Theory and Practice of GVAR Modeling*

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Abstract

The Global Vector Autoregressive (GVAR) approach has proven to be a very useful approach to analyze interactions in the global macroeconomy and other data networks where both the cross-section and the time dimensions are large. This paper surveys the latest developments in the GVAR modeling, examining both the theoretical foundations of the approach and its numerous empirical applications. We provide a synthesis of existing literature and highlight areas for future research.

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1 Introduction

Individual economies in the global economy are interlinked through many different channels in a complex way. These include sharing scarce resources (such as oil and other commodities), political and technological developments, labor and capital movements across countries, cross-border trade in financial assets as well as trade in goods and services. Even after allowing for such effects, there might still be residual interdependencies due to unobserved interactions and spillover effects not taken properly into account by using the common channels of interactions. Taking account of these channels of interactions pose a major challenge to modelling the global economy, conducting policy simulations and counterfactual scenario analyses.

The Global VAR (GVAR) approach, originally proposed in Pesaran et al. (2004), provides a relatively simple yet effective way of modelling interactions in a complex high-dimensional system such as the global economy. Although GVAR is not the first large global macroeconomic model of the world economy, its methodological contributions lay in dealing with the curse of dimensionality (i.e. the proliferation of parameters as the dimension of the model grows) in a theoretically coherent and statistically consistent manner. Other existing large models are often incomplete and do not present a closed system, which is required for simulation analysis, see Granger and Jeon (2007) for a recent overview of global models.

The GVAR model was developed in the aftermath of the 1997 Asian financial crisis to quantify the effects of macroeconomic developments on the losses of major financial institutions. It was clear then that all major banks are exposed to risk from adverse global or regional shocks, but quantifying these effects required a coherent and simple-to-simulate global macroeconomic model. The GVAR approach provides a useful and practical way of building such a model, and, although developed originally as a tool for credit risk analysis, it soon became apparent that it has numerous other applications. This paper surveys the GVAR approach, focusing on theoretical foundations of the approach as well as its empirical applications.

The GVAR can be briefly summarized as a two-step procedure. In the first step, small-scale country-specific models are estimated conditional on the rest of the world. These models are represented as augmented VAR models, denoted as VARX* and feature domestic variables and weighted cross-section averages of foreign variables, which are also commonly referred to as 'star variables', which are treated as weakly exogenous (or long-run forcing). In the second step, individual country VARX* models are stacked and solved simultaneously as one large global VAR model. The solution can be used for shock scenario analysis and forecasting as is usually done with standard low-dimensional VAR models.

The GVAR approach has been applied to a number of diverse problems. Individual units need not necessarily be countries, but could be regions, industries, goods categories, banks, municipalities, or sectors of a given economy, just to mention a few notable examples. Mixed cross-section GVAR models, for instance linking country data with firm-level data, have also been considered in the literature. The GVAR approach is conceptually simple, although it requires some programming skills since it handles large data sets, and it is not yet incorporated in any of the mainstream econometric software packages. Fortunately, an open source toolbox developed by Smith and Galesi (2014) together with a global macroeconomic data-set, covering the period 1979-2013, can be obtained from the web at: https://sites.google.com/site/gvarmodelling/. This toolbox has greatly facilitated empirical research using the GVAR methodology.

We begin the survey with an introduction to the GVAR approach as originally proposed by Pesaran et al. (2004), and briefly compare it to the other main approaches to modelling large data-sets (Section 2). We then review conditions (on the underlying unobserved high-dimensional VAR data generating process) that justify the individual equations estimated in the GVAR approach when N and T (the time dimension) are large, and of the same order of magnitude (Section 3). Next, we survey the impulse response analysis (Section 4), forecasting (Section 5), analysis of long-run (Section 6), and specification testing (Section 7) in the GVAR approach. Last but not least, we review empirical GVAR applications (Section 8). We separate forecasting from non-forecasting applications, and we divide the latter group of empirical papers into global applications (featuring countries) and the remaining sectoral/other applications, where cross-section units represent sectors, industries or regions within a given economy. The last section presents some concluding remarks.

2 Modelling interconnections using GVAR

The GVAR approach was originally proposed by Pesaran et al. (2004) (PSW) as a pragmatic approach to building a coherent global model of the world economy. We follow the exposition of PSW and introduce the GVAR approach initially without the inclusion of common variables.

Consider a panel of N cross-section units, each featuring k_i variables observed during the time periods $t = 1, 2, ..., T$. Let $\mathbf{x}_{it}$ denote a $k_i \times 1$ vector of variables specific to cross-section unit i in time period t, and let $\mathbf{x}_t = (\mathbf{x}'_{1t}, \mathbf{x}'_{2t}, ..., \mathbf{x}'_{Nt})'$ denote a $k \times 1$ vector of all the variables in the panel, where $k = \sum_{i=1}^{N} k_i$. At the core of the GVAR approach are small-scale country specific conditional models that can be estimated separately. These individual country models explain the domestic variables of a given economy, $\mathbf{x}_{it}$, conditional on country-specific cross-section averages of foreign variables, collected in the $k^* \times 1$ vector

$$\mathbf{x}^*_{it} = \tilde{\mathbf{W}}'_i \mathbf{x}_t, \tag{1}$$

for $i = 1, 2, ..., N$, where $\tilde{\mathbf{W}}_i$ is $k \times k^*$ matrix of country-specific weights, typically constructed using data on bilateral foreign trade or capital flows.[1] Both k_i and k^* are treated as small (typically 4 to 6). A larger number of domestic variables can be easily incorporated within the GVAR framework as well by using shrinkage type methods applied to the country-specific sub-models. $\mathbf{x}_{it}$ is modeled as a VARX* model, namely a VAR model augmented by the vector of the 'star' variables $\mathbf{x}^*_{it}$, and their lagged values,

$$\mathbf{x}_{it} = \sum_{\ell=1}^{p_i} \mathbf{\Phi}_{i\ell} \mathbf{x}_{i,t-\ell} + \mathbf{\Lambda}_{i0} \mathbf{x}^*_{it} + \sum_{\ell=1}^{q_i} \mathbf{\Lambda}_{i\ell} \mathbf{x}^*_{i,t-\ell} + \boldsymbol{\varepsilon}_{it}, \tag{2}$$

for $i = 1, 2, ..., N$, where $\mathbf{\Phi}_{i\ell}$, for $\ell = 1, 2, ..., p_i$, $\mathbf{\Lambda}_{i\ell}$, for $\ell = 0, 1, 2, ...q_i$, are $k_i \times k_i$ and $k_i \times k^*$ matrices of unknown parameters, respectively, and $\boldsymbol{\varepsilon}_{it}$ are $k_i \times 1$ error vectors. We continue to abstract from the deterministic terms and observed common effects from the country-specific conditional VARX* models in (2). Star variables $\mathbf{x}^*_{it}$ in country-specific models (2) can, under conditions reviewed in Section 3, be treated as weakly exogenous for the purpose of estimation of unknown coefficients of the conditional country models.

Let $\mathbf{z}_{it} = (\mathbf{x}'_{it}, \mathbf{x}^{*\prime}_{it})'$ be $k_i + k^*$ dimensional vector of domestic and country-specific foreign

[1] It is straightforward to accommodate different number of star variables across countries (k^*_i instead of k^*), if desired.

variables included in the sub-model of country i and re-write (2) as

$$\mathbf{A}_{i0}\mathbf{z}_{it} = \sum_{\ell=1}^{p} \mathbf{A}_{i\ell}\mathbf{z}_{it-\ell} + \boldsymbol{\varepsilon}_{it}, \tag{3}$$

where

$$\mathbf{A}_{i0} = \left(\mathbf{I}_{k_i}, -\boldsymbol{\Lambda}_{i0}\right), \; \mathbf{A}_{i\ell} = \left(\boldsymbol{\Phi}_{i\ell}, \boldsymbol{\Lambda}_{i\ell}\right) \text{ for } \ell = 1, 2, ..., p,$$

$p = \max_i \left(p_i, q_i\right)$, and define $\boldsymbol{\Phi}_{i\ell} = \mathbf{0}$ for $\ell > p_i$, and similarly $\boldsymbol{\Lambda}_{i\ell} = 0$ for $\ell > q_i$. Individual country-models in (3) can be equivalently written in the form of error-correction representation,

$$\Delta\mathbf{x}_{it} = \boldsymbol{\Lambda}_{i0}\Delta\mathbf{x}_{it}^{*} - \boldsymbol{\Pi}_i\mathbf{z}_{i,t-1} + \sum_{\ell=1}^{p} \mathbf{H}_{i\ell}\Delta\mathbf{z}_{i,t-1} + \boldsymbol{\varepsilon}_{it}, \tag{4}$$

where $\Delta = 1 - L$ is the usual first difference operator, and

$$\boldsymbol{\Pi}_i = \mathbf{A}_{i0} - \sum_{\ell=1}^{p} \mathbf{A}_{i\ell}, \text{ and } \mathbf{H}_{i\ell} = -\left(\mathbf{A}_{i,\ell+1} + \mathbf{A}_{i,\ell+2} + ... + \mathbf{A}_{i,\ell+p}\right).$$

Econometric theory for estimating VARX$^*\left(p_i, q_i\right)$ models with weakly exogenous $I\left(1\right)$ regressors have been developed by Harbo et al. (1998) and Pesaran et al. (2000). The assumption of weak exogeneity can be easily tested as outlined in Section 7.1 of PSW, and typically is not rejected, when the economy under consideration is small relative to the rest of the world and the weights used in the construction of the star variables are granular.

It is clear from (4) that country specific models allow for cointegration both amongst domestic variables as well as between domestic and foreign (star) variables. In particular, assuming $\mathbf{z}_{it}$ is $I\left(1\right)$, the rank of $\boldsymbol{\Pi}_i$, denoted as $r_i = rank\left(\boldsymbol{\Pi}_i\right) \leq k_i$, specifies the number of cointegrating relationships that exist among the domestic and country-specific foreign variables in $\mathbf{z}_{it}$; and $\boldsymbol{\Pi}_i$ can be decomposed as

$$\boldsymbol{\Pi}_i = \boldsymbol{\alpha}_i\boldsymbol{\beta}_i',$$

where $\boldsymbol{\alpha}_i$ is $k_i \times r_i$ full column rank loading matrix and $\boldsymbol{\beta}_i$ is the $\left(k_i + k^*\right) \times r_i$ full column rank matrix of cointegrating vectors. It is well known that this decomposition is not unique and the identification of long-run relationships requires theory-based restrictions (see Section 6).

Country models in (2) resemble the small open economy (SOE) macroeconomic models in the literature, where domestic variables are modelled conditional on the rest of the world. The data shrinkage given by (1) solves the dimensionality problem. Under what conditions it is valid to specify (2) is reviewed in Section 3. The estimation of country models in (2), which allows for cointegration within and across countries (via the star variables), is the first step of the GVAR approach.

The second step of the GVAR approach consists of stacking estimated country models to form one large global VAR model. Using the $(k_i + k^*) \times k$ dimensional 'link' matrices $\mathbf{W}_i = \left(\mathbf{E}_i', \tilde{\mathbf{W}}_i'\right)$, where $\mathbf{E}_i$ is $k \times k_i$ dimensional selection matrix that select $\mathbf{x}_{it}$, namely $\mathbf{x}_{it} = \mathbf{E}_i'\mathbf{x}_t$, and $\tilde{\mathbf{W}}_i'$ is the weight matrix introduced in (1) to define country-specific foreign star variables. We have

$$\mathbf{z}_{it} = \left(\mathbf{x}_{it}', \mathbf{x}_{it}^{*\prime}\right)' = \mathbf{W}_i\mathbf{x}_t. \tag{5}$$

Using (5) in (3) yields

$$\mathbf{A}_{i0}\mathbf{W}_i\mathbf{x}_t = \sum_{\ell=1}^{p} \mathbf{A}_{i\ell}\mathbf{W}_i\mathbf{x}_{t-\ell} + \boldsymbol{\varepsilon}_{it},$$

and stacking these models for $i = 1, 2, ..., N$, we obtain

$$\mathbf{G}_0\mathbf{x}_t = \sum_{\ell=1}^{p} \mathbf{G}_\ell\mathbf{x}_{t-\ell} + \boldsymbol{\varepsilon}_t, \tag{6}$$

where $\boldsymbol{\varepsilon}_t = (\boldsymbol{\varepsilon}_{1t}', \boldsymbol{\varepsilon}_{2t}', ..., \boldsymbol{\varepsilon}_{Nt}')'$, and

$$\mathbf{G}_\ell = \begin{pmatrix} \mathbf{A}_{1,\ell}\mathbf{W}_1 \\ \mathbf{A}_{2,\ell}\mathbf{W}_2 \\ \vdots \\ \mathbf{A}_{N,\ell}\mathbf{W}_N \end{pmatrix}.$$

If matrix $\mathbf{G}_0$ is invertible, then by multiplying (6) by $\mathbf{G}_0^{-1}$ from the left we obtain the solution to the GVAR model

$$\mathbf{x}_t = \sum_{\ell=1}^{p} \mathbf{F}_\ell\mathbf{x}_{t-\ell} + \mathbf{G}_0^{-1}\boldsymbol{\varepsilon}_t, \tag{7}$$

where $\mathbf{F}_\ell = \mathbf{G}_0^{-1}\mathbf{G}_\ell$ for $\ell = 1, 2, ..., p$. PSW established that the overall number of cointegrating relationships in the GVAR model (7) cannot exceed the total number of long-run relations $\sum_{i=1}^{N} r_i$ that exist in the underlying country-specific models.

