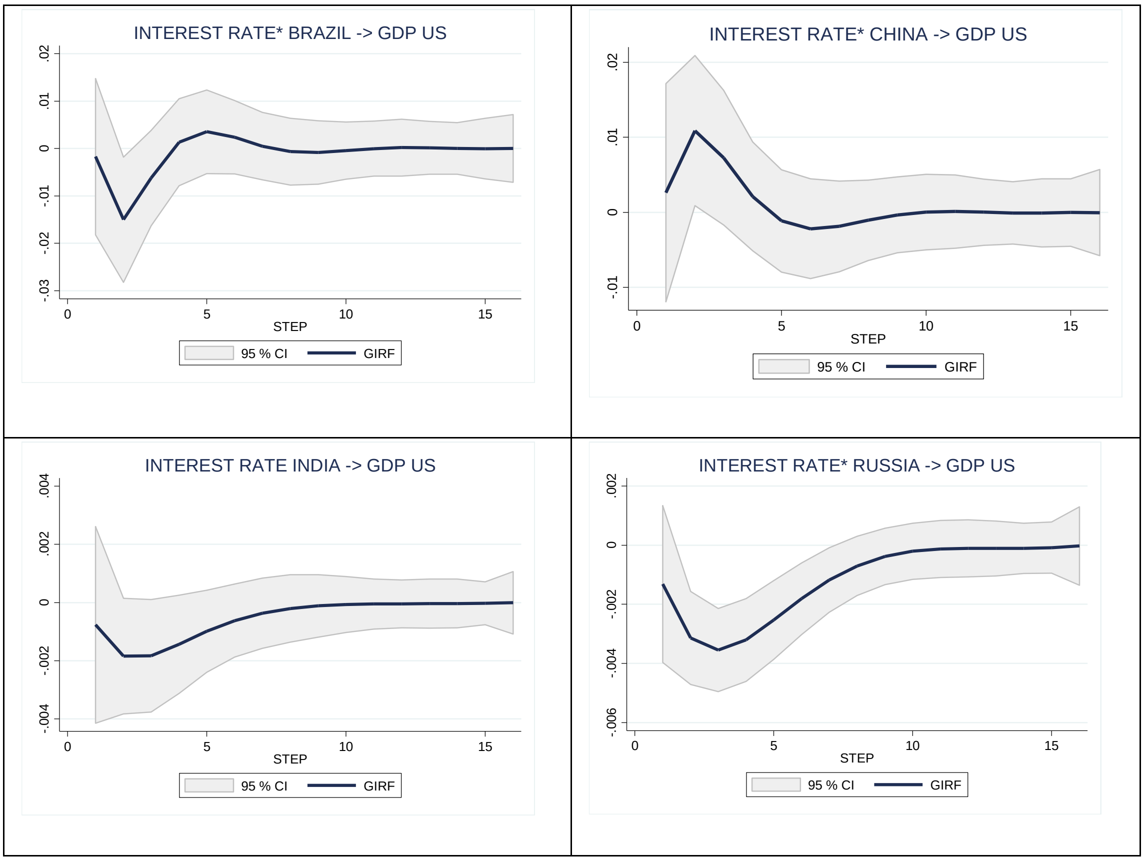


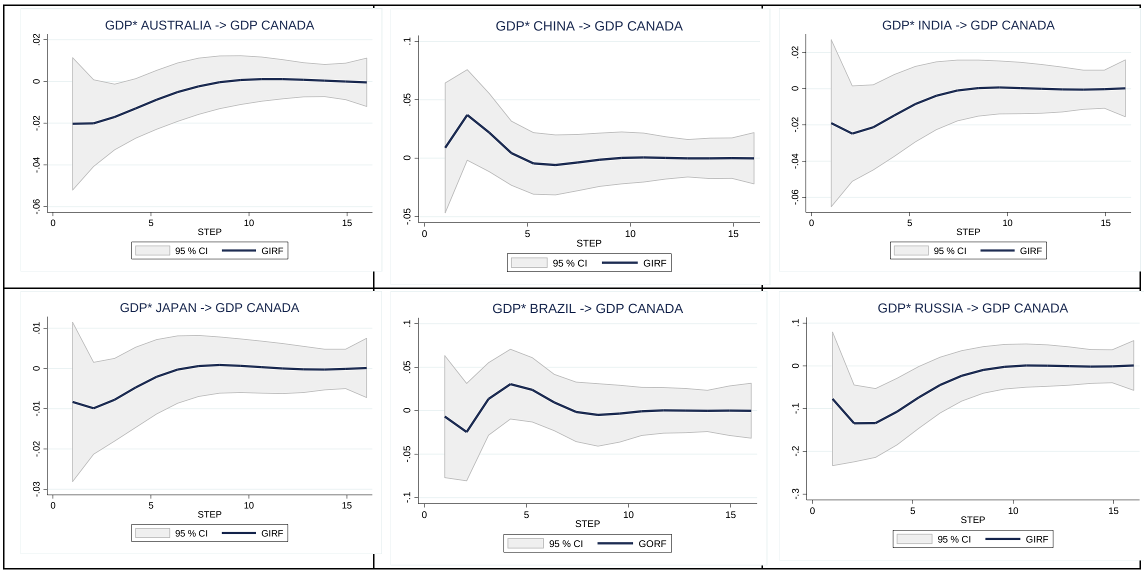
Table 6, summarizes thedescriptive statistics and the maximum deviations of each US GIRF as well as the statistical significance of these deviations.

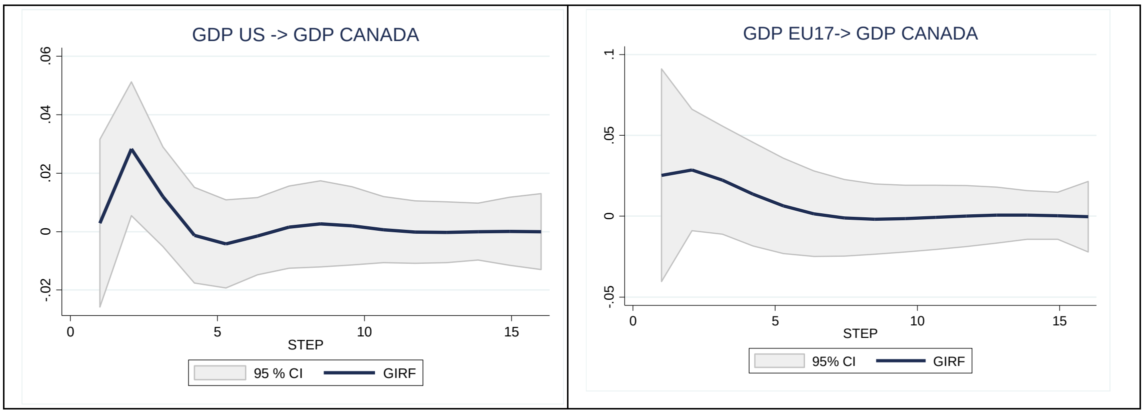
Table 6: Descriptive statistics, maximum deviation and Stat. Significance (US)

GIRF	Mean	Standard Deviation	Min	Max	Initial Equilibrium Position	Maximum deviation fromequilibrium
GDP* CHINA -> GDP US	0.001	0.007	-0.005	0.027	0.000	0.027
GDP*INDIA -> GDP US	0.000	0.002	-0.002	0.006	0.000	0.006
GDP* RUSSIA -> GDP US	0.000	0.005	-0.007	0.017	0.000	0.017
GDP* BRAZIL -> GDP US	-0.013	0.021	-0.078	0.000	0.000	-0.078
INTEREST RATE* BRAZIL -> GDP US	-0.001	0.006	-0.023	0.005	0.000	0.021
INTEREST RATE * CHINA ->GDP US	0.001	0.005	-0.001	0.021	0.000	0.021
INETERST RATE* INDIA -> GDP US	-0.001	0.001	-0.004	0.000	0.000	-0.004
INTERERST RATE* RUSSIA -> GDP US	-0.001	0.002	-0.006	0.000	0.000	-0.006

Next, the following two figures illustrate the response of Canada's GDP to a unit shock in the GDPs of the rest of the economies that enter the GVAR model (Figure 5).