If matrix $\mathbf{G}_0$ is not invertible, then $\text{rank}(\mathbf{G}_0) = k - m < k$ for some $m > 0$. This case is investigated in detail in Chudik, Grossman, and Pesaran (2014) who show that when $\mathbf{G}_0$ is singular (or becomes singular when $N \to \infty$) the system (6) is undetermined , and to complete the GVAR model m additional equations are required for $\mathbf{x}_t$ to be uniquely determined. Chudik, Grossman, and Pesaran (2014) show that these additional equations can be specified in the form of VAR models in cross-sectional averages of $\mathbf{x}_{it}$.

2.1 Introducing common variables

When common variables are present in the country models ($m_\omega > 0$), either as observed common factors or in the form of dominant variables as defined in Chudik and Pesaran (2013b), then the conditional country models need to be augmented by $\boldsymbol{\omega}_t$ and its lagged values, in addition to the country-specific vector of cross-section averages of the foreign variables, namely

$$\mathbf{x}_{it} = \sum_{\ell=1}^{p_i} \mathbf{\Phi}_{i\ell}\mathbf{x}_{i,t-\ell} + \mathbf{\Lambda}_{i0}\mathbf{x}_{it}^* + \sum_{\ell=1}^{q_i} \mathbf{\Lambda}_{i\ell}\mathbf{x}_{i,t-\ell}^* + \mathbf{D}_{i0}\boldsymbol{\omega}_t + \sum_{\ell=1}^{s_i} \mathbf{D}_{i\ell}\boldsymbol{\omega}_{t-\ell} + \boldsymbol{\varepsilon}_{it}, \tag{8}$$

for $i = 1, 2, ..., N$. Both types of variables (common variables $\boldsymbol{\omega}_t$ and cross-section averages $\mathbf{x}_{it}^*$) can be treated as weakly exogenous for the purpose of estimation. As noted above, the weak exogeneity assumption is testable. Also not all of the coefficients $\{\mathbf{D}_{i\ell}\}$ associated with the common variables need be significant and in the case when they are not significant, they could be excluded for the sake of parsimony.[2] The marginal model for the dominant variables can be estimated with or without the feedback effects from $\mathbf{x}_t$. In the latter case, we have the following marginal model,

$$\boldsymbol{\omega}_t = \sum_{\ell=1}^{p_\omega} \mathbf{\Phi}_{\omega\ell}\boldsymbol{\omega}_{t-\ell} + \boldsymbol{\eta}_{\omega t}, \tag{9}$$

which can be equivalently written in the error-correction form as

$$\Delta\boldsymbol{\omega}_t = -\boldsymbol{\alpha}_\omega\boldsymbol{\beta}_\omega'\boldsymbol{\omega}_{t-1} + \textstyle\sum_{\ell=1}^{p_\omega-1} \mathbf{H}_{\omega\ell}\Delta\boldsymbol{\omega}_{t-\ell} + \boldsymbol{\eta}_{\omega t}, \tag{10}$$

[2] Chudik and Smith (2013) find that contemporaneous US variables are significant in individual non-US country models in about a quarter of cases. Moreover, weak exogeneity of the US variables is not rejected in their application.

where $\boldsymbol{\alpha}_\omega \boldsymbol{\beta}'_\omega = \sum_{\ell=1}^{p_\omega} \boldsymbol{\Phi}_{\omega\ell}$, $\mathbf{H}_{\omega\ell} = -\left(\boldsymbol{\Phi}_{\omega,\ell+1} + \boldsymbol{\Phi}_{\omega,\ell+2} + ... + \boldsymbol{\Phi}_{\omega,\ell+p_\omega-1}\right)$, for $\ell = 1, 2, ..., p_\omega - 1$. In the case of $I(1)$ variables, representation (10) clearly allows for cointegration among the dominant variables. To allow for feedback effects from the variables in the GVAR model back to the dominant variables via cross-section averages, VAR model (9) can be augmented by lags of $\mathbf{x}^*_{\omega t} = \tilde{\mathbf{W}}_\omega \mathbf{x}_t$, where $\tilde{\mathbf{W}}_\omega$ is a $k^* \times k$ dimensional weight matrix defining k^* global cross-section averages,

$$\boldsymbol{\omega}_t = \sum_{\ell=1}^{p_\omega} \boldsymbol{\Phi}_{\omega\ell} \boldsymbol{\omega}_{i,t-\ell} + \sum_{\ell=1}^{q_\omega} \boldsymbol{\Lambda}_{\omega\ell} \mathbf{x}^*_{i,t-\ell} + \boldsymbol{\eta}_{\omega t}. \tag{11}$$

Assuming there is no cointegration among the common variables, $\boldsymbol{\omega}_t$, and the cross-section averages, $\mathbf{x}^*_{i,t-\ell}$, (11) can be written as

$$\Delta\boldsymbol{\omega}_t = -\boldsymbol{\alpha}_\omega \boldsymbol{\beta}'_\omega \boldsymbol{\omega}_{t-1} + \sum_{\ell=1}^{p_\omega - 1} \mathbf{H}_{\omega\ell} \Delta\boldsymbol{\omega}_{t-\ell} + \sum_{\ell=1}^{q_\omega - 1} \mathbf{B}_{\omega\ell} \Delta\mathbf{x}^*_{\omega,t-\ell} + \boldsymbol{\eta}_{\omega t}, \tag{12}$$

where $\mathbf{B}_{\omega\ell} = -\left(\boldsymbol{\Lambda}_{\omega,\ell+1} + \boldsymbol{\Lambda}_{\omega,\ell+2} + ... + \boldsymbol{\Lambda}_{\omega,\ell+q_\omega-1}\right)$, and consistently estimated by least squares. Different lag orders for the dominant variables (p_ω) and cross-section averages (q_ω) could be considered. Note that contemporaneous values of star variables do not feature in (12). Similar equations to (11) for dominant variables are estimated in Holly, Pesaran, and Yamagata (2011) and in a stationary setting in Smith and Yamagata (2011).

Conditional models (8) and the marginal model (12) can be combined and solved as a complete global VAR model in the usual way. Specifically, let $\mathbf{y}_t = (\boldsymbol{\omega}'_t, \mathbf{x}'_t)'$ be the $(k + m_\omega) \times 1$ vector of all observable variables. Using (5) in (8) and stacking country-specific conditional models (8) together with the model for common variables (11) yields

$$\mathbf{G}_{y,0} \mathbf{y}_t = \sum_{\ell=1}^{p} \mathbf{G}_{y,\ell} \mathbf{y}_{t-\ell} + \boldsymbol{\varepsilon}_{yt}, \tag{13}$$

where $\boldsymbol{\varepsilon}_{yt} = (\boldsymbol{\varepsilon}'_t, \boldsymbol{\eta}'_{\omega t})'$,

$$\mathbf{G}_{y,0} = \begin{pmatrix} \mathbf{I}_{m_\omega} & \mathbf{0}_{m_\omega \times k} \\ \mathbf{D}_0 & \mathbf{G}_0 \end{pmatrix}, \ \mathbf{G}_{y,\ell} = \begin{pmatrix} \boldsymbol{\Phi}_{\omega\ell} & \boldsymbol{\Lambda}_{\omega\ell} \tilde{\mathbf{W}}_\omega \\ \mathbf{D}_\ell & \mathbf{G}_\ell \end{pmatrix}, \text{ for } \ell = 1, 2, ..., p,$$

$\mathbf{D}_\ell = (\mathbf{D}'_{1\ell}, \mathbf{D}'_{2\ell}, ..., \mathbf{D}'_{N\ell})'$ for $\ell = 0, 1, ..., p$, $p = \max_i \{p_i, q_i, s_i, p_\omega, q_\omega\}$, and we define $\mathbf{D}_{i\ell} = \mathbf{0}$ for

$\ell > s_i$, $\mathbf{\Phi}_{\omega\ell} = \mathbf{0}$ for $\ell > p_\omega$, and $\mathbf{\Lambda}_{\omega\ell} = \mathbf{0}$ for $\ell > q_\omega$. Matrix $\mathbf{G}_{y,0}$ is invertible if and only if $\mathbf{G}_0$ is invertible. Assuming $\mathbf{G}_0^{-1}$ exists, the inverse of $\mathbf{G}_{y,0}$ is

$$\mathbf{G}_{y,0}^{-1} = \begin{pmatrix} \mathbf{I}_{m_\omega} & \mathbf{0}_{m_\omega \times k} \\ -\mathbf{G}_0^{-1}\mathbf{D}_0 & \mathbf{G}_0^{-1} \end{pmatrix},$$

which is a block lower triangular matrix, showing the causal nature of the common (dominant) variables, $\boldsymbol{\omega}_t$. Multiplying both sides of (13) by $\mathbf{G}_{y,0}^{-1}$ we now obtain the following GVAR model for $\mathbf{y}_t$:

$$\mathbf{y}_t = \sum_{\ell=1}^{p} \mathbf{F}_{y,\ell}\mathbf{y}_{t-\ell} + \mathbf{G}_{y,0}^{-1}\boldsymbol{\varepsilon}_{yt}, \tag{14}$$

where $\mathbf{F}_{y,\ell} = \mathbf{G}_{y,0}^{-1}\mathbf{G}_{y,\ell}$, for $\ell = 1, 2, ..., p$.

2.2 GVAR and other approaches to modelling large dimensional systems

The GVAR approach imposes an intuitive structure on cross-country interlinkages and the data shrinkage given by (1) effectively solves the dimensionality problem. No restrictions are imposed on the dynamics of the individual country sub-models, but this can be done if desired. For instance, in the case where the number of lags is relatively large (compared to the time dimension of the panel) and/or the number of country specific variables is moderately large, it is possible to combine the GVAR structure with shrinkage estimation approaches applied to the individual country models.[3]

There are three other main approaches developed for modeling data-sets with a large number of variables: models that utilize common factors, large Bayesian VARs, and Panel VARs. Factor models can be interpreted as data shrinkage procedures, where a large set of variables is shrunk into a small set of factors.[4,5] Estimated factors can be used together with the vector of domestic variables to form a small-scale model, as in factor-augmented VAR models (Bernanke, Bovian, and Eliasz (2005) and Stock and Watson (2005)). Large-scale Bayesian VARs, on the other hand,

[3] Bayesian estimation of country-specific sub-models that feature in the GVAR approach have been considered, for example, by Cuaresma et al. (2014) and Hubert (2014).

[4] Dynamic factor models were introduced by Geweke (1977) and Sargent and Sims (1977), which have more recently been generalized to allow for weak cross-sectional dependence by Forni and Lippi (2001), Forni et al. (2000) and Forni et al. (2004).

[5] Stock and Watson (1999), Stock and Watson (2002), Giannone, Reichlin, and Sala (2005) conclude that only few, perhaps two, factors explain much of the predictable variations, while Bai and Ng (2007) estimate four factors and Stock and Watson (2005) estimate as many as seven factors.

explicitly shrink the parameter space by imposing tight priors on all or a sub-set of parameters. Large-scale Bayesian VARs have been explored, among others, by Giacomini and White (2006), De Mol, Giannone, and Reichlin (2008), Carriero, Kapetanios, and Marcellino (2009), and Banbura, Giannone, and Reichlin (2010). Large Bayesian VARs share many similarities with Panel VARs. The difference between the two is that, while large Bayesian VARs typically treat each variable symmetrically, Panel VARs take into account structure of the variables, namely the division of the variables into different cross-section groups and variable types. Parameter space is shrunk in the Panel VAR literature by assuming that the unknown coefficients can be decomposed into a component that is common across all variables, a cross-section specific component, a variable-specific component, lag-specific component, and idiosyncratic effects, see Canova and Ciccarelli (2013) for a survey.

3 Theoretical justification of the GVAR approach

As noted earlier the GVAR approach builds on separate estimation of country-specific VARX* models assuming that the foreign variables can be treated as weakly exogenous. However, PSW did not provide a theoretical justification and it was left to the subsequent literature to derive conditions under which the weak exogeneity assumption is met. In this section we review the theoretical literature that has developed since the introduction of the GVAR.