Figure 5: Response of GDP Canada to GDP Australia, BRICs, Japan, EU17 and US





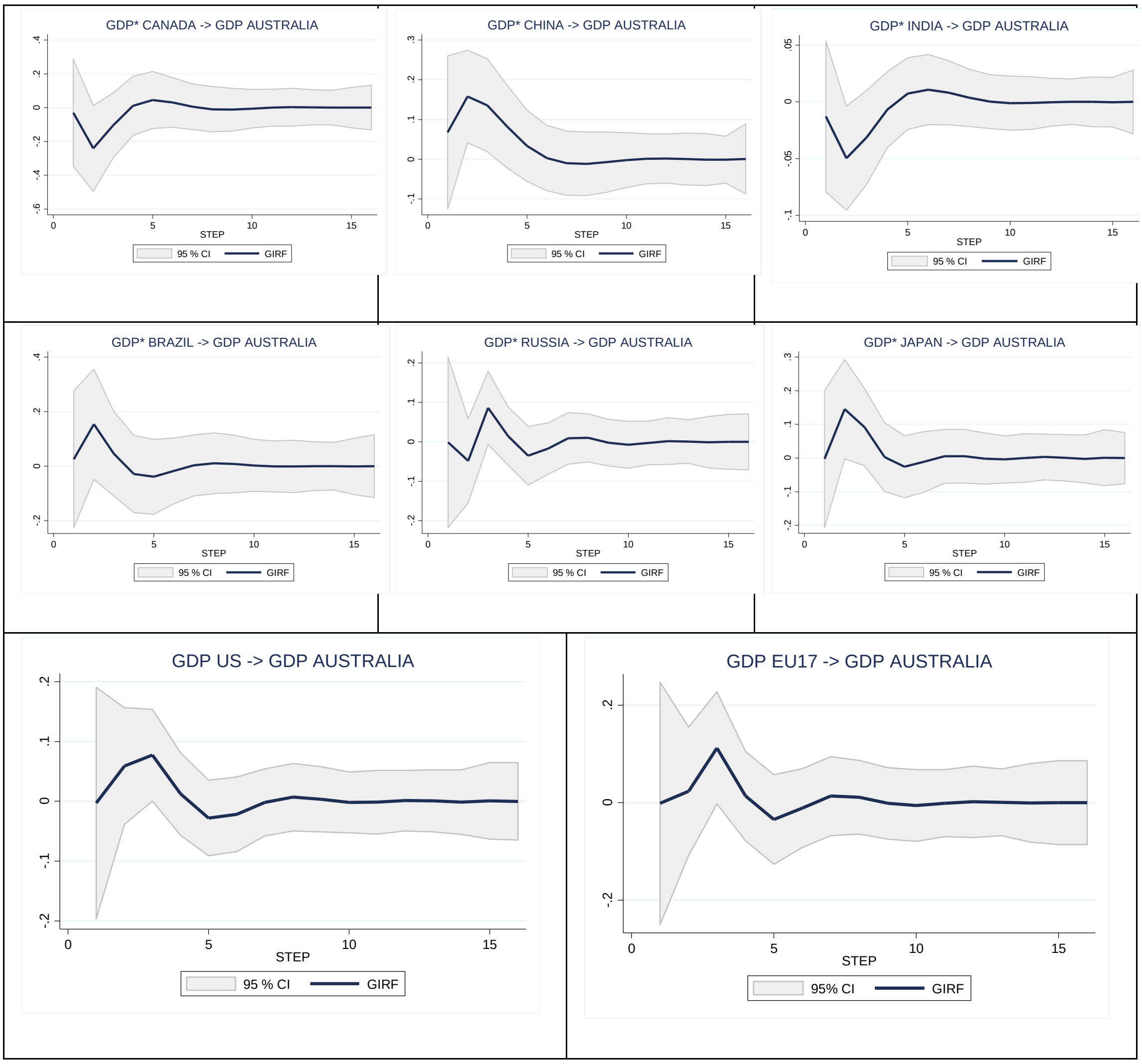
The descriptive statistics and the maximum deviations of each Canadian GIRF are summarized in Table 7.

Table 7: Descriptive statistics, maximum deviation and Stat. Significance (Canada)

GIRF	Mean	Standard Deviation	Min	Max	Initial Equilibrium Position	Maximum deviation fromequilibrium
GDP* AUSTRALIA -> GDP CANADA	-0.006	0.013	-0.04	0	0	-0.04
GDP* CHINA -> GDP CANADA	0.004	0.019	-0.003	0.071	0	0.071
GDP EU17 -> GDP CANADA	0.007	0.021	0	0.079	0	0.079
GDP* INDIA -> GDP CANADA	-0.007	0.016	-0.061	0	0	-0.061
GDP* JAPAN -> GDP CANADA	-0.002	0.007	-0.025	0.001	0	-0.025
GDP US -> GDP CANADA	0.003	0.011	-0.005	0.043	0	0.043
GDP* BRAZIL -> GDP CANADA	0.003	0.023	-0.061	0.055	0	-0.061
GDP* RUSSIA ->GDP CANADA	-0.045	0.078	-0.271	0	0	-0.271

The response of the Australian GDP in a unit shock on the GDP of the other economies that enter the GVAR is presented in Figure 6.

Figure 6: Response of GDP Australia to GDP Canada, BRICs, Japan, EU17 and US



Finally, the descriptive statistics and the maximum deviations of each Australian GIRF as are summarized in Table 8.

Table 8: Descriptive statistics, maximum deviation and Stat. Significance (Australia)

GIRF	Mean	Standard Deviation	Min	Max	InitialEquilibriumPosition	Maximum deviation fromequilibrium
GDP*CANADA -> GDP AUSTRALIA	-0.02	0.102	-0.391	0.099	0	-0.391
GDP* CHINA -> GDP AUSTRALIA	0.027	0.087	-0.021	0.326	0	0.326
GDP EU -> GDP AUSTRALIA	0.007	0.046	-0.072	0.165	0	0.165

GDP* INDIA -> GDP AUSTRALIA	-0.005	0.025	-0.097	0.011	0	-0.097	
GDP* JAPAN -> GDP AUSTRALIA	0.013	0.053	-0.074	0.158	0	0.158	
GDP US -> GDP AUSTRALIA	0.006	0.039	-0.049	0.139	0	0.139	
GDP* BRAZIL -> GDP AUSTRALIA	0.011	0.078	-0.12	0.281	0	0.281	
GDP* RUSSIA -> GDP AUSTRALIA	0.001	0.04	-0.061	0.132	0	0.132	

From an econometric perspective, we can see that the GIRFs settle down relatively quickly, a fact which implies that the model is stable and is also supported by the eigenvalues of the GVAR model whose moduli are, as expected, less that unity.

4.4 Robustness

Next, we need to ensure the robustness of our results, in the sense that they do not depend critically on the assumptions and calculation on which they were based. In this context, we have to critically assess the results based both on the time period and on the prior distributions used.

To begin with, we restrict the estimation of our model till the beginning of 2007, just before the outburst of the global crisis which changed the overall global dynamics. In this context, the respective GIRF results are presented in Figures B.1-B.6, Appendix. According to our findings, the basic difference between the GIRFs of the base model corresponding to the whole period, and those of the restricted model is the overall fluctuating character of the GIRFs.

More precisely, all the GIRFs of the restricted model present significantly more volatile behavior compared to the base model which could be due to the shorter period investigated and to the increased interconnections between the various economies which were significantly altered to a more similar movement, due to the impact of the enormous global recession. Nevertheless, in general terms, the dynamic responses of each variable in the universe of our model is, roughly speaking, unaffected by the time period studied, since in all cases the GIRFs settle down rather quickly, returning back to their initial equilibrium position, while significant deviations from equilibrium are the same in both periods. Therefore, the robustness of our base model does not seem to be seriously challenged by the change of period.