3.1 Approximating a global factor model

A first attempt at a theoretical justification of the GVAR approach was provided by Dées et al. (2007) (DdPS), who derived (2) as an approximation to a global factor model. Their starting point is the following canonical global factor model (abstracting again from deterministic terms and observed factors)

$$\mathbf{x}_{it} = \mathbf{\Gamma}_i \mathbf{f}_t + \boldsymbol{\xi}_{it}, \text{ for } i = 1, 2, ..., N. \tag{15}$$

For each i, $\mathbf{\Gamma}_i$ is a $k_i \times m$ matrix of factor loadings, assumed to be uniformly bounded ($\|\mathbf{\Gamma}_i\| < K < \infty$),[6] and $\boldsymbol{\xi}_{it}$ is a $k_i \times 1$ vector of country-specific effects. Factors and the country effects are

[6] We use $\|\mathbf{A}\|$ to denote the spectral norm of the matrix $\mathbf{A}$.

assumed to satisfy

$$
\begin{aligned}
\Delta \mathbf{f}_t &= \boldsymbol{\Lambda}_f(L)\,\boldsymbol{\eta}_{ft},\ \boldsymbol{\eta}_{ft} \sim IID(\mathbf{0}, \mathbf{I}_m), && (16)\\
\Delta \boldsymbol{\xi}_{it} &= \boldsymbol{\Xi}_i(L)\,\mathbf{u}_{it},\ \mathbf{u}_{it} \sim IID(\mathbf{0}, \mathbf{I}_{k_i}),\ \text{for } i = 1, 2, ..., N, && (17)
\end{aligned}
$$

where $\boldsymbol{\Lambda}_f(L) = \sum_{\ell=0}^{\infty} \boldsymbol{\Lambda}_{f\ell} L^{\ell}$, $\boldsymbol{\Xi}_i(L) = \sum_{\ell=0}^{\infty} \boldsymbol{\Xi}_{i\ell} L^{\ell}$, and the coefficient matrices $\boldsymbol{\Lambda}_{f\ell}$ and $\boldsymbol{\Xi}_{i\ell}$, for $i = 1, 2, ..., N$, are uniformly absolute summable, which ensures the existence of $Var(\Delta \mathbf{f}_t)$ and $Var(\Delta \boldsymbol{\xi}_{it})$. In addition, $[\boldsymbol{\Xi}_i(L)]^{-1}$ is assumed to exist.

Under these assumptions, after first differencing (15) and using (17), DdPS obtain

$$
[\boldsymbol{\Xi}_i(L)]^{-1}(1 - L)(\mathbf{x}_{it} - \boldsymbol{\Gamma}_i \mathbf{f}_t) = \mathbf{u}_{it}.
$$

Using the approximation

$$
(1 - L)[\boldsymbol{\Xi}_i(L)]^{-1} \approx \sum_{\ell=0}^{p_i} \boldsymbol{\Phi}_{i\ell} L^{\ell} = \boldsymbol{\Phi}_i(L, p_i),
$$

DdPS further obtain the following approximate VAR(p_i) model with factors

$$
\boldsymbol{\Phi}_i(L, p_i)\,\mathbf{x}_{it} \approx \boldsymbol{\Phi}_i(L, p_i)\,\boldsymbol{\Gamma}_i \mathbf{f}_t + \mathbf{u}_{it}, \tag{18}
$$

for $i = 1, 2, ..., N$. Note that lags of other units do not feature in (18), and the errors, $\mathbf{u}_{it}$, are assumed to be cross-sectionally independently distributed.

Unobserved common factors in (18) can be estimated by linear combinations of cross-section averages of observable variables, $\mathbf{x}_{it}$. As before, let $\tilde{\mathbf{W}}_i$ be the $k \times k^*$ matrix of country-specific weights and assume that it satisfies the granularity conditions given by

$$
\begin{aligned}
\left\| \tilde{\mathbf{W}}_i \right\| &< K N^{-\frac{1}{2}}, \text{ for all } i && (19)\\
\frac{\left\| \tilde{\mathbf{W}}_{ij} \right\|}{\left\| \tilde{\mathbf{W}}_i \right\|} &< K N^{-\frac{1}{2}}, \text{ for all } i, j, && (20)
\end{aligned}
$$

where $\tilde{\mathbf{W}}_{ij}$ are the blocks in the partitioned form of $\tilde{\mathbf{W}}_i = \left(\tilde{\mathbf{W}}_{i1}', \tilde{\mathbf{W}}_{i2}', ..., \tilde{\mathbf{W}}_{iN}' \right)'$, and the constant

$K < \infty$ does not depend on i, j or N. Taking cross-section averages of $\mathbf{x}_{it}$ given by (15) yields

$$\mathbf{x}_{it}^* = \tilde{\mathbf{W}}_i' \mathbf{x}_t = \boldsymbol{\Gamma}_i^* \mathbf{f}_t + \boldsymbol{\xi}_{it}^*,$$

where $\|\boldsymbol{\Gamma}_i^*\| = \left\| \tilde{\mathbf{W}}_i' \boldsymbol{\Gamma} \right\| \leq \left\| \tilde{\mathbf{W}}_i' \right\| \|\boldsymbol{\Gamma}\| < K$, $\boldsymbol{\Gamma} = (\boldsymbol{\Gamma}_1', \boldsymbol{\Gamma}_2', ..., \boldsymbol{\Gamma}_N')'$, and $\boldsymbol{\xi}_{it}^*$ satisfies

$$\Delta \boldsymbol{\xi}_{it}^* = \sum_{j=1}^{N} \tilde{\mathbf{W}}_{ij}' \Delta \boldsymbol{\xi}_{it} = \sum_{j=1}^{N} \tilde{\mathbf{W}}_{ij}' \boldsymbol{\Xi}_i (L) \mathbf{u}_{it}.$$

Assuming that $\Delta \boldsymbol{\xi}_{it}$, $i = 1, 2, ..., N$, are covariance stationary and weakly cross-sectionally dependent, DdPS show that for each t, $\Delta \boldsymbol{\xi}_{it}^* \overset{q.m.}{\rightarrow} \mathbf{0}$ as $N \rightarrow \infty$, which implies $\boldsymbol{\xi}_{it}^* \overset{q.m.}{\rightarrow} \boldsymbol{\xi}_i^*$. It now follows that under the additional condition that $\boldsymbol{\Gamma}_i^*$ has a full column rank,

$$\mathbf{f}_t \overset{q.m.}{\rightarrow} \left(\boldsymbol{\Gamma}_i^{*\prime} \boldsymbol{\Gamma}_i^* \right)^{-1} \boldsymbol{\Gamma}_i^* \left(\mathbf{x}_{it}^* - \boldsymbol{\xi}_i^* \right),$$

as $N \rightarrow \infty$, which justifies using $(1, \mathbf{x}_{it}^{*\prime})'$ as proxies for the unobserved common factors. Thus, for N sufficiently large, DdPS obtain the following country-specific VAR models augmented with $\mathbf{x}_{it}^*$,

$$\boldsymbol{\Phi}_i (L, p_i) \left(\mathbf{x}_{it} - \widetilde{\boldsymbol{\delta}}_i - \widetilde{\boldsymbol{\Gamma}}_i \mathbf{x}_{it}^* \right) \approx \mathbf{u}_{it}, \tag{21}$$

where $\widetilde{\boldsymbol{\delta}}_i$ and $\widetilde{\boldsymbol{\Gamma}}_i$ are given in terms of $\boldsymbol{\xi}_i^*$ and $\boldsymbol{\Gamma}_i^*$. (21) motivates the use of VARX* conditional country models in (2) as an approximation to a global factor model.

Note that the weights $\left\{ \tilde{\mathbf{W}}_i \right\}_{i=1}^{N}$ used in the construction of cross-sectional averages only need to satisfy the granularity conditions (19) and (20), and for large N asymptotics one might as well use equal weights, namely replace all cross-sectional averages by simple averages. For the theory to work, it is only needed that $\Delta \boldsymbol{\xi}_{it}^* \overset{q.m.}{\rightarrow} \mathbf{0}$, at a sufficiently fast rate as $N \rightarrow \infty$. For example, the weights could also be time-varying without any major consequences so long as the granularity conditions are met in each period. In practice, where the number of countries (N) is moderate and spill-over effects could also be of importance, it is advisable to use trade weights that also capture political and cultural interlinkages across countries.[7] Trade weights can also be used to allow for time variations in the weights used when constructing the star variables. This is particularly

[7] Data-dependent rules to construct weights $\left\{ \tilde{\mathbf{W}}_i \right\}$ are considered in Gross (2013).

important in cases where there are sizeable shifts in the trade weights, as has occurred in the case of China and its trading partners over the past three decades. Allowing for such time variations is also important in analyzing the way shocks transmit across the world economy. We review some of the empirical applications of the GVAR that employ time-varying weights below.

The analysis of DdPS has been further extended by Chudik and Pesaran (2011) and Chudik and Pesaran (2013b) to allow for joint asymptotics (i.e. as N and $T \to \infty$, jointly), and weak cross-sectional dependence in the errors in the case of stationary variables.

3.2 Approximating factor augmented stationary high dimensional VARs

Chudik and Pesaran (2011) (CP) consider the conditions on the unknown parameters of a high-dimensional VAR model that would deliver individual country models (2) when N is large. In particular, CP consider the following factor augmented high dimensional VAR model,

$$(\mathbf{x}_t - \mathbf{\Gamma f}_t) = \mathbf{\Theta}\left(\mathbf{x}_{t-1} - \mathbf{\Gamma f}_{t-1}\right) + \mathbf{u}_t, \tag{22}$$

where $\mathbf{x}_t$ is $k \times 1$ vector of endogenous variables, $\mathbf{\Gamma}$ is a $k \times m$ matrix of factor loadings, and $\mathbf{f}_t$ is an $m \times 1$ covariance stationary process of unobserved common factors. To simplify the exposition the lag order, p, is set to unity. CP assume that $\varrho\left(\mathbf{\Theta\Theta}'\right) < 1 - \epsilon$, where $\epsilon > 0$ is an arbitrary small constant that does not depend on N, and $\mathbf{u}_t$ is weakly cross-sectionally dependent such that $\left\|E\left(\mathbf{u}_t\mathbf{u}_t'\right)\right\| = \left\|\mathbf{\Sigma}_u\right\| < K$. The condition that the spectral radius of $\mathbf{\Theta\Theta}'$ is below and bounded away from unity is a slightly stronger requirement than the usual stationarity condition that assumes the eigenvalues of $\mathbf{\Theta}$ lie within the unit circle. The stronger condition is needed to ensure that variances exist when $N \to \infty$, as can be seen from the following illustrative example.

Example 1 *Consider the following simple VAR(1) model,*

$$\mathbf{x}_t = \mathbf{\Theta x}_{t-1} + \mathbf{u}_t.$$

Let

$$\underset{N\times N}{\mathbf{\Theta}} = \begin{pmatrix} \alpha & 0 & 0 & \cdots & 0 \\ \beta & \alpha & 0 & \cdots & 0 \\ 0 & \beta & \alpha & & 0 \\ \vdots & & \ddots & \ddots & \\ 0 & 0 & & \beta & \alpha \end{pmatrix},$$

and suppose that $\mathbf{u}_t \sim IID\left(0, \mathbf{I}_N\right)$. *Hence, we have*

$$\begin{aligned} x_{1t} &= \alpha x_{1,t-1} + u_{1t} \\ x_{it} &= \beta x_{i-1,t-1} + \alpha x_{i,t-1} + u_{it}, \text{ for } i = 2, 3, ..., N. \end{aligned}$$

This model is stationary for any given $N \in \mathbb{N}$, *if and only if* $|\alpha| < 1$. *Nevertheless, the stationarity condition* $|\alpha| < 1$ *is not sufficient to ensure that the variance of* x_{Nt} *is bounded in* N, *and without additional conditions* $Var\left(x_{Nt}\right)$ *can rise with* N. *To see this, note that*

$$\begin{aligned} x_{1t} &= (1-\alpha L)^{-1} u_{1t}, \\ x_{2t} &= (1-\alpha L)^{-2} \beta L u_{1t} + (1-\alpha L)^{-1} u_{2t}, \\ &\vdots \\ x_{Nt} &= \sum_{j=1}^{N} (1-\alpha L)^{-N-1+j} \beta^{N-j} L^{N-j} u_{jt}. \end{aligned}$$

Let $\lambda = \beta^2/(1-\alpha^2)$, *and note that*

$$\begin{aligned} Var(x_{1t}) &= 1/(1-\alpha^2), \\ Var(x_{2t}) &= \frac{1}{1-\alpha^2}\left(\lambda + 1\right), \\ &\vdots \\ Var(x_{Nt}) &= \frac{1}{1-\alpha^2}\left(\lambda^{N-1} + \lambda^{N-2} + ... + \lambda + 1\right). \end{aligned}$$

The necessary and sufficient condition for $Var(x_{Nt})$ *to be bounded in* N *is given by* $\alpha^2 + \beta^2 < 1$. *Therefore, the condition* $|\alpha| < 1$ *is not sufficient if* $N \to \infty$. *The condition* $\varrho\left(\mathbf{\Theta}\mathbf{\Theta}'\right) < 1 - \epsilon$ *implies*

$\alpha^2 + \beta^2 < 1$, *and is therefore sufficient (and in this example it is also necessary) for* $Var(x_{Nt})$ *to be bounded in* N.

Similarly, as in DdPS, it is assumed in (22) that factors are included in the VAR model in an additive way so that $\mathbf{x}_t$ can be written as

$$\mathbf{x}_t = \mathbf{\Gamma f}_t + \boldsymbol{\xi}_t, \tag{23}$$

where $\boldsymbol{\xi}_t = (\mathbf{I}_k - \mathbf{\Theta} L)^{-1} \mathbf{u}_t$, and the existence of the inverse of $(\mathbf{I}_k - \mathbf{\Theta} L)$ is ensured by the assumption on $\varrho(\mathbf{\Theta\Theta}')$ above. One could also consider the alternative factor augmentation setup,

$$\mathbf{x}_t = \mathbf{\Theta x}_{t-1} + \mathbf{\Gamma f}_t + \mathbf{u}_t, \tag{24}$$

where factors are added to the errors of the VAR model, instead of (22), where deviations of $\mathbf{x}_t$ from the factors are modelled as a VAR. But it is important to note that both specifications, (22) and (24), yield similar asymptotic results. The main difference between the two formulations lies in the fact that the factor error structure in (24) results in infinite order distributed lag polynomials (as large N representation for cross-section averages and individual units), whilst the specification (22) yields finite order lag representations. In the case of (24), the infinite lag order polynomials must be appropriately truncated for the purpose of consistent estimation and inference, as in Berk (1974), Said and Dickey (1984) and Chudik and Pesaran (2013a and 2013b).

For any set of weights represented by the $k \times k^*$ matrix $\tilde{\mathbf{W}}_i$ we obtain (using (23))

$$\mathbf{x}_{it}^* = \tilde{\mathbf{W}}_i' \mathbf{x}_t = \mathbf{\Gamma}_i^* \mathbf{f}_t + \boldsymbol{\xi}_{it}^*,$$

where $\mathbf{\Gamma}_i^* = \tilde{\mathbf{W}}_i' \mathbf{\Gamma}$ and

$$\boldsymbol{\xi}_{it}^* = \tilde{\mathbf{W}}_i' (\mathbf{I}_k - \mathbf{\Theta} L)^{-1} \mathbf{u}_t.$$

CP show that if $\tilde{\mathbf{W}}_i$ satisfies (19), then

$$\begin{aligned} \left\| E\left(\boldsymbol{\xi}_{it}^{*}\boldsymbol{\xi}_{it}^{*\prime}\right)\right\| &= \left\| \sum_{\ell=0}^{\infty} \tilde{\mathbf{W}}_i^{\prime}\boldsymbol{\Theta}^{\ell} E\left(\mathbf{u}_{t-\ell}\mathbf{u}_{t-\ell}^{\prime}\right)\boldsymbol{\Theta}^{\ell}\tilde{\mathbf{W}}_i \right\| \\ &\leq \left\|\tilde{\mathbf{W}}_i\right\|^2 \left\|\boldsymbol{\Sigma}_u\right\| \sum_{\ell=0}^{\infty}\left\|\boldsymbol{\Theta}^{\ell}\right\|^2 \\ &= O\left(N^{-1}\right), \end{aligned} \tag{25}$$

where $\left\|\tilde{\mathbf{W}}_i\right\|^2 = O\left(N^{-1}\right)$ by (19), $\left\|\boldsymbol{\Sigma}_u\right\| < K$ by the weak error ($\mathbf{u}_t$) cross-section dependence assumption, and $\sum_{\ell=0}^{\infty}\left\|\boldsymbol{\Theta}^{\ell}\right\|^2 < K$ by the assumption on the spectral radius of $\varrho\left(\boldsymbol{\Theta}\boldsymbol{\Theta}^{\prime}\right)$. (25) establishes that $\boldsymbol{\xi}_{it}^{*} \xrightarrow{q.m.} \mathbf{0}$ (uniformly in i and t) as $N, T \xrightarrow{j} \infty$. It now follows that

$$\mathbf{x}_{it}^{*} - \boldsymbol{\Gamma}_i^{*}\mathbf{f}_t \xrightarrow{q.m.} \mathbf{0}, \text{ as } N, T \xrightarrow{j} \infty, \tag{26}$$

which confirms the well known result that only strong cross-section dependence can survive large N aggregation with granular weights.[8] Therefore, the unobserved common factors can be approximated by cross-section averages $\mathbf{x}_t^{*}$ in this dynamic setting, provided that $\boldsymbol{\Gamma}_i^{*}$ has full column rank.

Now it is easy to see what additional requirements are needed on the coefficient matrix $\boldsymbol{\Theta}$ to obtain country VARX* models in (2) when N is large. The model for the country specific variables, $\mathbf{x}_{it}$, from the system (22) is given by

$$\mathbf{x}_{it} = \boldsymbol{\Theta}_{ii}\mathbf{x}_{it-1} + \sum_{j=1, j\neq i} \boldsymbol{\Theta}_{ij}\left(\mathbf{x}_{j,t-1} - \boldsymbol{\Gamma}_j\mathbf{f}_t\right) + \boldsymbol{\Gamma}_i\mathbf{f}_t - \boldsymbol{\Theta}_i^{\prime}\boldsymbol{\Gamma}_i f_{t-1} + \mathbf{u}_{it}, \tag{27}$$

where $\boldsymbol{\Theta}_{ij}$ are appropriate partitioned sub-matrices of

$$\boldsymbol{\Theta} = \begin{pmatrix} \boldsymbol{\Theta}_{11} & \boldsymbol{\Theta}_{12} & \cdots & \boldsymbol{\Theta}_{1N} \\ \boldsymbol{\Theta}_{21} & \boldsymbol{\Theta}_{22} & & \boldsymbol{\Theta}_{2N} \\ \vdots & & \ddots & \vdots \\ \boldsymbol{\Theta}_{N1} & \boldsymbol{\Theta}_{N2} & \cdots & \boldsymbol{\Theta}_{NN} \end{pmatrix}.$$

[8] See for instance Granger (1987), Forni and Lippi (1997), Pesaran (2003), Zaffaroni (2004), Pesaran (2006) and Chudik and Pesaran (2014).

Suppose now that

$$\|\mathbf{\Theta}_{ij}\| < \frac{K}{N}, \text{ for all } i \neq j. \tag{28}$$

This assumption implies that the matrix $\mathbf{\Theta}_{-i} = (\mathbf{\Theta}_{i1}, \mathbf{\Theta}_{i2}, ..., \mathbf{\Theta}_{i,i-1}, 0, \mathbf{\Theta}_{i,i+1}, ..., \mathbf{\Theta}_{iN})'$ satisfies the granularity condition (19), in particular $\|\mathbf{\Theta}_{-i}\|^2 < KN^{-1}$, and using (25) but with $\mathbf{\Theta}_{-i}$ instead of $\tilde{\mathbf{W}}_i$, we obtain

$$\sum_{j=1, j\neq i} \mathbf{\Theta}_{ij} \left(\mathbf{x}_{j,t-1} - \mathbf{\Gamma}_j \mathbf{f}_t\right) \overset{q.m.}{\to} \mathbf{0} \text{ as } N \to \infty. \tag{29}$$

Finally, substituting (26) and (29) in (27) we obtain the country specific VARX* $(1,1)$ model

$$\mathbf{x}_{it} - \mathbf{\Theta}_{ii}\mathbf{x}_{it-1} - \mathbf{\Lambda}_{i0}\mathbf{x}_t^* - \mathbf{\Lambda}_{i1}\mathbf{x}_{t-1}^* - \mathbf{u}_{it} \overset{q.m.}{\to} \mathbf{0} \ \text{ uniformly in } i, \text{ and as } N \to \infty, \tag{30}$$

where

$$\mathbf{\Lambda}_{i0} = \mathbf{\Gamma}_i \left(\mathbf{\Gamma}^{*\prime}\mathbf{\Gamma}^*\right)^{-1} \mathbf{\Gamma}^*, \text{ and } \mathbf{\Lambda}_{i1} = \mathbf{\Theta}_i' \mathbf{\Gamma}_i \left(\mathbf{\Gamma}^{*\prime}\mathbf{\Gamma}^*\right)^{-1} \mathbf{\Gamma}^*.$$

Requirement (28) with the remaining assumptions in this subsection are thus sufficient to obtain the VARX* models in (2) when N is sufficiently large. In addition to the derivations of large N representations of the individual country models, CP also show that the coefficient matrices $\mathbf{\Theta}_{ii}$, $\mathbf{\Lambda}_{i0}$ and $\mathbf{\Lambda}_{i1}$ can be consistently estimated under the joint asymptotics when N and $T \to \infty$, jointly, plus a number of further assumptions as set out in CP.

It is also important to consider the consequences of relaxing the restrictions in (28). One interesting case is when units have "neighbors" in the sense that there exists some country pairs $j \neq i$ for which $\|\mathbf{\Theta}_{ij}\|$ remains non-negligible as $N \to \infty$. Another interesting departure from the above assumptions is when $\|\mathbf{\Sigma}_u\|$ is not bounded in N, and there exists a dominant unit j for which $\|\mathbf{\Theta}_{ij}\|$ is non-negligible for the other units, $i \in S_j \subseteq \{1, 2, ..., N\}$. These scenarios are investigated in Chudik and Pesaran (2011) and Chudik and Pesaran (2013b), and shown to yield different specifications of the country-specific models featuring additional variables. In such cases to improve estimation and inference one could combine the GVAR approach with various penalized shrinkage methods such as the Bayesian shrinkage, Lasso or other related techniques where the estimation is subject to a penalty, which becomes increasingly more binding as the number of parameters is increased.[9]

4 Conducting Impulse Response Analysis with GVARs

We have seen that under plausible conditions country-specific models can be obtained as large N approximations to global factor augmented models of different forms. Moreover, individual country-specific models can be consistently estimated. In this section, we discuss conducting impulse response analysis with GVARs. The analysis of impulse responses is subject to the same issues as in the small-scale VARs, but further complicated due to the dimensionality of the GVAR model.

For expositional convenience initially suppose that the DGP is given by (7). This model features $k = \sum_{i=1}^{N} k_i$ country-specific errors collected in the vector $\boldsymbol{\varepsilon}_t = (\boldsymbol{\varepsilon}'_{1t}, \boldsymbol{\varepsilon}'_{2t}, ..., \boldsymbol{\varepsilon}'_{Nt})'$, and there are no common variables included in the model. Suppose also that there are k distinct *structural* (orthogonal) shocks. Identification of structural shocks, defined by $\mathbf{v}_t = \mathbf{P}^{-1}\boldsymbol{\varepsilon}_t$, requires finding the $k \times k$ matrix of contemporaneous dependence, $\mathbf{P}$, such that

$$\boldsymbol{\Sigma} = E\left(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}'_t\right) = \mathbf{P}\mathbf{P}'. \tag{31}$$

Therefore, by construction we have $E\left(\mathbf{v}_t\mathbf{v}'_t\right) = \mathbf{I}_k$, and the $k \times 1$ vector of structural impulse response functions is given by

$$\begin{aligned} \mathbf{g}_{vj}(h) &= E\left(\mathbf{x}_{t+h} \middle|\, v_{jt} = 1,\ \mathcal{I}_{t-1}\right) - E\left(\mathbf{x}_{t+h} \middle|\, \mathcal{I}_{t-1}\right), \\ &= \frac{\mathbf{R}_h\mathbf{G}_0^{-1}\mathbf{P}\mathbf{e}_j}{\sqrt{\mathbf{e}'_j\boldsymbol{\Sigma}\mathbf{e}_j}}, \end{aligned} \tag{32}$$

for $j = 1, 2, ..., k$, where $\mathcal{I}_t = \{\mathbf{x}_t, \mathbf{x}_{t-1}, ...\}$ is the information set consisting of all available information at time t, and $\mathbf{e}_j$ is a $k \times 1$ selection vector that selects the variable j, and the $k \times k$ matrices, $\mathbf{R}_h$, are obtained recursively as

$$\mathbf{R}_h = \sum_{\ell=1}^{p} \mathbf{F}_\ell \mathbf{R}_{h-\ell} \text{ with } \mathbf{R}_0 = \mathbf{I}_k \text{ and } \mathbf{R}_\ell = \mathbf{0} \text{ for } \ell < 0.$$

[9] See for instance Tibshirani (1996), Hastie et al. (2009) and De Mol et al. (2008) for a discussion of Lasso and Ridge shrinkage methods. Cuaresma et al. (2014) implemented a number of Bayesian priors in estimating country-specific models in the GVAR.

Expectation operators in (32) are taken assuming that the GVAR model (7) is the DGP. Decomposition (31) is not unique and identification of shocks requires $k(k-1)/2$ restrictions, which is of order $O(k^2)$.[10] Even for moderate values of k, motivating such a large number of restrictions is problematic, especially given that the existing macroeconomic literature focuses mostly on distinguishing between different types of shocks (e.g. monetary policy shocks, fiscal shocks, technology shocks, etc.), and does not provide a thorough guidance on how to identify country origins of shocks, which is necessary to identify all the shocks in the GVAR model.