Next, turning to the selection of priors, no doubt, the *prior distribution* is a key part of Bayesian inference and it is sometimes difficult to select a precise distribution to be used as prior. We know that picking a prior distribution that seems to best represent the set of uncertain parameters in the problem is hard, since this type of knowledge is quite difficult to specify precisely (e.g. Insua and Rugeri, 2000). Hence, it is important to study the sensitivity of posterior inferences.

In a robust approach, and in order to tackle this issue, our analysis was applied to numerous logically and empirically plausible priors selected from relevant *classes* of priors (e.g. Berger, 1985). In fact, in our sensitivity analysis, a collection of individual priors is used which was judged to be reasonable and compatible with the model, as extensively described in a previous section. In this framework, we produced 10,000 computations under the specified alternative priors and the calculated results – which are available upon request – were *not* found to be sensitive to these alternative priors used. This clearly implies that we can safely proceed based on these findings.

Of course, in case the results differed significantly, this would be taken as an indication that the analysis undertaken could not be trusted and further research would be necessary. However, our computational results were found to be robust, since they were, roughly speaking, approximately the same for all priors. For a discussion on the theoretical foundations of prior selection see, for instance, Kass and Wasserman (1996).

5. DISCUSSION

Now, we base our analysis of the results obtained by the Generalized Impulse Response Functions (GIRFs)on the respective 95% confidence intervals, as mentioned earlier. In general, most of the GIRFs suggest increased stability of the economies that enter the model, a finding which is largely consistent with the findings of Dées et *al.* (2005, 2007a), Pesaran et *al.* (2006) and Eickmeier and Ng (2015), who also utilize a large panel of economies.

More specifically, according to Figure 1 and Table 5, we infer that a shock in the BRICs' GDPdoes not create any long lasting deviations to EU17 GDP from its equilibrium position. More precisely, a shock in the GDPs of China and Russia, respectively, has a statistically significant short-run impact on EU17, which lasts less than five (5) quarters. In fact, a shock in the Chinese GDP has a positive impact on the GDP of EU17, while the opposite picture is in force regarding a shock in the Russian GDP. The positive impact of the Chinese GDP to the EU17 GDP could be attributed to the fact thatEU17 and China act as major competitors to the global financial and trade markets. As a result, a potential cut back to the exports of China will largely benefit EU17 since it would be able to substantially subsidize the Chinese exports to the global market.

On the other hand, the negative impact of the Russian GDP on the EU17 GDP could be attributed to the fact that the EU17 economy is largely energy-dependent on the Russian natural gas and oil.Meanwhile, a shock in either Brazil's or India's GDP does not seem to significantly affect EU17. Hence, EU17 seems to be, partly, vulnerable to the shocks of BRICS, a fact that could be attributed to theconstantly rising FDI flows from the BRICs to EU17. Therefore, it is evident that apotential sudden slowdown of the BRICs economies would have a short-run impact onEU17.

Next, according to Figure 3 and Table 6, a shock in the BRICs' GDP does not seem to statistically significantly affect the US GDP with the sole exception of China. More precisely, a shock in the Chinese GDP has a positive short-run impact on the US GDP, which lasts for almost a year, i.e. four (4) quarters. The positive impact of the Chinese GDP on the US GDP could be attributed to the strong trade and financial linkages between the two economies, which is - in general terms - consistent with the work of Bianconi et *al.*(2013).Additionally, the fact that a shock in the rest of the BRICs' economies GDP does not have a statistically significant impact on the US economy could be,at least partly, attributed to the *seignorance* of the US dollar, which seems to act as an adequate protective mechanism of the US economy. This, in turn implies, that a potential sudden slowdown in the BRICs' economies would have little impact on the USA. The empirical results are consistent with the literature arguing that EU17 is more vulnerable to shocks than the US (e.g. Aizenman et *al.* 2011).

Now, turning to the impact of a unit shock in the Interest rates of BRICs on EU17 GDP (Figure 2and Table 5), we infer that both the Brazilian and the Chinese Interest rates have a statistically significant short run-impact on the GDP of EU17. Nevertheless, both effects die out in less than five (5) months, when the EU17 GDP returns back to its initial equilibrium position. Both effects have a positive impact on EU17 GDP, a fact that could be attributed to the increased stability of EU17 when compared to the Chinese and the Brazilian economy, which in turn makes EU17 more attractive to international funds that are risk averse.

A shock in the rest of the BRICs' Interest rate, i.e. India and Russia, does not have a statistically significant impact on EU17 GDP. It should be noted that, according to our findings,againEU17 seems to be partly vulnerable to the BRICs' interest rate shocks.On the other hand, the US GDP seems to be affected by shocks in the interest rates of China (Figure 4 and Table 6). More precisely, the impact of the Chinese Interest rate on the US GDP is positive, in the short-run i.e. three (3) quarters, when the US GDP returns back to its initial equilibrium position. The positive relationship between the Chinese Interest rate and the US GDP could be attributed to the fact that the Yuan is pegged to the dollar while, at the same time, China withholds a significant amount of the US debt, in the form of bonds as reserves, so as to ensure the effective targeting of each exchange rate by the Central Bank.

As far as the response of Canadas' GDP to a unit shock in the GDPs of the rest of the economies is concerned (Figure 5 and Table 7), we can infer that a shock in the US GDP has a positive impact on the Canadian GDP in the short-run, which seems to die out rather quickly, i.e. in less than four (4)quarters. This positive impact could be attributed to the strong trade relationships of Canada with the USA, since the US economy is the main partner of Canada in terms of bilateral trade. Additionally, a shock in the BRICs' GDPs does not have a statistically significant effect on the Canadian GDP with the exception of the Russian GDP. In fact, a shock in the GDP of Russia has a positive short-run impact on the Canadian GDP, which in turn could be attributed to the fact that the two countries share common borders(*border effect).* Also, positive is the impact of a unit shock on either Japan's or Australia's GDP on the Canadian GDP. Nevertheless, all impacts die out in the short-run, i.e. in less than eight (8) quarters, with the Canadian GDP returning back to its initial equilibrium position.

Finally, the response of the Australian GDP on unit shocks on the GDP of the remaining economies is a characteristic example of a very stable GDP (Figure 4 and Table 8) that is practically unaffected by shocks in the rest of the economies. This stability is depicted by the fact that in all cases the confidence intervals do not deviate from zero, which represents the initial equilibrium position of the Australian GDP before the shocks took place. This increased stability of Australia's GDP could be attributed to the lack of significant trade and/or financial relationships between Australia and the rest of the economies that enter the model.

6. CONCLUSION

The point of departure of our investigation for constructing this model has been the need by financial institutions (i.e. banks, insurance companies and pension funds), for an upgraded – compared to previous versions of the GVAR – compact (macro)econometric management tool for commercial and central banking use. In this framework, the (macro)econometric model that we have developed can be used to examine the propagation of shocks across economies. In fact, it can be easily used for analyzing a number of transmission mechanisms, contagion effects and network interdependencies in a global (as well as domestic) setting.

As we know, financial institutions are increasingly vulnerable to the shocks in the economies in which they are exposed, the most characteristic example, probably, being bank lending to multi/international firms whose revenues are experiencing shocks with a country's aggregate demand (Pesaran et *al.* 2004).Hence, the risk analyses of a financial institution's activities need to take into consideration domestic as well as international economic conditions of regions that directly or even indirectly influence the institution loan's portfolio, without neglecting the dominant role of certain economies, such as the USA of EU. For example, the proposed model is able to account for inter-linkages between interest rate movements in China and output in the USA. Also, the use of a regional weighting scheme with dominant economies allows for efficient use of all available data.

In brief, the present paper contributed to the literature as follows: (a) it proposed system estimation for the GVAR with *K* dominants; (b) it provided two procedures in order to test for the existence of dominant entities; (c) it set out a formal method for selecting the dominant entities; (d) it incorporated the transmission channels of global finance and trade; (e) it considered the weights as being endogenous with random coefficients based on the World Input – Output Table (WIOT); (f) it estimated how a slowdown in BRICs will affect EU17 and USA; (g) it incorporated economies that account for 90% of global production; (h) Last, and maybe most importantly, it developed a novel estimation method which relies on Bayesian techniques.