One possible approach to the identification of the shocks is orthogonalized IR analysis of Sims (1980), who considered setting $\mathbf{P}$ to the Choleski factor of $\mathbf{\Sigma}$. But as is well known the choice of the Choleski factor is not unique and depends on the ordering of variables in the vector $\mathbf{x}_t$. Such an ordering is clearly difficult to entertain in the global setting, but partial ordering could be considered to identify a single shock or a subset of shocks. This is, for example, accomplished by Dées et al. (2007) who identify the US monetary policy shock (by assuming that the US variables come first, and two different orderings for the vector of the US variables are considered). Another well-known possibility to identify shocks in reduced-form VARs include the work of Bernanke (1986), Blanchard and Watson (1986) and Sims (1986) who considered *a priori* restrictions on the contemporaneous covariance matrix of shocks, and Blanchard and Quah (1989) and Clarida and Gali (1994) who consider restrictions on the long-run impact of shocks to identify the impulse responses. A number of authors have also suggested identification of impulse responses by sign restrictions (Faust, 1998, Canova and Pina, 1999, Canova and de Nicoló, 2002, Uhlig, 2005, Mountford and Uhlig, 2009, and Inoue and Kilian, 2013). But it is important to recognize that sign restrictions do not point identify the impulse responses. See Baumeister and Hamilton (2014). Identification of shocks in a GVAR is subject to the same issues as in standard VARs, but is further complicated due to the cross-country interactions and the high dimensionality of the model. Dées, Pesaran, Smith, and Smith (2014) provide a detailed discussion of the identification and estimation of the GVAR model subject to theoretical constraints.

In view of these difficulties, Pesaran et al. (2004), Pesaran and Smith (2006), Dées et al. (2007) and the subsequent literature adopted mainly the generalized IRF (GIRF) approach, advanced in Koop et al. (1996), Pesaran and Shin (1998) and Pesaran and Smith (1998). The GIRF

[10] This corrects the statement on p. 136 in Pesaran et al. (2004).

approach does not aim at identification of shocks according to some canonical system or *a priori* economic theory, but considers a counterfactual exercise where the historical correlations of shocks are assumed as given. In the context of the GVAR model (7) the $k \times 1$ vector of GIRFs is given by

$$\begin{aligned} \mathbf{g}_{\varepsilon j}(h) &= E\left(\mathbf{x}_{t+h} \middle| \, \varepsilon_{jt} = \sqrt{\sigma_{jj}}, \, \mathcal{I}_{t-1}\right) - E\left(\mathbf{x}_{t+h} \middle| \, \mathcal{I}_{t-1}\right), \\ &= \frac{\mathbf{R}_h \mathbf{G}_0^{-1} \boldsymbol{\Sigma} \mathbf{e}_j}{\sqrt{\mathbf{e}_j' \boldsymbol{\Sigma} \mathbf{e}_j}}, \end{aligned} \tag{33}$$

for $j = 1, 2, ..., k,\ h = 0, 1, 2, ...,$ where $\sqrt{\sigma_{jj}} = \sqrt{E(\varepsilon_{jt}^2)}$ is the size of the shock, which is set to one standard deviation (s.d.) of ε_{jt}.[11] The GIRFs can also be obtained for (synthetic) 'global' or 'regional' shocks, defined by $\varepsilon_{m,t}^g = \mathbf{m}'\boldsymbol{\varepsilon}_t$, where the vector of weights, $\mathbf{m}$, relates to a global aggregate or a particular region. The vector of GIRF for the global shock, $\varepsilon_{m,t}^g$, is

$$\begin{aligned} \mathbf{g}_m(h) &= E\left(\mathbf{x}_{t+h} \middle| \, \varepsilon_{m,t}^g = \sqrt{\mathbf{m}'\boldsymbol{\Sigma}\mathbf{m}}, \, \mathcal{I}_{t-1}\right) - E\left(\mathbf{x}_{t+h} \middle| \, \mathcal{I}_{t-1}\right), \\ &= \frac{\mathbf{R}_h \mathbf{G}_0^{-1} \boldsymbol{\Sigma} \mathbf{m}}{\sqrt{\mathbf{m}'\boldsymbol{\Sigma}\mathbf{m}}}. \end{aligned} \tag{34}$$

Closely related to the impulse-response analysis is the forecast-error variance decomposition, which shows the relative contributions of the shocks to reducing the mean square error of forecasts of individual endogenous variables at a given horizon h. In the case of orthogonalized shocks, $\mathbf{v}_t = \mathbf{P}^{-1}\boldsymbol{\varepsilon}_t$, and assuming for the simplicity of exposition that $m_\omega = 0$, the contribution of the j^{th} innovation, v_{jt}, to the mean square error of the h-step ahead forecast of x_{it} is:

$$\mathcal{SFEVD}(x_{it}, v_{jt}, h) = \frac{\sum_{\ell=0}^{h} \left[\mathbf{e}_i' \mathbf{F}^h \mathbf{G}_0^{-1} \mathbf{P} \mathbf{e}_j\right]^2}{\sum_{\ell=0}^{h} \mathbf{e}_i' \mathbf{F}^h \mathbf{G}_0^{-1} \boldsymbol{\Sigma} \mathbf{G}_0^{-1\prime} \mathbf{F}^{h\prime} \mathbf{e}_i}, \tag{35}$$

and since the shocks are orthogonal, it follows that $\sum_{j=1}^{N} \mathcal{SFEVD}(x_{it}, v_{jt}, h) = 1$ for any i and h. In the case of non-orthogonal shocks, the forecast-error variance decompositions need not sum to unity. Analogously to the GIRFs, generalized forecast error variance decomposition corresponding to (35) is given by

$$G\mathcal{FEVD}(x_{it}, \varepsilon_{jt}, h) = \frac{\sigma_{jj}^{-1} \sum_{\ell=0}^{h} \left[\mathbf{e}_i' \mathbf{F}^h \mathbf{G}_0^{-1} \boldsymbol{\Sigma} \mathbf{e}_j\right]^2}{\sum_{\ell=0}^{h} \mathbf{e}_i' \mathbf{F}^h \mathbf{G}_0^{-1} \boldsymbol{\Sigma} \mathbf{G}_0^{-1\prime} \mathbf{F}^{h\prime} \mathbf{e}_i}. \tag{36}$$

[11] Estimation and inference on impulse responses can be conducted by bootstrapping, see Dées et al. (2007) for details.

5 Forecasting with GVARs

Forecasting is another important application of the GVAR approach, which provides a viable alternative to other methods developed for data-sets with a large number of predictors. A difference between GVAR and other data-rich forecasting methods is that GVAR utilizes the structure of the panel, which is assumed to consist of many cross-section units (e.g. countries) with each cross-section unit consisting of a small number of variables. Other data-rich methods, such as Lasso, Ridge, or elastic net (see for instance Tibshirani (1996), De Mol et al. (2008) and Hastie et al. (2009)), factor models (Geweke (1977), Sargent and Sims (1977), and other contributions)[12], or Partial Least Squares (Wold (1982)) typically do not utilize such structure. See Eklund and Kapetanios (2008) and Groen and Kapetanios (2008) for recent surveys of data-rich forecasting methods.

As in the previous section, we shall assume that the DGP is given by the solution of the GVAR, (7). Taking expectations of both sides of (7) for $t = t_0 + h$, conditional on the information set Ω_{t_0}, we obtain

$$E\left(\mathbf{x}_{t_0+h} \middle| \Omega_{t_0}\right) = \sum_{\ell=1}^{p} \mathbf{F}_\ell E\left(\mathbf{x}_{t_0+h-\ell} \middle| \Omega_{t_0}\right) + \mathbf{G}_0^{-1} E\left(\boldsymbol{\varepsilon}_{t_0+h} \middle| \Omega_{t_0}\right), \tag{37}$$

for any $h = 0, 1, 2, ...$ In the case where the conditioning information set Ω_{t_0} is given by all available information up to the period t_0, $\Omega_{t_0} = \mathcal{I}_{xt_0} \equiv \{\mathbf{x}_{t_0}, \mathbf{x}_{t_0-1}, ...\}$ we have

$$E\left(\boldsymbol{\varepsilon}_{t_0+h} \middle| \mathcal{I}_{xt_0}\right) = 0 \text{ for } h > 0, \tag{38}$$

and standard forecasts $E\left(\mathbf{x}_{t_0+h} \middle| \mathcal{I}_{xt_0}\right)$ can be easily computed from (7) recursively using the estimates of $\mathbf{F}_\ell$ and $\mathbf{G}_0^{-1}$, and noting that (38) holds and $E\left(\mathbf{x}_{t'} \middle| \mathcal{I}_{xt_0}\right) = \mathbf{x}_{t'}$ for all $t' \leq t_0$. Forecasts from model (14) featuring observed common variables can be obtained in a similar way.

Generating conditional forecasts for non-standard conditioning information sets with mixed information on (future, present and past values of) variables in the panel is more challenging. This situation could arise for instance in cases where data for different variables are released at different dates, or when mixed information sets are intentionally considered to answer specific questions as

[12] For further development and application of the factor models see Forni and Lippi (2001), Forni et al. (2000), Forni et al. (2004), Stock and Watson (1999), Stock and Watson (2002), Giannone, Reichlin, and Sala (2005), Bai and Ng (2007) and Stock and Watson (2005).

in Bussière et al. (2012). Without loss of generality, and for expositional convenience, suppose that for some date t', the first k_a variables in the vector $\mathbf{x}_{t'}$ belong to Ω_{t_0} and the remaining $k_b = k - k_a$ variables do not, and partition $\boldsymbol{\varepsilon}_t$ as $\boldsymbol{\varepsilon}_t = (\boldsymbol{\varepsilon}'_{at}, \boldsymbol{\varepsilon}'_{bt})'$, and the associated covariance matrix, $\boldsymbol{\Sigma} = E\left(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}'_t\right)$ as

$$\boldsymbol{\Sigma} = \begin{pmatrix} \boldsymbol{\Sigma}_{aa} & \boldsymbol{\Sigma}_{ab} \\ \boldsymbol{\Sigma}_{ba} & \boldsymbol{\Sigma}_{bb} \end{pmatrix}. \tag{39}$$

Then it follows that $E\left(\boldsymbol{\varepsilon}_{at'} \middle| \Omega_{t_0}\right) = \boldsymbol{\varepsilon}_{at'}$, whereas $E\left(\boldsymbol{\varepsilon}_{bt'} \middle| \Omega_{t_0}\right) = \boldsymbol{\Sigma}_{ba}\boldsymbol{\Sigma}_{aa}^{-1}\boldsymbol{\varepsilon}_{at'}$. Let $\hat{\boldsymbol{\Sigma}}$ be an estimate of $\boldsymbol{\Sigma}$, then an estimate of $E\left(\boldsymbol{\varepsilon}_{t'} \middle| \Omega_{mt_0}\right)$ can be computed as

$$E\widehat{\left(\boldsymbol{\varepsilon}_{t\prime} \middle| \Omega_{t_0}\right)} = \begin{pmatrix} \widehat{\boldsymbol{\varepsilon}}_{at'} \\ \widehat{\boldsymbol{\Sigma}}_{ba}\widehat{\boldsymbol{\Sigma}}_{aa}^{-1}\widehat{\boldsymbol{\varepsilon}}_{at'} \end{pmatrix}.$$

for any given $t' \leq t_0 + h$. The conditional forecasts $E\left(\mathbf{x}_{t_0+h} \middle| \Omega_{t_0}\right)$ can then be computed recursively as in (37). One problem is that $\boldsymbol{\Sigma}$ and its four sub-matrices in (39) can have large dimensions relative to the available number of time series observations, and therefore it is not guaranteed that $\hat{\boldsymbol{\Sigma}}_{aa}$ will be invertible. Even if it were, the inverse of sample estimates of $\boldsymbol{\Sigma}$ does not necessarily have good small sample properties when $\boldsymbol{\Sigma}$ is high-dimensional. For these reasons, it is desirable to make use of other covariance matrix estimators with better small sample properties. There are several estimators proposed in the literature for estimation of high-dimensional covariance matrices that can be used, including Ledoit and Wolf (2004), Bickel and Levina (2008), Fan et al. (2008), Friedman et al. (2008), the shrinkage estimator considered in Dées et al. (2014), and the multiple testing approach by Bailey et al. (2014).

The implicit assumption in construction of the GVAR model (7) is invertibility of $\mathbf{G}_0$, which ensures that the model is complete as discussed in Section 2. Forecasting using GVARs when $\mathbf{G}_0$ is singular is investigated in Chudik, Grossman, and Pesaran (2014) who propose augmenting the country-specific equations with additional equations based on cross-section averages and argue that such augmented GVAR specification is preferable when $\mathbf{G}_0$ is singular, whereas the augmentation does not deteriorate the forecasting performance when $\mathbf{G}_0$ is not singular.

The majority of applications of the GVAR approach in the literature are to modelling of the global economy. Therefore, a brief discussion of important issues in forecasting the global economy is in order. There are two important issues in particular: the presence of structural breaks and model uncertainty. Structural breaks are quite likely, considering the diverse set of economies and the time period that span three or more decades, which covers a variety of historical events (financial crises, wars, regime changes, natural disasters, etc.). The timing and the magnitude of breaks and the underlying DGP are not exactly known, which complicates the forecasting problem. Pesaran, Schuermann, and Smith (2009a) address both problems by using a forecast combination method. They considered simple averaging across selected models (AveM) and estimation windows (AveW) as well as across both dimensions, models and windows (AveAve); and obtain evidence of superior performance for their double-average (AveAve) forecasts. These and other forecasting evidence is reviewed in more detail in the next section. Forecast evaluation in the GVAR model is also challenging due to the fact that the multi-horizon forecasts obtained from the GVAR model could be cross-sectionally as well as serially dependent. One statistics to evaluate forecasting performance of the GVAR model is proposed by Pesaran, Schuermann, and Smith (2009a) who develop a panel version of the Diebold and Mariano (1995, DM) DM test assuming cross-sectional independence.