According to our findings, the dominant economies are those of the USA and EU17, while the results suggested that EU17 is more vulnerable than the USA to the shocks of the BRICs, implying that a potential slowdown in the BRICs will primarily affect the EU17 economy. Consistent with the empirical literature, our findings show those both monetary and financial variables, such as interest rates and total credit, have a significant impact on the transmission of shocks.

Of course, our findings could have important policy implications. For instance, our results could be easily used by policy makers, including simulation and scenario analyses. In this context, simulation and scenario analyses could be conducted based on the employed macroeconomic and financial variables in order to study the response of GPD and Interest Rate shocks and especially whether they could reach specific thresholds affecting the economic and financial system's ability to absorb shocks originating in other countries' macroeconomic and financial factors. In such contexts, policy design should take into account the self-reinforcing feedback loops characterizing generalized crises rather than being limited to static exercises and scenarios in which only the domestic macroeconomic environment affects the financial system.

Needless to say, there are several ways in which the present study could be extended. For instance, it could be further investigated whether the US and international financial crisis played a distinct role in each country's financial system and, in this context, whether an endogenously determined structural break could be detected possibly changing the complex interactions between the various economies. Meanwhile, other important financial variables such spreads (e.g. of sovereign bonds compared to US Treasuries), institutional indicators (e.g. financial deepening), and the role of the so-called shadow banking (i.e. other financial institutions excluding Banks, Insurance Companies and Pension funds) could be investigated. Additionally, from a European perspective it would be interesting to split the European data into several regions or even major countries and replicate the empirical analysis in order to analyze how these different entities within the EU are impacted (differently) from other regions/countries.

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TECHNICAL APPENDIX A

In this work we consider the following model for each country ($i = 1, \dots, N$):

$$\underset{(1\times m)}{y'_{it}} = \underset{(1xm)}{a_{io}} + \sum_{l=1}^{L_i} y'_{i,t-l} \underset{(m\times m)}{A_{il}} + \sum_{l=0}^{L_2} y^{*'}{}_{i,t-l} \underset{(m\times m)}{B_{il}} + \sum_{l=0}^{L_3} \underset{(1\times k)}{x'_{t-l}} \underset{(k\times m)}{C_{il}} + u'_{it} \qquad \text{[A1]}$$

where a_{i0} denotes a (*1xm*) vector of *m* intercepts, $\underset{(1\times m)}{y'_{it}} = \left[y_{i,t_1}, \dots, y_{i,t_m} \right]$ denotes the transposed of a (*mx1*) vector $y_{i,t}$ of m variables for country i expressing the so-called endogenous variables; $\underset{(1\times m)}{y^{*'}{}_{i,t}} = \left[y^{*}_{i,t_1}, \dots, y^{*}_{i,t_m} \right]$ denotes the transposed of a (*mx1*) vector $y^{*}{}_{i,t}$, of m foreign-specific variables, and $x'_t = \left[x_{t_1}, \dots, x_{t_k} \right]$ denotes the transposed of a (*kx1*) vector of *k* global variables. In general, the *m* and *k* may be allowed to vary between countries i, that is m_i and k_i for each country $i = 1, \dots, N$. The model can be written in the form:

$$y'_{it} = \underset{(1\times K)}{z'_{it}} \underset{(K\times m)}{\Gamma_i} + u'_i$$

where $K = L_1 + L_2 + L_3 + 2$, and

$$z'_{it} = \left[y'_{i,t-1}, \dots, y'_{i,t-L_1}, y^{*'}_{i,t}, y^{*'}_{i,t-1}, \dots, y^{*'}_{i,t-L_2}, x'_t, x'_{t-1}, \dots, x'_{i,t-L_3} \right].$$

By stacking we obtain:

$$\underset{(T\times m)}{Y_i} = \underset{(T\times K)}{Z_i} \Gamma_i + U_i, \ i = 1, \dots, N \ \text{(A.2)}$$

which is a multivariate regression model for each country. This can be written in the standard form if we stack by columns:

$$\underset{(Tm\times 1)}{y_i} = (I \otimes Z_i) \underset{(Km\times 1)}{\gamma_i} + u_i,\ i = 1,\dots,N \quad \text{(A.3)}$$

where $u_i \sim N(O, \Sigma_{ii} \otimes I)$, and Σ_{ii} is an $m \times m$ covariance matrix for the i-th country. If we write the models in detail we have:

$$y_1 = (I \otimes Z_1)\gamma_1 + u_1$$

$$y_2 = (I \otimes Z_2)\gamma_2 + u_2,$$

$$\dots .$$

$$y_N = (I \otimes Z_N)\gamma_N + u_N,$$

leading to the following compact representation:

$$\underset{(NTm\times 1)}{Y} = X \underset{(NT\times Km)}{\gamma} + u \quad \text{(A.4)}.$$

The covariance of the error term is:

$$\begin{bmatrix} u'_{t1} \\ . \\ . \\ . \\ u'_{tN} \end{bmatrix} \sim N(0, \underset{(Nm\times Nm)}{\Omega} = \begin{bmatrix} \Sigma_{11}\ \Sigma_{12}\ \dots\ \Sigma_{1N} \\ \Sigma_{12}\ \Sigma_{22}\ \dots\ \Sigma_{2N} \\ \Sigma_{1N}\ \Sigma_{2N}\ \dots\ \Sigma_{NN} \end{bmatrix})$$

and each $\underset{(m\times m)}{\Sigma_{ij}}$, represents a covariance matrix between the error terms of countries i and j.

Moreover, $X = \begin{bmatrix} X_1 \\ X_2 \\ . \\ . \\ . \\ X_N \end{bmatrix}$ and $\gamma = \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ . \\ . \\ . \\ \gamma_N \end{bmatrix}$.

From these equations we obtain:

$$y'_{it} = \tilde{z}'_{it}\tilde{\Gamma}_i + z^{*'}_{it}\Delta_i + u'_{it} \text{ (A.5)}$$

Where $z^{*'}_{it} = \left[y^{*'}_{i,t}, y^{*'}_{i,t-1},..., y^{*'}_{i,t-L_2}\right]$ are the foreign specific variables, while $\tilde{z}'_{it}$ represents the own lags and the global variables. For all observations this model can be written as

$$Y_i = \tilde{Z}_i\tilde{\Gamma}_i + Z^*_i\Delta_i + U_i,\ i = 1,..., N \text{ , or} \quad \text{(A.6)}$$

$$y_i = \left(I \otimes \tilde{Z}_i\right)\tilde{\gamma}_i + \left(I \otimes Z^*_i\right)\delta_i + u_i = \tilde{X}_i\tilde{\gamma}_i + X^*_i\delta_i + u_i,\ i = 1,..., N \text{ (A.7)}$$

For the foreign-specific variables we have:

$$y^{*'}_{it} = \sum_{c=1}^{N} w_{ic}y'_{ct} = w'_{it} \underset{(N\times m)}{Y_t} \text{ (A.8)}$$

Where w_i represents the vector of trade weights of country i with every country $c \neq i = 1,..., N-1$, with $w_{ii} = 0$, $\sum_{c\neq i} w_{ic} = 1$. Writing the above equations in expanded form we have:

$$y^{*'}_{1t} = w'_{1t} \underset{(N\times m)}{Y_t},$$

$$y_{2t}^{*\prime} = w_{2t}' \underset{(N\times m)}{Y_t},$$

$$\dots$$

$$y_{Nt}^{*\prime} = w_{Nt}' \underset{(N\times m)}{Y_t} \quad \text{(A.9)}$$

And by stacking we obtain:

$$\underset{(N\times m)}{Y_t^*} = \underset{(N\times N)}{W_t} Y_t \, \text{(A.10)}$$

Where W represents the $N \times N$ matrix of trade weights, and Y_t^* is an $N \times m$ matrix whose rows represent the m foreign – specific variables for the row country, for a given observation.

The likelihood function of the system[8] can be obtained as follows if we combine observations of all countries, variables and time periods:

$$L(\gamma,\Omega) = |\Omega|^{-T/2} \exp\left\{-\tfrac{1}{2} tr(Y - X\Gamma)' \Omega^{-1}(Y - X\Gamma)\right\} \propto$$

$$|\Omega|^{-T/2} \exp\left\{-\tfrac{1}{2}(\gamma - \hat{\gamma})' (\Omega^{-1} \otimes X'X)(\gamma - \hat{\gamma})\right\} |\Omega|^{-(T-p)/2} \exp\left\{-\tfrac{1}{2} tr\Omega^{-1}(Y - X\Gamma)'(Y - X\Gamma)\right\} \propto \quad \text{(A.11)}$$

$$N\left(\gamma \mid \hat{\gamma}, \Omega \otimes (X'X)^{-1}\right) \times IW\left(\Omega \mid (Y - X\Gamma)'(Y - X\Gamma), \mathrm{N}Tm - (\mathrm{K}x + m + 1)\right),$$

Where IW denotes the inverted Wishart distribution

[8] For a single country see Kadiyala and Carlsson (1997, p. 101) and Koop (2013, pp. 178-179 and 195-199) or Korobilis (2013b, p. 4).

$$\Gamma = \left[\tilde{\gamma}_1 \ \dots \ \tilde{\gamma}_N \dots \tilde{\delta}_1 \ \dots \tilde{\delta}_n\right], \ X = \begin{bmatrix} \tilde{X}_1 \\ \dots \\ \tilde{X}_N \\ \tilde{Z}_1 \\ \dots \\ \tilde{Z}_N{}^* \end{bmatrix} \quad \text{(A.12)}$$

$$X_i = I \otimes Z_i, \ i = 1,\dots,N$$

Ever since West (1987) or Feller (1966, par. 6.2, p. 170) we know that :

$$\tfrac{a}{2}\exp\{-a|z|\} = \int_0^\infty \left(2\pi v^2\right)^{-1/2} v^2 \exp\{-\tfrac{a^2}{2}\}\frac{a^2}{2}dv, \ a > 0$$

and therefore: $Z \mid \tau^2 \sim N(0, \tau^2)$and independently $\tau^2 \sim Exp\left(\tfrac{\lambda^2}{2}\right)$ then Z follows a Laplace distribution which in the context of linear regression yields the LASSO:

$$\min : (y - X\beta)'(y - X\beta) + \lambda \sum_{j=1}^{k} |\beta_j|$$

Since the Laplace distribution is a scale-mixture of normals when the variance follows an exponential distribution and, in turn, this is consistent with the LASSO estimator, the scale-mixture property can be used in a Bayesian context to impose tight priors in the context of over-parametrized Bayesian vector autoregressions.

Koop (2013, pp. 197-199) describes a procedure involving priors on large covariance matrices which have the standard decomposition $\Sigma^{-1} = \Psi\Psi'$ and Ψ is upper-triangular. For the diagonal elements he assumes independent gamma priors of the form $\psi_{jj}^2 \sim G(1, 1)$ if data are standardized. For the off-diagonal elements he proposes an

SSVS prior which is essentially N(0,1) or N(0,0.1) with equal probabilities ½. Recently, Huang and Wand (2013) have proposed a prior for large sparse positive definite matrices where control is allowed over the standard deviations and the correlation coefficients. The proposed family is defined as follows:

$$\underset{(K'\times K')}{\Sigma} \mid a_1,\ldots a_p \sim IW\left(\overline{A}, \nu + K' - 1\right) \text{(A.13)}$$

where $\overline{A} = 2\nu diag\left(a_1^{-1},\ldots,a_{K'}^{-1}\right)$, where K'=Km

$$a_k \sim IG\left(\tfrac{1}{2}, \tfrac{1}{A_k^2}\right), k = 1,..,K' \quad \text{(A. 14)}$$

We remind the density of the Wishart $W(k,S)$ which is:

$$p(\Sigma) \propto |S|^{k/2} \exp\left\{-\tfrac{1}{2} trS\Sigma^{-1}\right\},\ k > 0 \text{ (A. 15)}$$

and Σ, S are positive definite matrices.

In this construction $\nu, A_1,\ldots,A_p$ are positive parameters. Large values of $A_1,\ldots,A_p$ imply weakly informative priors on the standard deviations while the choice $\nu = 2$ leads to uniform priors on the correlation coefficients. The explicit form of the prior is

$$p(\Sigma) \propto |\Sigma|^{-(\nu+2K')/2} \prod_{k=1}^{\nu} \left\{\tfrac{1}{A_k^2} + \nu\left(\Sigma^{-1}\right)_{kk}\right\}^{-(\nu+K')/2} \text{ (A. 16)}$$

The marginal distribution of each correlation coefficient is

$$p\left(\rho_{ij}\right) \propto \left(1-\rho_{ij}^2\right)^{\frac{\nu}{2}-1},\ -1 < \rho_{ij} < 1 \text{(A.17)}$$

Moreover, the marginal distribution of each standard deviation follows a half-*t* distribution with parameters ν, A_k, that is:

$$\sigma_{ii}^2 \mid a_i \sim IW\left(\nu, \tfrac{2\nu}{a_i}\right), \text{ and independently } a_i \sim IG\left(\tfrac{1}{2}, \tfrac{1}{A_i^2}\right),\ i = 1,\ldots,K' \text{ (A.18)}$$

The important property of the distribution which makes it particularly appealing in MCMC computation is that its conditional distribution is still inverse Wishart (conditional on the a_i s) and the posterior conditionals of a_i s are inverse-Gamma distributions (Huang and Wand, 2013, p. 7). Therefore, Gibbs sampling can be implemented easily but there is direct control over the priors of standard deviations and the correlation coefficients.

From (A.11) **γ** appears through a multivariate normal distribution $\mathrm{N}\,(\gamma / \hat{\gamma}, \Omega \otimes (\mathrm{X}'\mathrm{X})^{-1})$ where X'X is of dimension *p* x *p* and can be readily inverted in most cases. Since $\underset{(\mathrm{N}m\, x\, \mathrm{N}m)}{\Omega} = [\underset{(mxm)}{\sum} ij]$ it can be readily computed and Cholesky factorized when m and N are even large, and therefore can be also inverted when m and N are moderate as in our case.

From (A. 11) the conditional posterior of γ is

$$\mathrm{N}\,(\gamma / \hat{\gamma}, \Omega \otimes (\mathrm{X}'\mathrm{X})^{-1})\, p(\gamma) \text{ (A. 19)}$$

We draw $\gamma = \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ . \\ . \\ . \\ \gamma_N \end{bmatrix}$ by country as follows. Suppose:

$$\mathrm{N}\,(\gamma_i / \hat{\gamma}, \gamma_{-1}, \mathrm{V_i})\, \mathrm{p}\,(\gamma_\imath / \gamma_{-\imath}) \text{ (A.20)}$$

denotes the conditional posterior. Then:

$$\gamma_i / \hat{\gamma}, \gamma_{-1} \text{ from (A.19) where } \mathrm{V_i} = \Omega \otimes (\mathrm{X'X})^{-1}$$

and V_i denotes the appropriate covariance (Zellner 1971). Since $p(\gamma)=\prod_{i=1}^{N}\Pi p(\gamma_i)$ it follows $p(\gamma_i / \gamma_{-i}) \propto p(\gamma_i)$ and $p(\gamma_i) \propto \prod_{j=1}^{K} p(\gamma_{ij}), p(\gamma_{ij})$ is a Laplace

$$\gamma_{ij} / a_j \sim N(\overline{\gamma_{ij}}, \tau_j{}^2) \text{ and } \tau_j^2 \sim \exp(\lambda_j^2 / 2) \quad (A.21)$$

the result in (A. 11) can be combined with the result in (A. 20) to yield a normal conditional posterior for γ_i / $\gamma_{-i.}$ Apparently, this decomposition of sampling γ in blocks can be beneficial in larger systems.

With the explicit form of the prior in (A.16) - given a parameterization with given hyper-parameters v and A_K^2 – from (A. 11) the conditional posterior of Ω I is

$p(\Omega/\gamma, \theta) \propto$ IW (Ω / (Y-XΓ)'(Y-XΓ), NT_m – (Kxm+1).