6 Long-run properties of GVARs

6.1 Analysis of long-run

Individual country VARX* models in (2) allow for cointegration among domestic variables as well as between domestic and country-specific cross-section averages of foreign variables. Let $\mathbf{z}_{it} = (\mathbf{x}'_{it}, \mathbf{x}^{*\prime}_{it})'$ be a $(k_i + k^*) \times 1$ vector of domestic and country-specific foreign variables for country i, and denote r_i cointegrating relations among the variables in the vector $\mathbf{z}_{it}$ as $\boldsymbol{\beta}'_i \mathbf{z}_{it}$, where $\boldsymbol{\beta}_i$ is a $(k_i + k^*) \times r_i$ dimensional matrix consisting of r_i cointegrating vectors. The overall number of cointegrating vectors in the stacked GVAR model is naturally reflected in the eigenvalues of the companion representation of the GVAR model. These eigenvalues characterize the dynamic properties of the model which can also be used to examine the overall stability of the GVAR. In particular, when the overall number of cointegrating relations is $r = \sum_{i=1}^{N} r_i$, then $k - r$ eigenvalues of the GVAR model fall on the unit circle, and the remaining eigenvalues fall within the unit circle for the model to be stable.

6.1.1 Testing for number of cointegrating vectors

Testing for the number of cointegrating relations can be conducted using Johansen's trace and maximum eigenvalue test statistics as set out in Pesaran et al. (2000) for models with weakly exogenous $I(1)$ regressors. Small sample evidence typically suggests that the trace test performs better than the maximum eigenvalue test, but both are subject to usual size distortions when the time dimension is not sufficiently large.[13] Selecting the number of cointegrating vectors is important, since misspecification of the rank of the cointegrating space can have severe impact on the performance of the resulting GVAR model, with adverse implications for stability, persistence profiles and impulse responses.

6.1.2 Identification of long-run relations

Once the number of cointegrating vectors is determined, it is possible to proceed with the identification of long-run structural relations and, if desired, to impose over-identifying restrictions from long-run economic theory. These restrictions can then be tested using the log-likelihood ratio test statistics. See Garratt et al. (2006) for a comprehensive review of long-run structural modelling in the macroeconometric literature. The first contribution on the identification of long-run relations in the GVAR literature is Dées, Holly, Pesaran, and Smith (2007) who used bootstrapping to compute critical values for the likelihood ratio tests of overidentifying restrictions on the long-run relations of the country-specific models.

6.1.3 Persistence profiles

The speed of convergence with which the adjustment to long-run relations takes place in the global model can be examined using persistence profiles (PPs). PPs refer to the time profiles of the effects of system or variable-specific shocks on the cointegrating relations, and provide visual evidence regarding the empirical adequacy of the long-run relations. In particular, when the speed of convergence towards a cointegrating relation turns out to be very slow, then this is an important indication that the corresponding cointegrating vector is wrongly imposed, which could arise if the number of cointegrating vectors is not correctly specified, or if long-run over-identifying restrictions

[13] The maximum eigenvalue test statistics is also less robust to departures from normal errors, see Cheung and Lai (1993) for a Monte Carlo evidence.

are imposed that are not supported by the data. See Pesaran and Shin (1996) for a discussion of PPs in cointegrated VAR models and Dées, Holly, Pesaran, and Smith (2007) for implementation of PPs in the GVAR.

6.2 Permanent/transitory component decomposition

Given that the GVAR model provides a coherent description of short-run as well as long-run relations in the global economy, it can be used to provide estimates of steady-states or the permanent components of the variables in the GVAR model. Assuming no deterministic components are present, then the vector of permanent components is simply defined as long-horizon expectations:

$$\mathbf{x}_t^P = \lim_{h\to\infty} E_t\left(\mathbf{x}_{t+h}\right). \tag{40}$$

When the GVAR contains deterministic components, $\mathbf{x}_t^P$ will be given by the sum of the deterministic components and long-horizon expectations of de-trended variables. The vector of deviations from steady-states in both cases is given by

$$\widetilde{\mathbf{x}}_t = \mathbf{x}_t - \mathbf{x}_t^P.$$

Assuming that the information set is non-decreasing over time, it follows from (40) that $\mathbf{x}_t^P = \lim_{h\to\infty} E_t\left(\mathbf{x}_{t+h}^P\right)$, which ensures that the steady-states are time consistent, in the sense that

$$E_t\left(\mathbf{x}_{t+s}^P\right) = \lim_{h\to\infty} E_t\left(\mathbf{x}_{t+s+h}^P\right) = \mathbf{x}_t^P \text{ for any } s = 0, 1, 2, ...,$$

and, in the absence of deterministic components, $\mathbf{x}_t^P$ satisfies the martingale property, $E_t\left(\mathbf{x}_{t+1}^P\right) = \mathbf{x}_t^P$. Such a property is a natural requirement of any coherent definition of steady-states, although it is interesting that this property is not satisfied by the commonly used Hodrick-Prescott (HP) measure of steady-states.

Permanent components can be easily obtained from the estimated GVAR model using the Beveridge-Nelson decomposition, as illustrated in detail by Dées, Holly, Pesaran, and Smith (2007) and Dées, Pesaran, Smith, and Smith (2009). Estimates of steady-states are crucial for the mainstream macroeconomic literature, which focuses predominantly on modelling the business cycle (defined as deviations from the steady-states). The GVAR provides a coherent method for constructing steady-states that reflect global influences and long-run structural relationships within as well as across countries in the global economy.

7 Specification tests

It has become a norm in applied economic research to perform a number of specification tests and robustness checks. DdPS apply a suite of residual-based break tests to check the stability of the coefficients and/or the error variances. Although, in the context of cointegrated models, the possibility of a structural break is relevant for both long-run as well as short-run coefficients, the focus is on the stability of short-run coefficients, as the availability of data hinders any meaningful tests of the stability of cointegrating vectors. In particular, DdPS performed the following tests: Ploberger and Krämer (1992) maximal OLS cumulative sum (CUSUM) statistics; its mean square variant; Nyblom's (1989) tests for the parameter constancy against non-stationary alternatives; the Wald form of Quandt's (1960) likelihood ratio statistics; the mean Wald statistics of Hansen; and Andrews and Ploberger (1994) Wald statistics based on exponential average. The last three tests are Wald-type tests considering a single break at an unknown point. The heterokedasticity-robust version of the tests were also conducted. Stability tests performed are based on residuals of the individual country models, which depend on the dimension of the cointegrating space, and do not require the cointegrating relationships to be identified. The critical values of the tests, computed under the null of parameter stability, can again be calculated using the sieve bootstrap samples. The detail of the bootstrap procedure is given in DdPS (2007, Supplement A). In the context of global macroeconomic modelling, DdPS and other applied papers typically find relatively few incidence of parameter instability, with the main source of instability being due to breaks in error variances as opposed to the slope coefficients. Once breaks in error variances are allowed for, the remaining parameters are reasonably stable. Initially, this seems to be a surprising result, but could be explained by the fact that the equations in the GVAR model are specified conditional on star variables. It is possible to have breaks in processes for the individual variables, but at the same time obtain a stable conditional model if there is evidence of co-breaking across the variables in the global economy.

A number of robustness checks could also be performed to test the sensitivity of the findings to variations of different modelling assumptions. For example, the sensitivity of findings to the number of lags selected in individual country-specific models could be investigated. Selecting shorter lags than required will also manifest itself in serial correlation of residuals. Sensitivity of findings could also be investigated with respect to the choice of the aggregation weights. While weights based on bilateral trade are employed in most applications, the weights based on other measures, such as cross-border financial data, could also be considered, depending on the application in hand. Time-varying pre-determined weights could be considered as well to take into account shifts in bilateral trade over the last couple of decades. Another important modelling choice is the selection of the number of cointegrating relations and possibly over-identifying long-run restrictions. While both can be tested, the small sample performance of these tests could be subject to considerable type I and type II errors, depending on the available sample size. Validity of the chosen long-run relations can be examined by persistence profiles. Another important robustness exercise is to check the sensitivity of findings to the choice of the sample period used for estimation.

8 Empirical applications of the GVAR approach

Since the introduction of the GVAR model by Pesaran et al. (2004), there have been numerous applications of the GVAR approach developed over the last decade in academic literature. The GVAR approach has also found its way in policy institutions, including International Monetary Fund (IMF) and European Central Bank (ECB), where this approach is one of the main techniques used to understand interlinkage across individual countries.[14]

The GVAR handbook edited by di Mauro and Pesaran (2013) provides an interesting collection of a number of GVAR empirical applications from 27 contributors. The GVAR handbook is a useful non-technical resource aimed at a general audience and/or practitioners interested in the GVAR approach. This handbook provides a historical background of the GVAR approach (Chapter 1), describes an updated version of the basic DdPS model (Chapter 2), and then provides 7 appli-

[14] See the following IMF policy publications for examples of the use of GVAR approach by fund staff: 2011 and 2014 Spillover Reports, 2006 World Economic Outlook, October 2010 and April 2014 Regional Economic Outlook: Asia and Pacific Department, April 2014 Regional Economic Outlook: Western Hemisphere Department, November 2012 Regional Economic Outlook: Middle East and Central Asia Department, October 2008 Regional Economic Outlook: Europe, April and October 2012 Regional Economic Outlook: Sub-Saharan Africa, and IMF country reports for Algeria, India, Italy, Russia, Saudi Arabia, South Africa, and Spain.

cations of the GVAR approach on international transmission of shocks and forecasting (Chapters 3-9), 3 finance applications (Chapters 10-12), and 5 regional applications. The applications in the handbook span various areas of the empirical literature. Chapters on international transmission on forecasting investigate, among others, the problem of measuring output gaps across countries, structural modelling, the role of financial markets in the transmission of international business cycles, international inflation interlinkages, and forecasting the global economy. Finance applications include a macroprudential application of the GVAR approach, a model of sovereign bond spreads, and an analysis of cross-country spillover effects of fiscal spending on financial variables. Regional applications investigate the increasing importance of the Chinese economy, forecasting of the Swiss economy, imbalances in the Euro Area, regional and financial spillovers across Europe, and modelling interlinkages in the West African Economic and Monetary Union. We refer the reader to this Handbook for further details on these interesting applications.

The remainder of this section reviews the empirical literature using the GVAR approach focussing on the different types of questions being addressed. We separate forecasting applications from the other applications of the GVAR approach. We divide the latter literature depending on the definition of cross-section units into two broad categories: 'global' finance and macro applications, where units are individual countries, countries grouped into regions, or a mixture of countries/regions and other cross-section units (so-called mixed cross-section GVARs), and 'sectoral and other' applications, in which the main cross-section units are sectors, individual consumer price categories, or other types of cross-section units other than countries.

8.1 Forecasting applications

Pesaran, Schuermann, and Smith (2009a) is the first GVAR forecasting application to the global economy. These authors utilize the version of the GVAR model developed in DdPS and focus on forecasting real as well as financial variables, namely one and four quarters ahead forecasts for real output, inflation, real equity prices, exchange rates and interest rates. As we mentioned earlier in Section 5, forecasting the global economy is challenging due to the likely presence of multiple structural breaks and model uncertainty. The main finding of Pesaran, Schuermann, and Smith (2009a) is that simple averaging across model specifications and estimation windows can make a significant difference. In particular, the double-averaged GVAR forecasts (across windows and models) perform better than the typical univariate benchmark competitors, especially for output, inflation and real equity prices. Further forecasting results and discussions are presented in a rejoinder, Pesaran, Schuermann, and Smith (2009b).

Ericsson and Reisman (2012) provide an empirical assessment of the DdPS version of GVAR with an impulse indicator saturation technique, which is a new generic procedure for evaluating parameter constancy. Their results indicate the potential for an improved, more robust specification of the GVAR model.

Forecasting key South African variables with a GVAR is investigated in de Waal and van Eyden (2013a). This paper considers small and large versions of the GVAR model and compares GVAR forecasts with forecasts generated from a vector error correction model (VECM) augmented with foreign variables as well as with univariate benchmarks. De Waal and van Eyden find that modelling the rest-of-the-world economies in a coherent way using the GVAR model can be useful for forecasting domestic variables for South Africa. In particular, they find that forecast performance of the large version of the GVAR model is generally superior to the performance of the customized small GVAR, and that forecasts of both GVAR models tend to be better than the forecasts of the augmented VECM, especially at longer forecast horizons.

Forecasting regional labor markets with GVARs is undertaken in Schanne (2011) using German regional labor market data. Schanne focuses on forecasting different labor market indicators and finds that including information about labor market policies and vacancies, and accounting for the lagged and contemporaneous spatial dependence can improve the forecasts relative to a simple bivariate benchmark model. On the other hand, business cycle indicators seem to help little with labor market predictions.

Conditional forecasting using a mixed conditioning informations set is considered in Bussière, Chudik, and Sestieri (2012), who apply a GVAR model to analyze global trade imbalances. In particular, they compare the growth rates of exports and imports of the 21 countries in the sample during the Great Trade Collapse of 2008-09 with the model's prediction, conditioning on the observed values of real output and real exchange rates. The objective of this exercise is to assess whether the collapse in world trade that took place during 2008-2009 can be rationalized by standard macro explanatory variables (domestic and foreign output as proxies for demand terms and real exchange rates as proxies for relative prices) alone or if other factors may have played a role.

The standard macro explanatory variables alone are found to be quite successful in explaining the collapse of the global trade for most of the economies in the sample. This exercise also uncovers that it is easier to reconcile the Great Trade Collapse of 2008-09 in the case of advanced economies as opposed to emerging economies.

Forecasting of trade imbalances is also considered in Greenwood-Nimmo, Nguyen, and Shin (2012b). They compute both central forecasts and scenario-based probabilistic forecasts for a range of events and account for structural instability by use of country-specific intercept shifts identified by taking into account both statistical evidence and *a priori* knowledge of historic economic conditions and events. The authors find that predictive accuracy of the GVAR model is broadly comparable to that of standard benchmark models over short horizons and superior over longer horizons. Similarly to Bussière, Chudik, and Sestieri (2012), they conclude GVAR models may be a useful forecasting tool for policy institutions.

Forecasting of global growth with GVARs is considered in a number of papers. Chudik, Grossman, and Pesaran (2014) focus on the information content of purchasing manager indices (PMIs) for nowcasting and forecasting of real output growth. Cuaresma et al. (2014) present Bayesian estimates of the GVAR, and report improved forecasts when the GVAR model is based on country models estimated with shrinkage estimators. Forecasting with a Bayesian GVAR is also considered by Hubert (2014), who allows for a time varying variance-covariance structure. Garratt, Lee, and Shields (2014) model real output growth for G7 economies using survey output expectations by Consensus Economics, and find that both cross-country interdependencies and survey data are important for density forecasts of real output growth of G7 economies. Forecasting with a regime-switching GVAR model is considered in Binder and Gross (2013) who find that combining the regime-switching and the GVAR methodology improves out-of-sample forecast accuracy significantly in an application to real GDP, price inflation, and stock prices.

8.2 Global finance applications

The first GVAR model in the literature, developed by PSW, is applied to the problem of credit risk modelling with a global perspective. PSW investigate the effects of various global risk scenarios on a bank's loan portfolio. The use of a GVAR model for modelling credit risk has also been explored in Pesaran, Schuermann, and Treutler (2007) who investigated the potential for portfolio diversification across industry sectors and across different countries and find that full firm-level parameter heterogeneity along with credit rating information matters a great deal for capturing differences in simulated credit loss distributions. Further results on the modelling of credit risk with a global perspective are provided by Pesaran, Schuermann, Treutler, and Weiner (2006). The GVAR-based conditional credit loss distribution is used, for example, to compute the effects of a hypothetical negative equity price shock in Southeast Asia on the loss distribution of a credit portfolio with global exposures over one or more quarters ahead. Pesaran, Schuermann, Treutler, and Weiner (2006) find that the effects of such shocks on losses are asymmetric and non-proportional, reflecting the highly nonlinear nature of the credit risk model. de Wet, van Eyden, and Gupta (2009) develop a South African-specific component of the GVAR model for the purpose of credit portfolio management in South Africa. Their set of domestic factors for South Africa is extended beyond those used in PSW in such a way to take into account both retail and corporate credit risk. Castrén, Dées, and Zaher (2010) use a GVAR model to analyze the behavior of euro area corporate sector probabilities of default under a wide range of shocks. They link the core GVAR model with a satellite equation for firm-level Expected Default Frequencies (EDFs) and find that, at the aggregate level, the median EDFs react most to shocks to GDP, exchange rate, oil prices and equity prices.

A number of other empirical GVAR papers focus on modelling various types of risk (sovereign, non-financial corporate or banking sector risks). Favero (2013) focuses on sovereign risk and, in particular, models time-varying interdependence among 10-year sovereign bond spreads of euro area member states in a GVAR. Gray, Gross, Paredes, and Sydow (2013) analyze interactions between banking sector risk, sovereign risk, corporate sector risk, real economic activity, and credit growth for 15 European countries and the United States. The goal is to analyze the impact and spillover effects of shocks and to help identify policies that could mitigate banking system failures, sovereign credit risk and recession risk policies including bank capital increases, purchase of sovereign debt, and guarantees. Alessandri, Gai, Kapadia, Mora, and Puhr (2009) develop a quantitative framework for evaluating systemic risk due to banks' balance sheets which also allows for macro credit risk, interest income risk, market risk, and asset side feedback effects. These authors show that a combination of extreme credit and trading losses can precipitate widespread defaults and trigger contagious default associated with network effects and fire sales of distressed assets. Chen, Gray, N'Diaye, Oura, and Tamirisa (2010) investigate how bank and corporate default risks are transmitted internationally. They find strong macro-financial linkages within domestic economies as well as globally, and report significant global spillover effects when originating from an important economy.

Dreger and Wolters (2011) investigate the implications of an increase in liquidity in the years preceding the global financial crises on the formation of price bubbles in asset markets. They find that the link between liquidity and asset prices seems fragile and far from being obvious. Implications of liquidity shocks and their transmission are also investigated in Chudik and Fratzscher (2011). In addition to liquidity shocks, Chudik and Fratzscher (2011) identify risk shocks and find that while liquidity shocks have had a more severe impact on advanced economies during the recent global financial crisis, it was mainly the decline in risk appetite that affected emerging market economies. The tightening of financial conditions was a key transmission channel for advanced economies, whereas for emerging markets it was mainly the real side of the economy that suffered. Effects of risk shocks are also scrutinized in Bussière, Chudik, and Mehl (2011) for a monthly panel of real effective exchange rates featuring 62 countries. Bussière, Chudik, and Mehl (2011) find that the responses of real effective exchange rates of euro area countries to a global risk aversion shock after the creation of euro have been similar to the effects of such shocks on Italy, Portugal or Spain before the European monetary union, i.e. of economies in the euro area's periphery. Moreover, their findings suggest that the divergence in external competitiveness among euro area countries over the past decade, which is at the core of today's debate on the future of the euro area, is more likely due to country-specific shocks rather than to global shocks. Dovern and van Roye (2013) use a GVAR model to study the international transmission of financial stress and its effects on economic activity and find that financial stress is quickly transmitted internationally. Moreover, they find that financial stress has a lagged but persistent negative effect on economic activity, and that economic slowdowns tend to limited financial stress.

Gross and Kok (2013) use a mixed cross-section (23 countries and 41 international banks) GVAR specification to investigate contagion among sovereigns and private banks. They find that spill-over potential in the credit default swap (CDS) market was particularly pronounced in 2008 and more recently in 2011-12. Moreover, contagion primarily tended to move from banks to sovereigns in 2008, whereas the direction seems to have been reversed in 2011-12 in the course of the sovereign debt crisis. Last but not least, their results indicate that the system of banks and sovereigns has become more closely connected over time.

Interrelation between volatility in financial markets on macroeconomic dynamics is investigated in Cesa-Bianchi, Pesaran, and Rebucci (2014), who augment the GVAR model of DdPS with a global volatility module. Assuming that news (represented by unobserved factors) affect financial markets more quickly than the real economy and making use of the GVAR structure, Cesa-Bianchi, Pesaran, and Rebucci (2014) find a statistically significant and economically sizable impact of future output growth on current volatility, and no effect of an exogenous change in volatility on the business cycle over and above those driven by the common factors. They interpret this evidence as suggesting that volatility is a symptom rather than a cause of economic instability.

Implication of global financial conditions on individual economies is also the object of a study by Georgiadis and Mehl (2014), but with a very different focus than earlier studies, which mostly focus on transmission of financial risk. Georgiadis and Mehl (2014) investigate the hypothesis that global financial cycles determine domestic financial conditions regardless of an economy' exchange regime. Using a quarterly sample for 59 economies spanning 1999Q1:2009Q4 period, the authors reject this hypothesis and find that the classic Mundell-Flemming trilema remains valid, despite the extent of financial globalization since the 1990s.

8.3 Global macroeconomic applications

DdPS update the PSW GVAR model by expanding the country coverage (to 33 with 25 of these modelled separately and the remaining countries grouped into a single euro area economy) as well as the time coverage, and provide further theoretical results, some of which were reviewed above. Their focus is on the enhancement of the global model and its use to analyze transmission of shocks across countries with a particular attention on the implications for the euro area economy. Using a variety of shocks, including shocks to US equity prices, oil prices, US short-term interest rates, as well as US monetary policy shocks (identified by using partial ordering of variables), DdPS find that financial shocks are transmitted relatively rapidly and often get amplified as they travel from US to euro area. The impact of US monetary policy shocks on euro area is, however, rather limited.

8.3.1 Global inflation

Galesi and Lombardi (2009) study the effects of oil and food price shocks on inflation. They find that the inflationary effects of oil price shocks are felt mostly in the developed countries while less sizeable effects are observed in the case of emerging economies. Moreover, food price increases also have significant inflationary direct effects, especially for emerging economies, and significant second-round effects are reported in a number of other countries. Inflation is also the focus of Anderton, Galesi, Lombardi, and di Mauro (2010) who construct a GVAR model to examine oil price shocks and other key factors affecting global inflation. They consider calculating the impact of increased imports from low-cost countries on manufacturing import prices and estimate Phillips curves in order to shed light on whether the inflationary process in OECD countries has changed over time. They find that there seem to be various significant pressures on global trade prices and labor markets associated with structural factors, and argue that these are partly due to globalization which, in addition to changes in monetary policy, seem to be behind some of the changes in the inflationary process over the period under consideration.

Using the GVAR model, Dées, Pesaran, Smith, and Smith (2009) provide estimates of New Keynesian Phillips Curves (NKPC) for eight developed industrial countries and discuss the weak instrument problem and the characterization of the steady-states. It is shown that the GVAR generates global factors that are valid instruments and help alleviate the weak instrument problem. The use of foreign variables as instruments is found to substantially increase the precision of the estimates of the output coefficient in the NKPC equations. Moreover, it is argued that the GVAR steady-states perform better than the Hodrick-Prescott (HP) measure. Unlike HP, the GVAR measures of the steady-states are coherent and reflect long-run structural relationships within as well as across countries.

8.3.2 Global imbalances and exchange rate misalignments

The effects of demand shocks and shocks to relative prices on global imbalances are examined in Bussière, Chudik, and Sestieri (2012), using a GVAR model of global trade flows. Their results indicate that changes in domestic and foreign demand have a much stronger effect on trade flows as compared to changes in relative trade prices. Using the GVAR approach, global imbalances are also investigated, although with a different focus, in Bettendorf (2012). Estimating exchange rate misalignments using a GVAR model is undertaken in Marçal, Zimmermann, Prince, and Merlin (2014). This paper contrasts GVAR-based measures of misalignment with traditional time series estimates that treat individual countries as separate units. Large differences between a GVAR and more traditional time series estimates are reported, especially for small and developing countries.

8.3.3 Role of US as a dominant economy

The role of the US as a dominant economy in the global economy is examined in Chudik and Smith (2013) by comparing two models: one that treats the US as a globally dominant economy, and a standard version of the GVAR model that does not separate the impact of US variables from the cross-section averages of foreign economies, as in DdPS. They find some support for the extended version of the GVAR model. The role of the US as a dominant economy is also investigated by Dées and Saint-Guilhem (2011) who find that the role of the US is somewhat diminished over time.

8.3.4 Business cycle synchronization and rising role of China in the world economy

Dreger and Zhang (2013) investigate interdependence of business cycles in China and industrial countries and study the effects of shocks to the Chinese economy, particularly stemming from recent fiscal stimulus packages.Cesa-Bianchi, Pesaran, Rebucci, and Xu (2012) investigate the interdependence between China, Latin America and the world economy. Feldkircher and Korhonen (2014) consider the effects of the rise of China on emerging markets in particular. All these studies find a significant degree of business cycle synchronization in the world economy with the effects of Chinese economy rising on both advanced and emerging economies. Cesa-Bianchi, Pesaran, Rebucci, and Xu (2012), using a GVAR model with time-varying trade weights, find that the long-term impact of a China GDP shock on typical Latin American economies has increased by three-fold since the mid-1990s, and the long-term impact of a US GDP shock has halved. Feldkircher and Korhonen (2014) find that a 1% shock to Chinese output translates to a permanent increase of 1.2% in Chinese real GDP and a 0.1% to 0.5% rise in output in the case of large economies. The countries of Central Eastern Europe and the former Commonwealth of Independent States also experience an output rise of 0.2%, while countries in Southeastern Europe see a permanent 0.1% reduction in output. By contrast China seems to be little affected by shocks to the US economy.

Boschi and Girardi (2011) investigate the business cycle in Latin America using a 9 country/region version of the GVAR, and quantify the relative contribution of domestic, regional and international factors to the fluctuation of domestic output in Latin American countries. In particular, they find that only a modest proportion of Latin America countries' domestic output variability is explained by industrial countries' factors and that domestic and regional factors account for the main share of output variability at all simulation horizons.