$p(\Omega/\gamma, \theta) \propto$ IW (Ω/ $\overline{A}, \nu - 1, \alpha_1, ..., \alpha_{Km}$) (A. 22)

where all the parameters are defined in (A. 13), (A. 14) and v >0.

In (A.22) the two IW can be combined and the α's can be drawn as in (A. 15) given the A^2_K>0 which are defined in advance.

From (A. 17) and (A. 18) it is reasonable to change informative values for v>2 and if the data are standardized $\alpha_i \approx 1$ so that $A^2 i \approx 4$, although these parameters can vary to maximize *ex – post* forecasting performance.

Conditionally on the weights the Gibbs sampler relying on posterior conditional distributions described above is straightforward. Moreover the posterior conditional distributions of weights in W_t can be drawn en bloc using a Gibbs sampler update relying on the Kalman filter. This procedure reduced considerably the autocorrelation inherent in MCMC and, in lags of order 50, it was negligible.

TECHNICAL APPENDIX B

The Input – Output model describes an economic system based on the following equation for the various (*n*) economic entities:

$$X_i = x_{i1} + x_{i2} + \dots + x_{in} + y_i,\ i = 1, 2, \dots, n \quad \textbf{[B.1]}$$

where: $X_i \geq 0$ is the output of economy *i*, y_i is the final demand for the product of economy *i*, x_{ij} is the product of economy *i* used by economy *j*. Equation (B.**1**) can be written as follows, in matrix form:

$$\mathrm{X} = AX + \mathrm{Y} \quad \textbf{[B.2]}$$

where: X is the vector of outputs, Y is the vector of final demand, and *A* is the so-called input or technical coefficients matrix whose typical element is equal to:

$$(a_{ij})_{nxn} = \frac{x_{ij}}{X_j} \quad \textbf{[B.3]}$$

where: $a_{ij} \geq 0$ is interpreted as the quantity of output from economy *i* required to produce one unit of output in economy *j*[9]. Solving equation **[B.2]** for X, we obtain:

$$\mathrm{X} = (I_n - A)^{-1}\mathrm{Y} \quad \textbf{[B.4]}$$

in which I_n is the $n \times n$ identity matrix, $(I_n - A)^{-1}$ is the so-called Leontief inverse and Y is the column vector of final demand. In the IO approach, the main tools of analysis are the technical coefficients matrix *A* and the Leontief inverse matrix $(I_n - A)^{-1}$, namely the matrix of input-output multipliers of changes in final demand into levels of outputs.

[9] For a detailed discussion of the technical coefficients and their use see, among others, ten Raa (2007).

Now, based on the matrix of technical coefficients *A,* we construct matrix Q, which has the following form:

$$Q \equiv \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nn} \end{pmatrix}$$

where each element of Q is given by the expression:

$$x_{ij} \equiv a_{ij} X_j \,\textbf{[B.5]}$$

and the x_{ij} element of matrix Q expresses the product of economy i that is used from economy j, X_j is the total output of the j-th economy and $a_{ij}$is interpreted as the quantity of output from economy i required to produce one unit of output in economy j, as we have seen earlier. Notice that, in general, $x_{ij} \neq x_{ji}, \forall i, j \in \{1, \ldots, n\}$.

In matrix Q, the row elements express the quantities of goods and services, in value terms, supplied by one economy to itself and all others. Similarly, column elements express quantities obtained by an economy from itself and all others. In general, matrix *Q* expresses an inter-country flow matrix.

Next, we construct the transpose of matrix *Q*, i.e. Q^T**.** In matrix Q^T, the row elements express quantities obtained by an economy from itself and all other economies, whereas the column elements express quantities supplied by an economy to itself and all others. Now, let matrix P be defined as the difference between matrix *Q* and its transpose, Q^T, or in matrix notation: $P \equiv Q - Q^T$

Thus, the typical element, p_{ij}, of matrix P is equal to :

$$p_{ij} \equiv x_{ij} - x_{ji}$$

Each element, p_{ij}, measures the net amount of goods and services of an economyr, in value terms, that flows between itself and each other economy, in a respective year.

Obviously, *P* is a matrix with zeros in the main diagonal. In matrix form:

$$P \equiv \begin{pmatrix} 0 & \dots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{1n} & \dots & 0 \end{pmatrix}$$

since, by definition, every element of its main diagonal indicates the quantities that each economy obtains and supplies to itself, which, in a general equilibrium framework, are equal to each other. Hence, $p_{ii} = 0, and\ p_{ij} = -p_{ji}, \forall i, j \in \{1, \dots, n\}$. Apparently, *P* represents a net inter-country flow matrix.

Since we are interested in constructing the so-called weight matrix, according to the spirit of the GVAR model at the international level (Pesaran et *al.* 2004), we proceed as follows: Let NQ, be the matrix whose typical element, nq_{ij}, is given by the following expression: $nq_{ij} \equiv |p_{ij}| = |x_{ij} - x_{ji}|$ **[B.6]**

A net inter-country flow weight is defined as the ratio of net flows of goods and services between economy *i* and economy *j*, over the total absolute net flows of goods and services realized by economy *i*. Or, in mathematical terms:

$$w_{ij} \equiv \frac{nq_{ij}}{\sum_{j=1}^{n} nq_{ij}} \textbf{[B.7]}$$

Obviously, W is a matrix with zeros in the main diagonal since $nq_{ii} = 0 \text{ and, in general,} w_{ij} \neq w_{ji}, \forall i \neq j$. In matrix form:

$$W \equiv \begin{pmatrix} 0 & \dots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \dots & 0 \end{pmatrix}$$

For instance, the element w_{12} indicates the net flows of goods and services, between economy 1 and economy 2, as a proportion of the total net flows of sector 1.