International linkages of the Korean economy are investigated in Greenwood-Nimmo, Nguyen, and Shin (2012a). They uncover that the real economy and the financial markets are highly sensitive to the oil price changes even though it has little effect on inflation and that the interest rate is set largely without recourse to overseas conditions except to the extent that they are captured by the exchange rate. They find that the Korean economy is most affected by US, the eurozone, Japan and China.

Understanding interlinkages between emerging Europe and the global economy is investigated in Feldkircher (2013) who develop a GVAR model covering 43 countries. The main findings are that emerging Europe's real economy reacts to a US output shock as strongly as it does to a corresponding euro area shock. Moreover, Feldkircher (2013) uncovers a negative effect of tightening in the euro area's short-term interest rate on output in the long-run throughout the Central, Eastern and Southeastern Europe and the Commonwealth of Independent States.

Sun, Heinz, and Ho (2013) use the GVAR approach with combined trade and financial weights to investigate cross-country linkages in Europe. Their findings show strong co-movements in output growth and interest rates but weaker linkages between inflation and real credit growth within Europe.

The impact of foreign shocks on South Africa is studied in de Waal and van Eyden (2013b). Using time-varying weights they uncover increasing role of China and decreasing role of the US, reflecting the substantial increase in South Africa's trade with China since the mid-1990s. The impact of a US shock on South African GDP is found to be insignificant by 2009, whereas impact of a shock to Chinese GDP on South African GDP is found to be three times stronger in 2009 than in 1995. These findings are in line with the way the global crisis of 2007-09 affected South Africa, and highlight increased risk to the South African economy from shocks to Chinese economy.

Spillovers from shocks in systemic economies (China, euro area, and the US) to the Middle

East and North Africa (MENA) region as well as spillovers from shocks in MENA oil exporters and Gulf Cooperation Countries to the rest of the world are estimated in a GVAR model by Cashin, Mohaddes, and Raissi (2014b). These results show in particular sensitivity of MENA countries to shocks in China, in line with an increasing role of China in the global economy.

8.3.5 Impact of EMU membership

Two papers, Pesaran, Smith, and Smith (2007) and Dubois, Hericourt, and Mignon (2009) investigate counterfactual scenarios of a monetary union membership. Pesaran, Smith, and Smith (2007) analyze counterfactual scenarios using a GVAR macroeconometric model and investigate empirically the consequences of a scenario had UK joined Euro in 1999. They report probability estimates that output could have been higher and prices lower in the UK and in the euro area as a result of the entry. They also examine the sensitivity of these results to a variety of assumptions about UK entry. The aim of Dubois, Hericourt, and Mignon (2009) is to answer the counterfactual question of the consequences of no euro launch in 1999. They find that monetary unification promoted lower interest rates and higher output in most euro area economies, relative to a situation where national monetary policies would have followed a German-type monetary policy. An opposite picture emerges if national monetary policies had adopted British monetary preferences after September 1992.

8.3.6 Commodity price models

Gutierrez and Piras (2013) construct a GVAR model of the global wheat market, where the feedback between the real and the financial sectors, and also the link between food and energy prices are taken into account. Their impulse response analysis reveals that a negative shock to wheat consumption, an increase in oil prices, and real exchange rate devaluation all have inflationary effects on wheat export prices, although their impacts are different across the main wheat export countries.

While oil prices are included in the majority of GVAR models as an important observed common factor, these studies generally do not focus on the nature of oil shocks and their effects. Identification of oil price shocks is attempted in Chudik and Fidora (2012) and Cashin, Mohaddes, Raissi, and Raissi (2014). Both papers argue that the cross-section dimension can help in the identification of (global) oil shocks and exploit sign restrictions for identification. The former paper investigates the effects supply-induced oil price increases on aggregate output and real effective exchange rates and find that adverse oil supply shocks have significant negative impacts on real output growth of oil importers within which emerging markets tend to be more affected as compared to the more mature economies. Moreover, oil supply shocks tend to cause an appreciation (depreciation) of oil exporters' (oil importers') real effective exchange rates but also lead to an appreciation of the U.S. dollar. Cashin, Mohaddes, Raissi, and Raissi (2014) identify demand as well as supply shocks and find that economic consequences of the two types of shocks are very different. They also find negative impacts of adverse oil supply shocks for energy importers, while the impacts on oil exporters that possess large proven oil/gas reserves is positive. A positive oil-demand shock, on the other hand, is found to be associated with long-run inflationary pressures, an increase in real output, a rise in interest rates, and a fall in equity prices in almost all countries in their sample.

Impact of the commodity price boom over the past decade and its mild cooling since 2001 on the output growth in Latin America and the Caribbean is estimated in a GVAR model by Gruss (2014). It is found that, even if commodity prices remain unchanged at their high levels, the growth in the commodity exporting region would be significantly lower than during the commodity price boom period.

8.3.7 Housing

Hiebert and Vansteenkiste (2009) adopt the GVAR approach to investigate house price spillovers across euro area countries, using three housing demand variables: real house prices, real per capita disposable income, and the real interest rate for 10 euro area countries. Their results suggest limited house price spillovers in the euro area, in contrast with the impacts of a shock to domestic long-term interest rates, with the latter causing a permanent shift in house prices after around 3 years. Moreover, house price spillovers are found to be quite heterogenous across countries.

Jannsen (2010) investigates the international effects of housing crises, focusing on US, Great Britain, Spain and France. Among other findings, Jannsen's results show that on average a housing crisis has the most severe effects in the first two years - particularly between the fifth and the seventh quarter after the house prices have reached their peak, and the output gap is not expected to close within five years. However, when several important industrial countries face a housing bust at the same time, economic activity in other countries is likely to be dampened as well via international transmission effects, leading to significant losses of GDP growth in a number of countries, notably in Europe.

8.3.8 Effects of fiscal and monetary policy

There are a number of studies that use the GVAR approach to examine the international effects of the fiscal policy shocks. Favero, Giavazzi, and Perego (2011) highlight the heterogenous nature of the fiscal policy multipliers and show that the effects of the fiscal shocks on output differ depending on the nature of the debt dynamics, the degree of openness of the economies under consideration, and the fiscal reaction functions across countries. Hebous and Zimmermann (2013) estimate spillovers of a fiscal shock in one euro area member country on the rest, and find that positive effects of area-wide fiscal shocks are larger than those of the domestic shocks of comparable magnitude, and thus coordinated fiscal action is likely to be more effective.

Cross-country effects of monetary policy are investigated by Georgiadis (2014a) who study the global spillovers from US monetary policy shocks. The issue of the transmission of euro area monetary policy across the euro area member states is investigated in a related paper (Georgiadis (2014b)). In both papers, monetary policy shocks are identified by sign restrictions. Georgiadis finds that the effects of US monetary policy shocks on aggregate output are heterogenous across countries with the foreign output effects larger than the domestic effects for many of the economies in the global economy. Substantial heterogeneity is also observed in the transmission of euro area monetary policy shocks, where countries with more wage and fewer unemployment rigidities are found to exhibit stronger output effects.

Role of the US monetary policy shocks is also examined in Feldkircher and Huber (2014), who in addition to monetary policy shocks, also identify the US aggregate demand and supply shocks in a Bayesian version of the GVAR model. Among, the variety of interesting findings reported in Feldkircher and Huber (2014), the US monetary policy shocks are found to have most pronounced effects on real output internationally.

8.3.9 Labor market

GVAR model developed by Hiebert and Vansteenkiste (2010) is used to analyze spillovers in the labor market in the US. Using data on 12 manufacturing industries over the period 1977-2003, Hiebert and Vansteenkiste (2010) analyze responses of a standard set of labor-market related variables (employment, real compensation, productivity and capital stock) to exogenous factors (such as a sector-specific measure of trade openness or a common technology shock), along with industry spillovers using sector-specific manufacturing-wide measures. Their findings indicate that increased trade openness negatively affects real compensation, has negligible employment effects and leads to higher labor productivity. The impacts of technology shocks are found to have significantly positive effects on both real compensation and employment.

8.3.10 Role of credit

The role of credit in the international business cycles is investigated using a GVAR approach in Eickmeier and Ng (2011), Xu (2012) and Konstantakis and Michaelides (2014). The first paper focuses on the transmission of credit supply shocks in the US, the euro area and Japan. Using sign restrictions on the short-run impulse responses to financial shocks that have the effect of reducing credit supply to the private sector, Eickmeier and Ng (2011) find that negative US credit supply shocks have stronger negative effects on domestic and foreign GDP, compared to credit supply shocks from the euro area and Japan. Domestic and foreign credit and equity markets respond to the credit supply shocks as well, and exchange rate responses are consistent with a flight to quality to the US dollar. Xu (2012) also investigates the effects of the US credit shocks and the importance of credit in explaining business cycle fluctuations. Her findings reveal the importance of bank credit in explaining output growth, changes in inflation and long term interest rates in countries with developed banking sector. Using GIRFs she finds strong evidence of the spillover of US credit shocks to the UK, the Euro area, Japan and other industrialized economies. Konstantakis and Michaelides (2014) use the GVAR approach to model output and debt fluctuations in the US and the EU15 economies. They analyze the transmission of shocks to debt and GDP using GIRFs and find that the EU15 economy is more vulnerable to foreign shocks as compared to the US. Moreover, the effects of a shock to the US debt has a significant and persistent impact on the EU15 and US economies, whereas a shock to EU15 debt does not have a statistically significant impact on the US economy.

8.3.11 Macroeconomic effects of weather shocks

In a unique study, Cashin, Mohaddes, and Raissi (2014a) investigate macroeconomic impacts of El Niño weather shocks measured by the Southern Oscillation Index (SOI). Arguably, El Niño weather events are exogenous in nature, and have profound impact on the economic performance. SOI is added to a standard GVAR framework as an observable common factor and effects of a shock to SOI on economic variables across the globe are investigated. The authors found considerable heterogeneities in the responses of El Niño weather shocks: some countries experience a short-lived fall in economic activity (Australia, Chile, Indonesia, India, Japan, New Zealand and South Africa), while others experience a growth-enhancing effect (the US and the European region). Some inflationary pressures are observed as well in response to the El Niño weather shocks, due to short-lived commodity price increases.

8.4 Sectoral and other applications

The GVAR approach does not necessarily need to have a country dimension and other cross-section units could be considered. Holly and Petrella (2012) adopt the GVAR approach to model highly disaggregated manufacturing sectors. They uncover that factor demand linkages can be important for the transmission of both sectoral and aggregate shocks.

Vansteenkiste (2007) models regional housing market spillovers in the US. Using state-level data on the 31 largest US states she uncovers strong interregional linkages for both real house prices and real income per capita. Vansteenkiste (2007) also considers the effects of real interest rates shocks on house prices and finds that an increase of 100 basis points in the real 10-year government bond yield results in a relatively small long-run fall in house prices of between 0.5 and 2.5%.

Holly, Pesaran, and Yamagata (2011) investigate adjustment to shocks in a system of UK regional house prices, treating London as a dominant region and linking UK house prices to the international developments via New York house price changes. They show that shocks to house prices in the London region impact other UK regions with a delay, and these lagged effects then echo back to London housing market as the dominant region. They also show that due to close financial inter-linkages between London and New York, house price changes in New York tend to pre-date house price changes in London.

Chudik and Pesaran (2014) use highly disaggregated consumer price category data for Germany, France and Italy to investigate the sources of inflation persistence. They allow for neighborhood effects in their disaggregate GVAR model of consumer price categories, and highlight the importance of the interaction of common factor persistence and dynamic parameter heterogeneity in explaining the slow observed response of aggregate inflation to macroeconomic shocks.

9 Concluding remarks

Although the GVAR approach was originally developed for the purpose of credit risk modelling by Pesaran et al. (2004), it soon became clear that there are numerous possibilities for the application of this approach. Indeed, already there are numerous empirical applications of the GVAR approach developed over the past decade. Moreover, new theoretical insights are provided on the conditions that justify the individual building blocks of the GVAR model in a large N, large T setting where all variables are endogenously determined. Despite these developments, there are still areas that could greatly benefit from future research.

First, a deeper econometric understanding of the GVAR approach as $N, T \xrightarrow{j} \infty$ would be helpful. This includes several different areas, such as a better understanding of cross-country cointegration in high-dimensional VARs when N is large, a more detailed analysis of the consequences of aggregation implicit in the data-shrinkage applied to observations for the rest-of-the-world economies, or linking the GVAR approach to the spatial literature.

The second important area is the integration of the GVAR the DSGE approaches to macroeconometric modelling. Since the GVAR approach provides a coherent reduced form VAR representation of the global economy, and solution of DSGE model is a VAR model, it will be useful to bring the two approaches together. A first step in this direction is provided by Dées, Pesaran, Smith, and Smith (2014), who consider a number of issues, including measurement of steady-states, the specification of short-run country-specific models and the identification and estimation of the model subject to the theoretical constraints required for a determinate rational expectation model. Full integration of the GVAR and the DSGE approaches would require development of N-country open economy DSGE models capable of modelling long-run as well as short-run business cycle movements.

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