ECONOMETRIC APPENDIX B

Figure B.1: Response of EU17 GDP to BRICs GDP

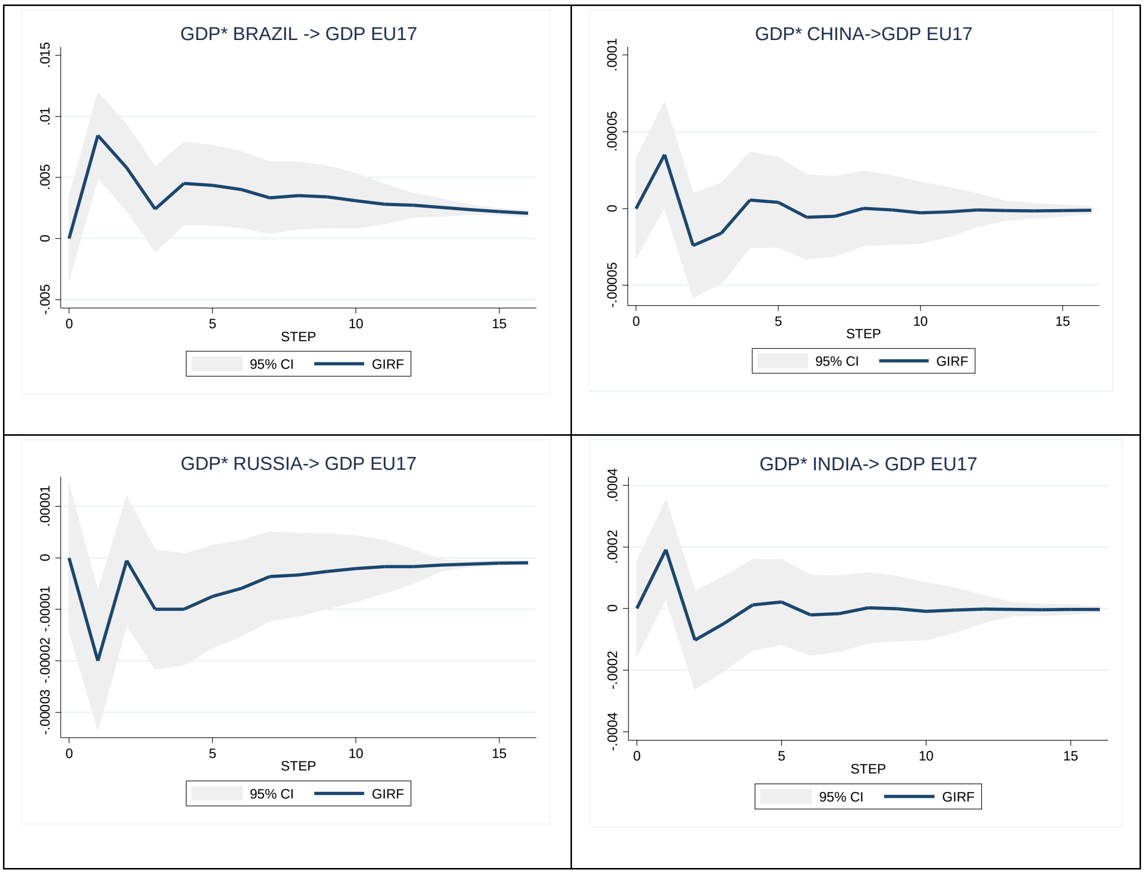
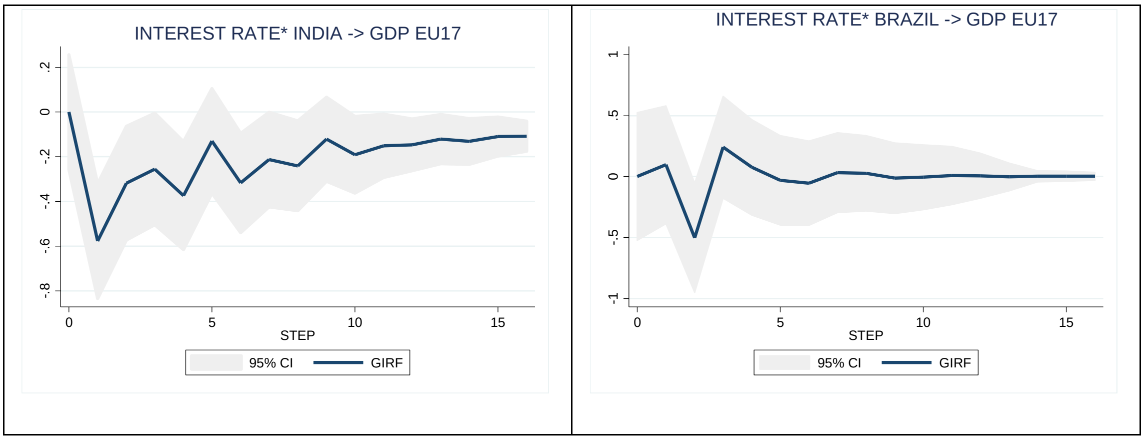


Figure B.2: Response of EU17 GDP to BRICs Interest Rate



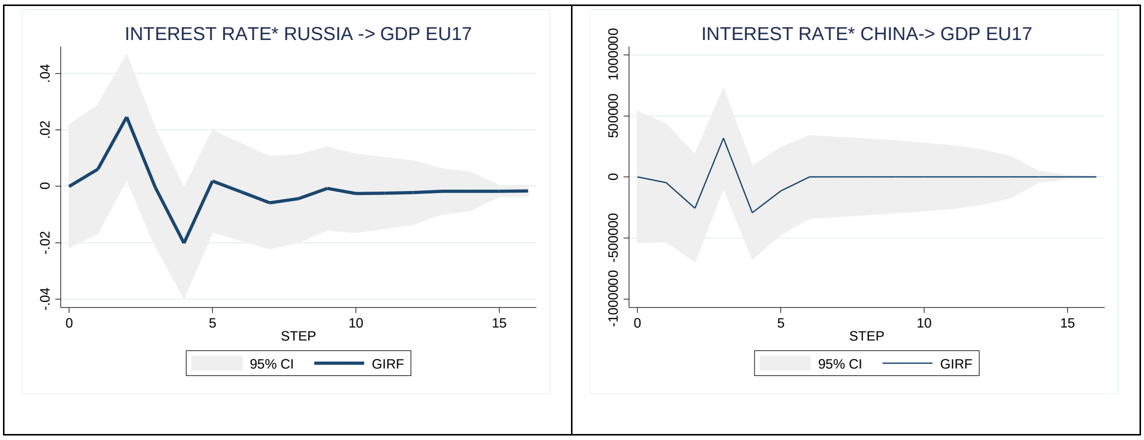


Figure B.3: Response of US GDP to BRICs GDP

Figure B.4: Response of US GDP to BRICs Interest Rate

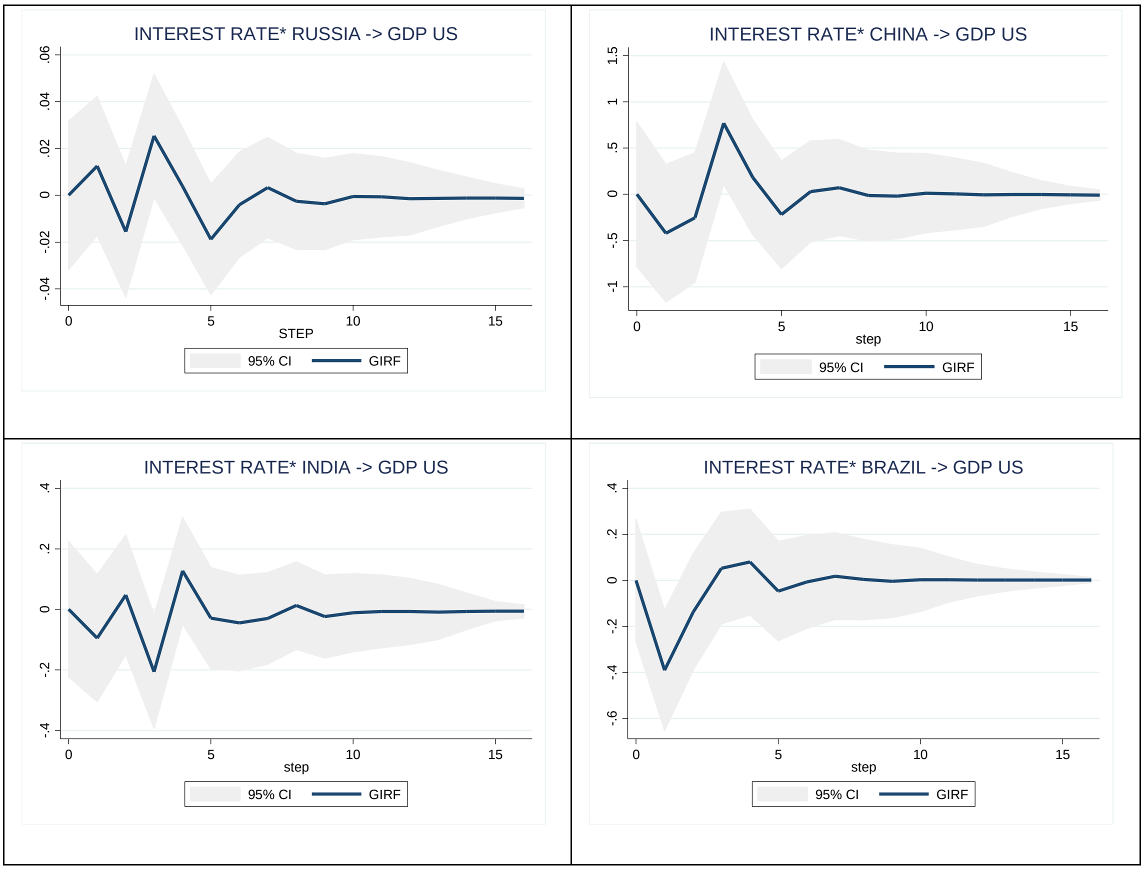
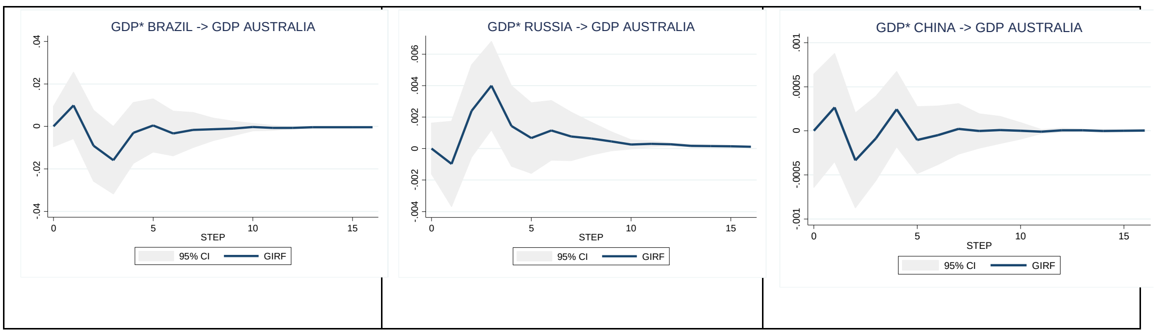


Figure B.5: Response of GDP Australia to GDPBRICs, Japan, Canada, US and EU17



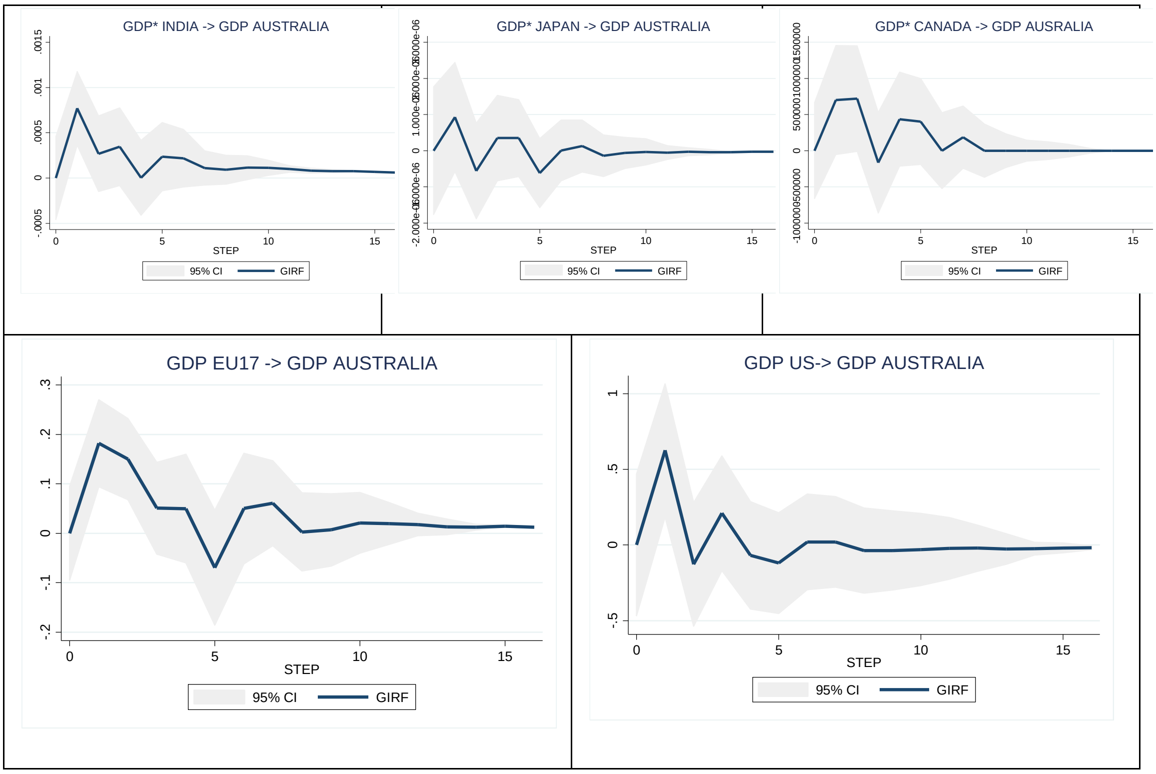
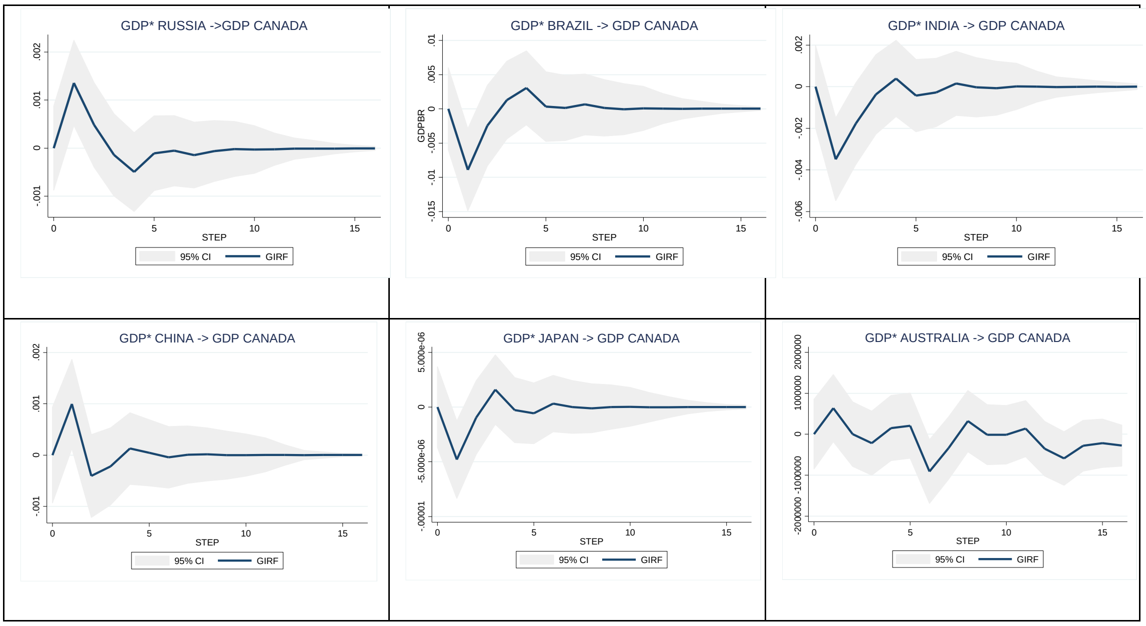
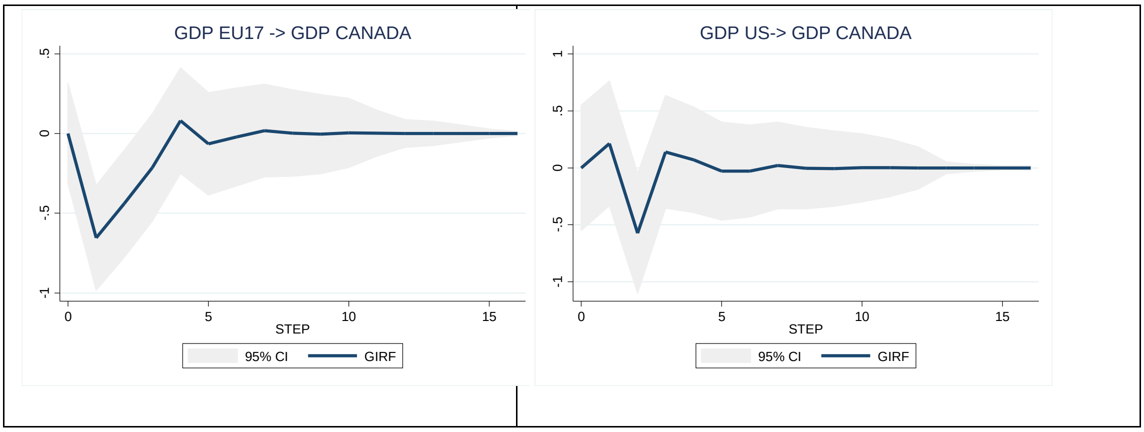


Figure B.6: Response of GDP Canada to GDP BRICs, Japan, Australia, US and EU17




GDP EU17 -> GDP CANADA
GIRF
95% CI
STEP
GDP US-> GDP CANADA
95% CI
GIRF
STEP